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Tesi di Ricerca

The energy requirements for rising adaptation needs: mechanisms and impacts

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Abstract

L'uso di energia può agevolare l'adattamento ai cambiamenti climatici in molti modi, rendendo possibile il mantenimento di standard di vita dignitosi. Tuttavia, la nostra comprensione del fabbisogno energetico come elemento di interazione tra l'adattamento al cambiamento climatico, i sistemi energetici e lo sviluppo sostenibile è limitata, in particolare rispetto all'uso di tecnologie ad alta intensità energetica come il condizionamento dell'aria. La tesi sviluppa e applica un insieme di approcci modellistici ed empirici, per identificare: i) la dimensione del fabbisogno energetico per l'adattamento quando si tiene conto degli aggiustamenti di lungo periodo nei consumi e nei mercati, ii) le implicazioni che l'energia per l'adattamento può avere sugli investimenti e sui costi dal lato dell'offerta di energia, iii) a quali condizioni e in che misura possono sorgere compromessi tra l'energia per l'adattamento, l'efficacia delle politiche di mitigazione e l'ambiente. In primo luogo, sulla base di una nuova revisione sistematica della letteratura, la tesi mostra quali sono le opportunità per migliorare i modelli utilizzati nell'analisi degli scenari di mitigazione. L'armonizzazione del feedback sull'adattamento energetico in un modello di valutazione integrato mostra che le azioni di adattamento energivore possono compromettere il raggiungimento degli obiettivi di contenimento delle emissioni di carbonio, portando a maggiori emissioni di gas serra e di inquinanti atmosferici locali, e a maggiori costi del sistema energetico. Una serie di analisi empiriche chiarisce gli effetti dei cambiamenti climatici sul picco giornaliero della domanda di elettricità in Europa e in India, tenendo conto della crescita endogena delle apparecchiature per la climatizzazione residenziale (AC). Le analisi empiriche sono svolte al fine di migliorare la comprensione e la quantificazione degli impatti, con metodologie che permettono di mantenere un elevato dettaglio temporale e spaziale. Infine, le analisi sviluppate si soffermano su un tema trasversale alla letteratura relativa alla stime degli impatti del cambiamento climatico: la determinazione di stime empiriche capaci di misurare l'effetto di lungo periodo dell'adattamento attraverso la scomposizione tra effetti metereologici transitori e cambiamenti di lungo periodo nel clima.

Abstract

Energy can power adaptation to climate change in many ways, making it possible to maintain decent living standards and comfortable spaces. Yet, our understanding of the energy requirements as a channel of interaction between the impacts of adaptation and sustainable development is limited. In particular, little or no quantification can be found on the trade-offs between adapting through the use of energy-intensive technologies such as air-conditioning, sustainable development and mitigation to climate change. This thesis develops and applies a portfolio of model-based and empirical approaches to identify: i) the size of the energy requirements for adaptation when long-run adjustments in consumption and markets are accounted for, ii) the implications that energy for adaptation can have on supply-side investments and costs, iii) under what conditions and to what extent tradeoffs between energy for adaptation, mitigation policy effectiveness, and the environment can arise. First, informed by a novel systematic review of the literature, the thesis identifies the opportunities to enhance models used in the analysis of mitigation scenarios, such as the ones reviewed by the IPCC, by using new and differentiated empirical evidence. The harmonization of the energy-adaptation feedback in an integrated assessment model shows that energy-intensive adaptation actions may jeopardize achieving low-carbon targets, as under the current mitigation policies electricity used to cool buildings and industrial processes would require substantial additional capacity for power generation, leading to higher greenhouse gas emissions, local air pollutants, and energy system costs. Ignoring this feedback underestimates the benefits of early mitigation, as the costs to decarbonize the power system in ambitious mitigation scenarios would be lower than previous estimates. In order to enhance the geographical and temporal scope of the impacts with respect to the global integrated assessment, a set of empirical analysis elucidate the effects of mid-century climate change on daily peak electricity demand in Europe and India, accounting for the endogenous growth of residential air-conditioning (AC). The adjustments in AC prevalence over time synergistically amplify electricity consumption, yielding the benefit of reduced exposure to extreme heat at the cost of increased carbon dioxide (CO_2) emissions and associated mitigation challenges in power systems that are not decarbonized. Finally, the empirical analyses focus on a cross-cutting theme in the literature on climate change impacts: the determination of empirical estimates capable of measuring the long-term effect of adaptation through the decomposition between transient meteorological and slowly evolving climate effects.

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1 Introduction

1.1 Background and motivation

Energy demand, for centuries met from the combustion of fossil fuels, has been and still is a primary source of greenhouse gas emissions. Global energy-related CO_2 emissions totaled 33 Gt in 2021, which contributed to CO_2 reaching its highest ever average annual concentration in the atmosphere of 421 parts per million in May 2022 – around 50% higher than when the industrial revolution began [1]. Yet, the connection between energy and the climate system is bilateral. Energy is today a key input to resilience, as many of the adaptation actions that individuals and industries have implemented so far are energy-intensive [2]. Among the Nationally Determined Contributions (NDCs) submitted in the context of the Paris Agreement 20 types of adaptation measures involve energy consumption, 6 of them with the potential to be energy savings, while the other 14 options are more likely to increase energy use [3]. Several energy services make it possible to maintain conditions of thermal comfort across all sectors of the economy under varying weather conditions. Other examples include water pumping, desalinization and water purification [4, 5]. Growing evidence shows that higher temperatures and more frequent and prolonged extremes lead to more electricity for space cooling [6, 7, 8], for refrigeration [9], and for entertainment appliances if people spend more time indoors [10]. While space heating is expected to require less energy [11, 12, 13, 14, 15, 16, 17], the extent and occurrence of cold waves can actually go in the opposite direction [18]. Extreme temperatures also directly affect labour and capital productivity [19], leading industrial and commercial activities to adjust their energy usage as well. The impacts of heat on labor productivity are well-documented [20] and the benefits of air-conditioning on preventing production losses in the manufacturing and service sectors have recently been identified [21]. The performance of equipment, such as data centers, and the mechanical functioning of machines are also sensitive to the surrounding temperature conditions, and high operating temperatures can cause electronic components to lose functionality [22]. These are examples of adaptation actions that would have direct impacts on the energy system, with an ultimate feedback on the climate and the environment.

Among the many adaptation actions available across sectors and regions for cooling indoor environments, air-conditioning (AC) is a technology that has experienced an extensive growth in adoption in recent years. The consumption of electricity for household AC has been growing very rapidly in the last two decades: by more than 12%/year over 2000-2018 in China, India, Indonesia and Turkey, and between 6 to 10%/year in Australia, Brazil, Canada, the European Union [23]. AC now accounts for 10% to 15% of the annual maximum electricity demand in emerging economies with warm climates, such as India, Indonesia and Mexico, while it reaches 30% in richer countries with a higher prevalence, such as the US [24]. Cooling needs are therefore expected to be an increasingly important driver of future energy demand [25].

In its latest assessment, the Intergovernmental Panel on Climate Change (IPCC) reports with high confidence that adaptation actions focusing on sectorial and short-term benefits can lead to maladaptive responses and build up risk over time [26]. There are multiple channels though which adapting by means of energy-intensive technologies may result in forms of maladaptation [27]. Firstly, since low-energy-demand development pathways increase the flexibility needed to achieve low temperature mitigation scenarios and reduce the need for negative emissions [28], energy-intensive adaptation actions may jeopardize achieving low-carbon targets. Secondly, the contemporaneous use of energy-intensive appliances during extreme weather events such as heatwaves may amplify peak power consumption up to levels that exceed system capacity, adversely affecting the grids' reliability and causing power outages at times of high need [29] and eventually resulting in an exacerbation of heat-related heath impacts [30]. This issue is particularly pressing in already vulnerable developing countries, where long-standing infrastructural and new climate change-induced risks may compound.

As the climate warms, the likelihood of such impacts increases with more intensive adoption of AC, which itself responds positively to higher temperatures and increases in per-capita income [31, 32, 33, 34]. Adaptation to climate change though the use of energy-intensive durable stock such as cooling and heating appliances will evolving in the future based on multiple drivers [35]: socio-economic (population expansion, economic growth, shifts in the sectoral composition of economies); behavioural (the actions of individuals and organizations); and technological (pace of technological adoption and development). The lack of comprehensive empirical and model evidence on the combined influence of these drivers gives rise to substantial uncertainties around the mechanisms though which future cooling and heating needs will affect our society and the environment.

1.2 Objectives and research questions

Estimating the potential size of future energy needs for adaptation has important implications for the transition towards sustainability and decarbonized economies. The thesis investigates the mechanisms and impacts of the rising energy requirements for adaptation though a suite of methodologies, approaches and novel datasets, and aims to shed light on several blind spots concerning energy for adaptation. Broadly, the following research questions motivate the work:

- What is the size of the energy for adaptation when long-run adjustments in consumption and markets are accounted for?
- What implications can energy for adaptation have on the energy supply-side, particularly on investments and costs?
- To what extent future AC adoption will be driven by compounding socio-economic and climate effects?
- Under what conditions and to what extent a negative feedback between energy for adaptation, mitigation policy effectiveness and the environment can arise?

From one side, answering these question requires the development of Integrated Assessment Models (IAMs) that harmonize climate impacts and policies in a consistent manner, bringing together two research communities that have traditionally worked in parallel. Despite the growing evidence indicating that adaptation-driven energy use will play an increasingly important role in future energy scenarios, the integrated assessment modeling literature and literature on energy scenarios still fail to account for adaptation-driven energy demand in their scenarios. Most of the IAMs still need to integrate the climate-energy feedback into their assessments. The Illustrative Mitigation Pathways (IMPs) developed by Working Group III do not account for adaptation costs, and we still lack a comprehensive characterization of mitigation pathways in the presence of adaptation actions. As a consequence, we lack a thorough understanding of how an increase in the energy needs for adapting to climate change might affect the economy, energy systems, and the environment in the process of transitioning towards cleaner energy systems, industries and commercial activities. The interplay between energy needs for adaptation and increasingly ambitious mitigation targets remains an understudied topic. There is very limited model-based evidence on the extent to which adaptation to climate change might further feed into the energy and socio-economic system by requiring more energy, and therefore initiate a negative feedback loop. How such an interaction actually plays out varies across regions, and depends on the configuration of the energy system, socioeconomic development, and local climate. The modeling work conducted in this thesis seek to shed light on how adaptation responses to climate change affect energy systems, and therefore the achievement of mitigation goals, as well as their economic costs.

From the other side, the existing empirical assessments of the determinants of the energy used for adaptation across economic sectors and regions provide limited insights. Available studies mostly estimated short-term elasticities based on contemporaneous weather realizations [36, 37, 38]. There are several reasons why coefficients estimating short-term adjustment effects are ill-suited for providing an indication of the impacts of climate change over the medium or long term [39]: adaptation (adjusting among a set of technological opportunities but also through technological change), general equilibrium effects (adjustment of prices and factor reallocations) and intensification of climate effects.

Measuring adaptive behaviours when assessing the relationship between energy demand and thermal comfort is of key importance: adaptation shapes agents' use of energy-intensive durable stock in responses to transitory temperature shocks (henceforth "intensive margin") and agents' new adoption of energy-intensive durable stock in response to the permanent shifts in climate (henceforth "extensive margin") [40]. Adaptation though the extensive margin takes time to influence energy demand because, given the fixity of capital goods in the short-term, actors are constrained in their response to unanticipated weather shocks. Although a narrow group of studies has recently proposed methods for the indirect identification of the long-run effects [41, 42], most of the available empirical studies estimated the sensitivity of energy demand to weather based on the intensive margin [43, 44, 14, 37, 36, 45, 38, 16]. One of the key aspects requiring innovation is therefore the identification of the energy demand adjustments along the extensive margin. In this thesis I assemble novel datasets comprising high-frequency electricity demand statistics and regional-level data on AC prevalence and socio-economic development to conduct new empirical assessments that measure extensive margin adjustments directly over time in a specific location, allowing to control for several unit- and time-specific confounding factors. The empirical works conducted in the thesis seek to understand how different drivers have affected energy demand in the past, in order to provide an indication on the mechanisms at play and to quantify future trajectories of change, taking into account the compound effects that can result from rising exposure to climate change and socio-economic growth.

1.3 Outline

In Chapter 2, I conduct a systematic review that aims to disentangle through which modeling approaches and to what degree, climate change affects future energy demand in the existing projections from leading global Integrated Assessment Models. The key hypothesis I evaluate is whether IAM-based projections under-estimate the building sector's energy demand when energy use is driven solely by income and population and not by changes in climatic conditions and the associated adaptation needs. Furthermore, I evaluate if different modeling approaches affect the results, once climate and socioeconomic heterogeneity of the scenarios have been taken into account. The Chapter evaluates whether and to what extent the following modeling differences affect the energy demand projections: i) the relationship between the energy system and the economy, and their interactions; ii) the detail of the energy sector; iii) the modeling of the relation between climate and space cooling. In order to identify the role of the latter modeling aspect on energy demand projections, I develop a novel classification of the methodological choices concerning the intensive margin (short-run) and extensive margin (long-run) demand responses to weather. The results underscore that models lacking extensive margin adjustments, and models that focus on residential demand, highly underestimate the additional cooling needs of the building sector.

Chapter 3, by integrating the "adaptation-energy feedback loop" into the World Induced Technical Change Hybrid model - WITCH, proposes one of the first modeling frameworks that fully integrates the energy needs for adaptation endogenously into mitigation pathways, so that climate policy design is directly influenced by adaptation energy needs. Such integrated framework goes well beyond the existing literature and makes it possible to analyze how decarbonization and policy design changes when adaptation needs are taken into account.

The model development consists of three novel elements. First, I empirically estimate a reduced-form relationship (statistical emulator) between country-level annual average temperature and the annual occurrence of extreme cold and hot days using historical data. Second, I model the direct relationship between changes in the occurrence of extreme temperature days and the demand for electricity, gas and oil in the residential, commercial, and industrial sectors using empirical estimates from the recent empirical literature. Third, I quantify the impacts of climate-induced changes in final energy use on the energy investments and costs, on the costs of mitigation policies, and on the mitigation co-benefits on air pollution. Findings underscore that climate adaptation considerably affects the shape and the costs of mitigation pathways, and indicate how the design of cost-effective mitigation policies would change.

Chapter 4 builds upon the work conducted in the previous two and proposes a framework that identifies what are the future opportunities and requirements for including the energy-adaptation feedback into IAMs, finding bridges across different research communities. The focal point of the discussion is to what extent IAMs can to be updated though novel empirical results, which are the most pressing blind spots in the empirical literature and the novel insights that could derive from such integration.

Chapter 5 addresses some of the gaps in the empirical literature identified in Chapter 4. Chapter 5 is dividing into three main chapters, each presenting distinct but interrelated empirical analyses.

In the first empirical analysis, I combine historical observations for a rich Europe and a hot India to understand the future expansion in air-conditioning ownership and utilization, driven by increases in future daily maximum temperature, per capita income and urbanization. I empirically analyze the high-frequency intensive margin component of electricity demand, captured by the day-to-day co-variation between peak and total load and maximum daily temperature at different levels of regional AC prevalence. By coupling the reduced form adaptation responses with mid-century projections of changes in daily maximum temperatures alsimulated by 25 Global Climate Models (GCMs) I project the future contribution of the extensive- and intensive-margin, as well as their joint amplifying effect on peak and total electricity consumption.

Furthermore, in Chapter 5 I propose a set of alternative methodologies that aim to evaluate if the extensive margin can be identified without direct information on AC prevalence. Such frameworks would provide an important contribution as they can shed light on climate impacts in world regions with poor or lacking accounts of AC ownership data. The first alternative methodology replicates the analysis of high-frequency electricity demand in Europe and India by exploiting low-filter variations of income and climate. By doing so, I provide a comparison of the projected impacts of climate change based on alternative empirical specifications. The second alternative methodology applied to a complementary dataset. Monthly and sector-specific electricity demand statistics in Brazil are used to derive a set of reduced-form responses of demand to thermal discomfort though an econometric specification (the Error Correction Model), providing the long-term effects of climatic and socio-economic drivers on electricity consumption. Finally, the last section of Chapter 5 extends the analysis based on low-filter variations of income and climate to a global dataset of annual country-level energy demand and macroeconomic statistics. The empirical analysis developed focuses on two distinct but interrelated cases: i) the relation between energy consumption and temperature across sectors and energy carriers; ii) the relation between income growth and temperature.

Chapter 6 draws the conclusion of the thesis, focusing on the policy implications of the results, on the caveats of the methods and scope of the work presented and on the scope for further research.

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2 Review of IAMs methods and contributions

2.1 Preface

Energy scenarios are predominantly generated by Integrated Assessment Models (IAMs), which describe the relation- ship between human (economy, technology, energy) and natural (climate, environment) systems. Most of these models still need to integrate climate-energy feedback into their assessments. The few studies that have taken into account the climate-energy interactions have typically taken the form of single-model exercises focusing on buildings' energy demand, and have provided projections that are hardly comparable quantitatively to other studies, since each model is based on specific methodological approaches, calibration sources and scenario assumptions.

This Chapter systematically reviews and compares IAMs' quantitative projections of energy demand that include the additional energy use or savings induced by thermal adaptation to heating and cooling needs at a global level. The studies selected are grouped in a novel classification according to different aspects: the details of the energy system, the relationship between energy and the economy, and the technical representation of the specific demand for heating and cooling. Such a first-of-its kind classification makes it possible to systematically understand why the energy projections of different models vary depending on how adaptation needs are modeled.

The proceedings of this Chapter have been published as a Topical Review in Environment Research Letters (ERL), and are co-authored by Enrica De Cian. I conducted the data gathering and analysis and wrote the draft of the manuscript, while Enrica De Cian provided scientific input and contributed to revising the final version of the manuscript [1].

2.2 Introduction

There is broad consensus in the literature about the overall impact that climate change may have on the demand for cooling and heating services, and the energy necessary to deliver them: cooling needs will be an increasingly important driver of future energy demand, while heating requirements are expected to diminish [1, 2]. Several articles have reviewed the literature around the topic: [3, 4] present a summary of the approaches and results of the studies estimating the

[1] The Chapter is derived from: Colelli, Francesco Pietro, and Enrica De Cian. "Cooling demand in integrated assessment models: a methodological review." Environmental Research Letters 15.11 (2020): 113005.

impacts of climate change on energy demand, but do not include a detailed analysis of the estimates and methodologies of the studies adopting engineering and/or energy models in IAMs; [5] presents the different modeling approaches for estimating cooling and heating demand in IAMs, and the macro-economic results across the literature, but do not include a quantitative comparison of heating and cooling projections or an evaluation of the possible factors driving the heterogeneous results of models. [6] report total energy projections of over 200 integrated assessment model scenarios, without identifying the additional contribution of climate change across climate scenarios, and do not provide detailed insight on the reasons behind the heterogeneous results of different models'. [7] conduct an analysis of the literature's projections by presenting a qualitative assessment of the projected sign of the variation in energy demand, while do not quantify the magnitude of the variations obtained by different IAM models at global and regional levels. Finally, [2] conduct a systematic analysis of results from 220 papers on potential impacts of climate change on the energy system. Regarding heating and cooling needs, they come to a general conclusion regarding the expected sign of future change, but they do not analyze the mechanisms and the heterogeneities across models, since the Chapter aims at a more general assessment of the vulnerability of the overall energy sector.

Despite such evidence, there is a lack of systematic, detailed analysis of IAMs' results in quantifying and comparing the magnitude of future cooling and heating demand projections. The following analysis includes only the IAMs that have explicitly addressed heating and cooling needs with the objective of (i) reviewing the methodological approaches used, (ii) highlighting their importance for the economy and the environment, (iii) identifying the main sources of variation and heterogeneity that should be addressed by future studies. Results show that projections underestimate the building sector's energy demand when energy use is driven solely by income and population drivers and not by changing climatic conditions and subsequently by rising adaptation needs. Models lacking extensive margin adjustments highly underestimate the additional cooling needs of the building sector. The review also highlights the much larger uncertainty that characterizes the commercial sector, which often, due to the lack of specific data or evidence, is modeled similarly to the residential sector.

The remainder of the Chapter is organized as follows. Section 2.3 describes the methodology used for identifying, selecting, and classifying the literature. Section 2.4 presents in detail the major methodological approaches used to model heating and cooling demand. Section 2.5 presents the results and a critique of the implications and the sources of variations. Section 2.6

concludes and offers suggestions for future research.

2.3 Methods

In order to identify the IAM-based studies that have evaluated the long-term potential impacts of thermal adaptation on the energy sector and that simultaneously take into account climate and socioeconomic changes, a three-stage literature review procedure is adopted (Figure 1). Previous reviews are analyzed in order to investigate the major gaps in the literature, and to develop the review's topics accordingly (Phase 1 in Figure 1). At this stage, the studies that model cooling and heating demand without considering climate change impacts (such as [8, 9] or that are based on regional assessments: [10, 11, 12] for the US, [13] for Europe, [14] for China and [15] for developing countries) are excluded. These initial screening criteria are adopted in order to restrict the analysis to a comparable set of IAM-based projections, so as to facilitate the investigation of the main drivers affecting the models' results. Two review topics are identified: a projection of the energy demand of future buildings due to changes in heating and cooling thermal-comfort adaptation at the global level, projections of the ex-post macroeconomic impacts at the global level of changes in the energy demand of buildings in heating and cooling. The collection of publication data was obtained by adopting different methods (Phase 2 in Figure 1). First, a set of keywords is combined and used for searching on the Elsevier Scopus database (see Supplementary Material).

Second the search is extended to Google Scholar to identify peer-review articles from journals that were not indexed in the Elsevier Scopus database. Third, citation tracing is adopted to supplement the database search. Both forward tracing and backward tracing of seminal papers (such as [16] and key literature review papers on the them [3, 17, 7] is adopted. This approach makes it possible to identify the main group of IAM-based studies to be reviewed, in order and to identify the empirical studies adopted by such works in calibrating their models. Finally, in order to include also the contributions from the grey literature, the studies available from Institutional Websites of the key organizations such as the International Energy Agency (IEA) and the Energy Information Administration (EIA) are included. The resulting publications are filtered through an analysis of the titles and abstracts based on subjective selection criteria. Only studies with a global focus are retained. In order to accept data as evidence, include it in the analysis, and add each study's projections to the dataset, a further filtering procedure is adopted (Phase 3 in figure 1): only those articles presenting a clear definition of the methodology

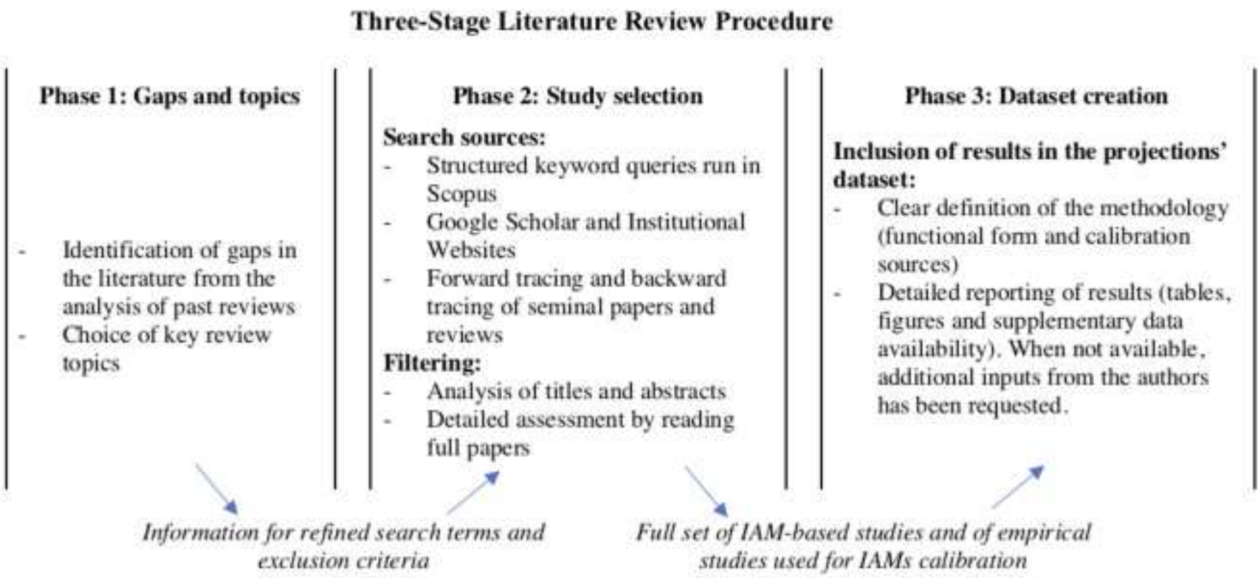

Figure 1. Overview of the literature review procedure..

adopted and a detailed enough description of the results obtained are included in the final set of studies. Additional inputs from the authors were requested when needed. As a result of such combined search and filtering procedure, 14 publications which constitute the main group of IAM-based articles analyzed are identified. Projections of energy demand and macroeconomic impacts retrieved from the selected studies are classified on the basis of the socio-economic and climate assumptions adopted. Such data analysis could make it possible to assemble a database of global energy demand projections including 88 model runs (69 of which on energy demand and 19 of which on the macroeconomic impacts of variations in energy demand). Each model run is characterized by different socioeconomic and climate assumptions and providing information for a combination of sectors (residential, commercial), end-uses (cooling, heating) and years (2050, 2100), for a total of more than 350 combinations [2].

2.4 Classification

Available classifications of IAMs' methodological framework [18] provide a useful guide for distinguishing the overall aim and key underlying mechanisms of different models, but they are too general to shed light on how the modeling of the feedback between energy demand and climate change can affect energy projections. In order to investigate how different modeling approaches can affect energy demand projections, the methodologies adopted by the studies identified are

[2] available as Supplementary Data in 2020 Colelli and De Cian, Environ. Res. Lett. 15 113005

classified into a novel set of categories, based on three modeling aspects: the representation of the economy; the representation of the energy sector; the climate transmission to the energy sector.

2.4.1 Economy

The relationship between the energy system and the economy can be modeled: (i) in a partial equilibrium (PE) fashion, with models representing only the energy or building sector; (ii) considering the general equilibrium (GE) interactions and representing the interaction between the energy sector and all other sectors.

2.4.2 Energy sector

The energy sector can be modeled through: (i) process-based, bottom-up simulations, in which engineering bottom-up models are applied to simulate the energy performance of building archetypes, and to forecast specific end uses or top-down simulations; (ii) top–down models which do not articulate end-use services, but rely on aggregate national statistics and macroeconomic drivers to obtain empirically reduced-form responses of energy demand. GE approaches generally use projections from top-down simulation as inputs or shocks to exogenously perturbate the final energy demand in the CGE model. Bottom-up simulations can be further divided in relation to the type of model used to study heating and cooling energy demand: energy system models and energy demand models. Energy system models cover both demand and supply and are a comprehensive representation of the energy sector. The energy system models enable a technology-rich, bottom-up analysis of the global energy system. Energy demand models rely on aggregate end-use energy functions describing the relationships between energy demand and underlying socio-economic factors, with different geographical scopes, end-uses and carriers. Most studies rely on multi-model frameworks that couple a GE model or an integrated assessment framework with a more detailed energy or building sector bottom-up model.

2.4.3 Transmission of climate shocks to final energy demand

The literature identifies two separate mechanisms through which climate shocks are transmitted to energy demand [17, 19]: short-term demand responses to weather (henceforth ‘intensive margin’) and long-term demand responses driven by an increase in the prevalence of air conditioner appliances (henceforth ‘extensive margin’). The short-term intensive margin transmission of weather conditions to energy demand characterizes both cooling and heating services in a similar way. Yet, long-term adjustments due to appliance prevalence have usually been considered explicitly only for cooling services, on the assumption that saturation of heating appliances has already occurred across the world. While extensive margin adjustments amplify demand for cooling services due to the utilization of newly acquired appliances, capital stock replacement of heating appliances, under the hypothesis that more efficient appliances will replace less efficient ones, would reduce the energy demand per unit of calorific output. The approaches used to model the ‘intensive margin’ can be schematized in two different categories: (i) scaling factor; (ii) exogenous shift parameter. The ‘scaling factor’ approach involves including, in the energy demand function for the thermal adaptation ($EDCC_{t,r,s}$), a multiplicative term based on the variation in the future climate variable ($CLIM^{fut}_{t,r,s}$) with respect to the historical climate ($CLIM^{hist}_{r,s}$), equation 59). In some cases, the scaling factor includes an empirically estimated parameter $\beta_{r,s}$ that modulates the proportional variation in the climate indicator, either in a linear (equation 58) or an exponential fashion (equation 59):

$$EDCC_{t,r,s} = \beta_{r,s} \frac{CLIM^{fut}_{t,r,s}}{CLIM^{hist}_{r,s}} ED_{t,r,s} \tag{1}$$

$$EDCC_{t,r,s} = (\frac{CLIM^{fut}_{t,r,s}}{CLIM^{hist}_{r,s}})^{\beta}_{r,s} ED_{t,r,s} \tag{2}$$

where:

s service; t time step; r region

Equations (1a)–(1b) are the most commonly used approach that is found both in the engineering and end-use demand models—they add the scaling factor to the building energy consumption model [20, 1, 21], and by energy system bottom-up analyses—they add the scaling factor to their stylized income– demand relationship [16],[22, 23, 24] Equation (3a) is adopted by [25], while equation (3b) is adopted by [26].

The climate variables most commonly used to capture thermal stress are cooling degree days (CDDs) and heating degree days (HDDs). The CDDs (HDDs) are defined as the number of degrees above (below) the thermal comfort threshold, measured in terms of day count [27]. When scaling factor method relies on the computation of CDDs and HDDs from the historical and future mean air temperature, the increase in energy demand across different warming scenarios therefore will depend on two transmission mechanisms: (1) how mean temperature increases affect CDDs and HDDs; (2) how variations in the CDDs and HDDs affect the cooling and heating demand via the scaling factors (Equations 1 and 3). Therefore, if the relationship between mean temperature and degree days is non-linear (Mourshed 2012), the relationship between temperature and energy demand is also non-linear, even when models include a simple proportional factor between energy and degree days.

The 'exogenous shift parameters' approach varies key model parameters of the energy demand function, on the basis of coefficients estimated empirically with historical data. This approach entails a different representation of the responses to climate shocks with respect to the 'scaling factor'. First, elasticities are differentiated by fuel type (typically oil, gas and electricity) rather than by end-user service. A fuel-specific coefficient provides a measure of the shock that compounds the contribution of different thermal adaptation services. Second, climate indicators used by empirical studies are more commonly mean temperature levels [28] or temperature bins [29], rather than CDDs and HDDs. A V-shaped or a linearspline response function of energy demand to climate (figure 3) makes it possible to associate the coefficients of low temperature levels or bins to heating requirements, while cooling needs are associated with the coefficients related to high temperature levels or bins. Within this approach, a climate change impact shock Ψ is obtained by combining the estimated coefficients β with exposure under historical ($\widetilde{CLIM}_{c,t}^{Hist}$) and future ($\widetilde{CLIM}_{c,t}^{Fut}$) climate (equation(4a)). The resulting shock is applied to energy demand without climate change (ED) to obtain demand with climate change ($EDCC$):

$$\Psi_{f,t,r} = \{[(\frac{exp(\beta_{f,r}^{\hat{CLIM}} \cdot \widetilde{CLIM}_{r,t}^{Fut})}{exp(\beta_{f,r}^{\hat{CLIM}} \cdot \widetilde{CLIM}_{r,t}^{Hist})})] - 1\} \cdot 100 \qquad (3)$$

where:

f fuel; t time step; r region

Computable GE (CGE) models [30, 31, 32] have used climate-induced shocks on energy demand, such as those estimated by [28, 29], or by [33] to calibrate the exogenous shifts in their models. It is important to distinguish between the empirical studies estimating those shocks, which are top-down PE studies that do not take price adjustments into account, and the CGE modeling studies, which are top-down assessments that explicitly account for GE adjustments. The parameter of the response of thermal adaptation to temperature (β) can be estimated by using dynamic models (such as error correction models) that make it possible to identify long-term elasticities, combining the contributions of the intensive and extensive margins in a single parameter. In this manner, modeling studies using exogenous shifts calibrated on long-term elasticities implicitly account for the prevalence of AC.

The extensive margin has been modeled through a market penetration model that explicitly estimates the market penetration of air-cooling appliances. Most studies ([16, 22, 23, 24, 34, 21]) rely on the two-stage penetration model by [35] and [36], in which Penetration (P) of air-cooling appliances is a function of two components: the Climate Maximum, CM (Figure 2, panel a), which identifies the maximum share of AC adoption modulated by the climate conditions (measured by the CDDs) if no income constraint existed; and Availability, AV (Figure 2, panel a), which identifies the share of the Climate Maximum which is actually achievable given the income level of the population (I). Penetration is defined as the product of these two components (Figure 2, panel b). A few studies rely on other approaches. [1] uses a 'stock model' approach. The modeling of penetration is based on the stock of cooling equipment that is necessary to meet the required energy service demand. Assumptions on average equipment lifetime are applied by using a Weibull distribution to determine the rate at which each equipment category diminishes over time. Annual sales volumes and corresponding energy performance assumptions are calculated with respect to remaining stock and energy service demand in a given year. [26] model the extensive margin as a unitless calibration coefficient, modulating the per capita energy service demand per unit of HDD/CDD and floorspace (a 'saturation parameter'). A narrow number of studies do not account for extensive margin developments [25, 20].

Whether the way the transmission of climate shocks to thermal adaptation services across different sectors — residential and commercial — is represented in models varies across IAMs. As for the intensive margin, models that rely on the scaling factor assume that a given climate shock identically affects the response of the two sectors. In its most general formulation, the scaling factor approach makes it possible to disentangle the difference between residential and commercial short-term shocks, since a sector-specific modulation parameter can be included in the function. Nevertheless, in all cases analyzed this modulation parameter is either set to unity [20, 23, 24] or assumed to be constant across sectors [26]. As for the extensive margin, the device penetration ratio obtained in the residential sector is generally used for the commercial sector [23, 24]. On the other hand, studies that model transmission via the 'exogenous shift parameters' adopt sector-specific parameters, such as the panel econometric models used for

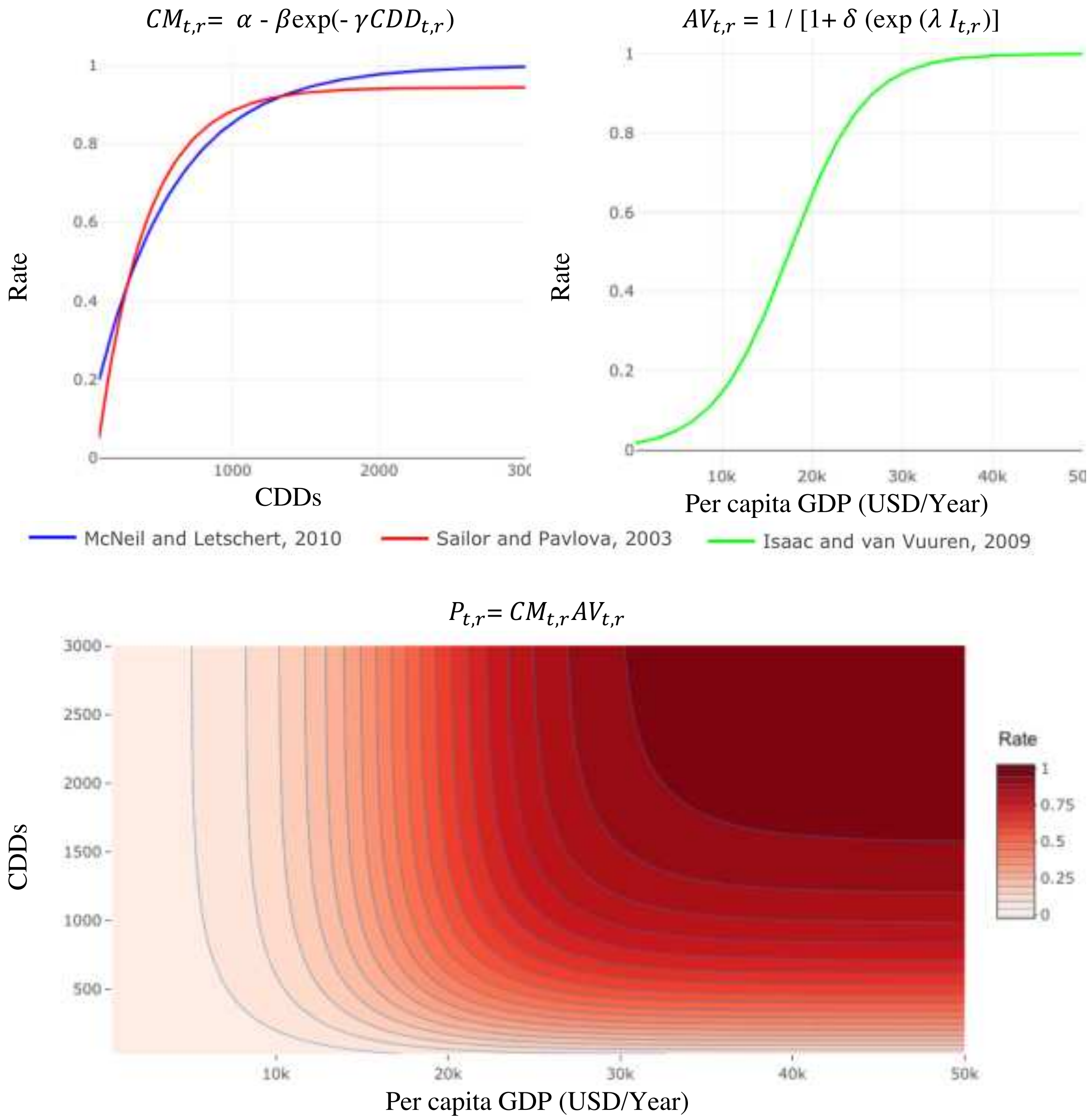

Figure 2. Available air-cooling penetration functions.

calibration estimate of the equations separately for each sector [29].

2.4.4 Combined classification

Table 1 summarizes the resulting classification of the studies reviewed, based on the different modeling characteristics pertaining to the relationship between the economy and the energy system, its level of detail, breaking down the climate feedback of final use of energy into five overall model types. Type 1 models (bottom-up, PE models with a market penetration module for AC) have been adopted most frequently, followed by Type 3 (CGE coupled with a process-based representation of the energy sector and a market penetration module for AC) and Type 5 (top-down CGE simulation approaches deploying exogenous shifts) models. Type 2 models (top-down PE simulation approaches deploying exogenous shifts) have been adopted only by two studies, while Type 4 (CGE coupled with a processbased representation of the energy sector characterizing only the intensive margin) shows the contribution made by a single study. The comparison of consistent scenarios between Types 3 and 4 makes it possible to discern the effect of including the extensive margin in CGE. The comparison of consistent scenarios between Type 2 and Type 5 sheds light on the role of adaptive behaviors induced by changes in prices and interactions across markets.

Table 1: IAMs Classification

Studies	Models	Economy	Energy sector	Intensive margin	Extensive margin	Type
Isaac and van Vuuren (2009); Mima and Criqui (2009); IEA (2018); Levesque *et al* (2018); Arnell *et al* (2019)	TIMER-IMAGE; POLES; IEA ETP; EDGE	Partial eq.	Process-based, bottom-up	Scaling factor	Market penetration	Type 1
De Cian *et al* (2013); van Ruijven *et al* (2019).	–	Partial eq.	Top-down simulation	Exogenous shift parameters		Type 2
Hasegawa *et al* (2016); Park *et al* (2018); Clarke *et al* (2018)	AIM/GCE; GCAM	General eq. (CGE)	Process-based, bottom-up	Scaling factor	Market penetration	Type 3
Labriet *et al* (2015)	TIAM-WORLD GEM-E3	General eq. (CGE)	Process-based, bottom-up	Scaling factor	Not modeled	Type 4
Eboli *et al* (2010); Roson and der Mensbrugghe (2012); Francesco Bosello *et al* (2012)	ICES-POLES; ENVISAGE	General eq. (CGE)	Top-down simulation	Exogenous shift parameters		Type 5

2.5 Analysis of IAM projections

2.5.1 Energy demand for cooling and heating

Model results underscore that at the global level the increases in energy demand driven by higher cooling needs more than compensate for the decreases in energy demand due to lower heating needs. Figure **??** shows the distribution of the results obtained across different climate change scenarios (RCPs[3]) for cooling services, heating services and combinations for all buildings and the residential sector only.

The projections point to an important increase in energy for thermal adaptation as the combination of cooling demand increases and heating demand decreases. The evidence of the increase (decrease) in cooling (heating) demand is consistent across warming scenarios and over time. Depending on the combination of service, sectors, and RCP scenarios, there are important differences in the magnitude of the projections. Uncertainty increases over time, especially in relation to cooling demand when commercial activities are also included. The boxplots show that the range of projection results is much wider for cooling demand than for heating demand and for total building demand than for residential demand.

In the scenario assuming no variations in the climatic conditions, the median total demand for thermal adaptation increases up to 77 (85) EJ and by a factor of 1.30 (1.43) with respect to 2016 (59 EJ), in 2050 (2100). In the low warming scenarios, RCP 1.9 and RCP 2.6, the median total demand increases up to 92–96 (120–130) EJ and by a factor of 1.5–1.6 (2–2.2) in 2050 (2100). In the moderate warming scenario RCP 4.5 the median total demand increases up to 75 (115) EJ and by a factor of 1.26 (1.93) in 2050 (2100). In the high warming scenarios RCP 6 and RCP 8.5 the median total demand increases up to 73–97 (130– 147) EJ and by a factor of 1.23–1.63 (2.2–2.47) in 2050 (2100).

The heterogeneity across SSPs and IAM models is presented in Panel b. Median values of thermal energy demand exhibit moderate variability across SSPs especially for the residential sector and in the first half of the century. Differences across socioeconomic scenarios are instead more evident in the building sector in 2100, for both cooling and heating demand. Overall, heterogeneity across scenarios is more marked when focusing on climate shocks of different magnitude (Panel a), than on socioeconomic scenarios (Panel b). This result points

[3]Different temperature change scenarios have been converted to RCP scenarios by using the median of each RCP range for 2080–2100 in IPCC (2014): 0.3°C to 1.7°C under RCP 2.6, 1.1°C to 2.6°C under RCP 4.5, 1.4°C to 3.1°C under RCP 6.0 and 2.6°C to 4.8°C under RCP 8.5.

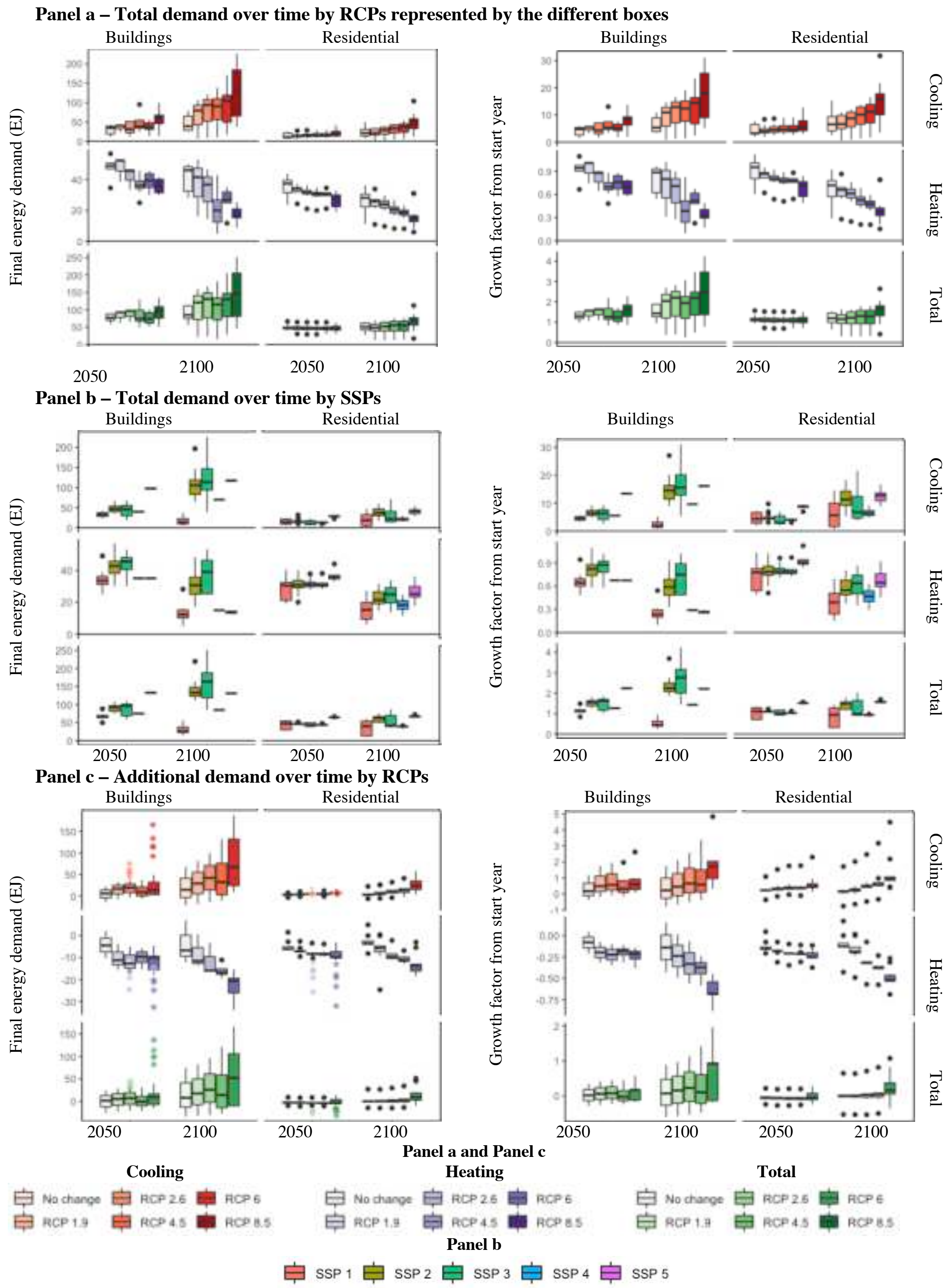

Figure 3. Energy demand of cooling and heating across IAMs by RCP (panel a) and SSPs (Panel b) and additional demand due to climate change (panel c). Data from: [20, 1, 21, 26, 34, 22, 16, 24]. The star markers refer to the results from [33]. The 'No Change' scenario represents the cases in which current climate conditions (CDDs/HDDs) are assumed throughout the time period. Historical values for 2016 are computed by using data from [1, 24].

to the need for further investigation of the way in which different mechanisms of propagation between climate and energy demand can affect model projections. The additional contribution of climate-induced shock on energy demand for thermal adaptation is obtained by computing the difference between the projected demand in a given RCP scenario and its counterpart in the 'no climate change' scenario, sharing the same socio-economic assumptions (SSPs). This approach makes it possible to single out the climate transmission effect from the impact of socioeconomic trends (Panel c).

As for cooling, the climate change-induced median variations in energy demand for the building sector range from 4 EJ to 17 EJ (from 20 EJ to 84 EJ) in 2050 (2100), depending on the climate scenario. When also heating is considered, thermal adaptation in buildings is projected to require additional energy ranging from a median value of 0.01 EJ (16 EJ) under the RCP 1.9 and to 8.5 EJ (61 EJ) under the RCP 8.5 in 2050 (2100). Current energy usages amount to 52 EJ for heating and 7 EJ for cooling, for a total of 59 EJ, in buildings, and to 39 EJ for heating and 3 EJ cooling, for a total of 42 EJ, in the residential sector. Even in the low warming scenarios, RCP 1.9 and RCP 2.6, net final demand goes up by a median value of 16–22 EJ in 2100, though a net reduction cannot be excluded. The realization of a very low warming scenario, RCP 1.9, with respect to the RCP 2.6, would reduce the median net final demand by 3.7 EJ (6 EJ) in 2050 (2100), that is by 6% (10%) of net final demand in 2016. The commercial sector accounts for the largest share in the incremental contribution of climate change to energy demand, as specific projections of residential sectors show that the additional demand required ranges from 2 EJ to 0.5 EJ (from 1.4 EJ to 14 EJ) in 2050 (2100). The relative importance of the variations in the energy demand for residential buildings, with respect to the no-climate change scenario, are amplified at the regional level.

2.5.2 Impacts on the economy

With respect to the economic implications, most CGE-based studies underscore that, since energy is only a small part of the overall macroeconomic inputs, climate-induced impacts on energy demand have little economic repercussion; such repercussions are mainly driven by impacts on the agricultural sector, sea level rise, health and tourism impacts (more details are presented in the Supplementary Materials). While early studies [31, 32, 37, 20] generally found a very limited macroeconomic impact in terms of welfare change at the global level, more recent analysis have identified a higher role of the energy demand with respect to the macroeconomic impacts of climate change [23, 24] reaching up to 0.94% under the RCP 8.5 in 2100. The few studies reporting the impact of thermal adaptation on global emissions with respect to the emissions in the no climate change scenario tend to find only marginal impacts. [20] quantify the total emissions from the increase in energy demand for buildings in 2100 to be 1.2 (2.5) Gt CO2/year under RCP 6 (RCP 8.5), while [16] find an increase related to residential energy demand of 1.17 Gt CO2/year under RCP 8.5. The feedback between the energy and climate systems due to changes in heating and cooling services at the global level should not be considered negligible even if the overall magnitude of the increase is low. Moreover, it is important to keep in mind that these two studies might underestimate the needs of energy for adaptation because the extensive margin is not modeled [20] or because the commercial sector is not included [16].

2.6 Sources of variation

Notwithstanding the robust general trends with respect to heating and cooling demand, model results show significant heterogeneity. Figure 4 presents a disaggregation of the incremental energy demand projected by different IAM categories (Types 1–5), for residential (left quadrant) and buildings (right quadrant). Only part of the groups identified provide projections in each combination of year (2050 and 2100), energy service (cooling, heating and combined) and sector (residential, buildings). Therefore, only the projections which make it possible to simultaneously compare the highest number of groups are included, namely the projections reporting the value of the incremental energy demand in 2050. The results suggest that models lacking extensive margin adjustments (Type 4) highly underestimate the additional cooling needs of the building sector, finding an overall reduction in energy demand. Instead, the requirements for heating are in line with other modeling approaches. This result points to the importance of including the extensive margin in the structure of IAMs energy demand. Other major modeling differences are ruled out, as Type 4 models differ from Type 3 models only as regards their representation of the extensive margin. There is no univocal relationship between the results of projections and the modeling of the interactions between the economy and the energy system. Among the processed-based, bottom-up models, PE IAMs (Type 1) tend to project a median energy increment in line with the level projected by those GE IAMs adopting the same type of modeling of climate shock (Type 3). Scenarios from Type 1 models show a much smaller dispersion compared to Type 3. Type 1 models—bottom up models—might be more optimistic

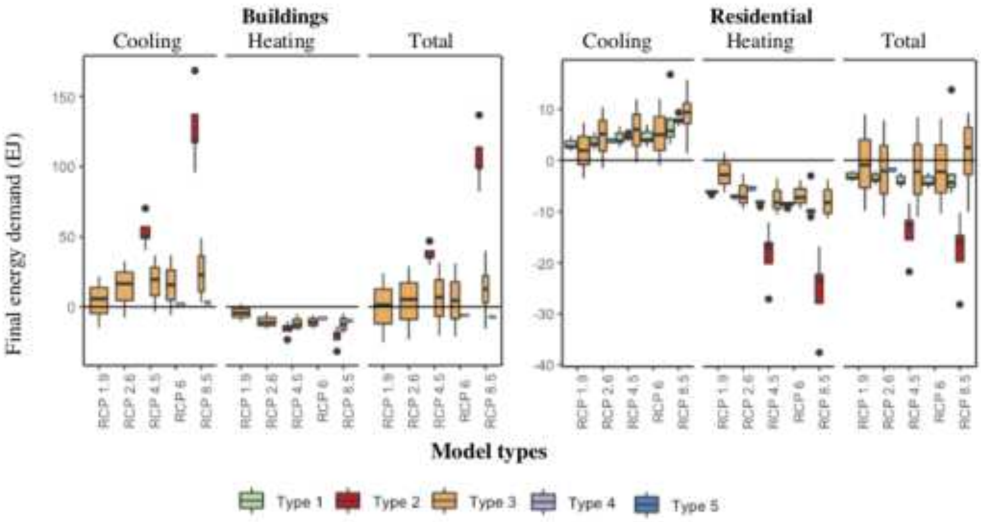

Figure 4. Additional demand of cooling and heating by model types. Additional contribution due to climate change in 2050 by model types. Left quadrant: building (commercial and residential) sector. Right quadrant: residential sector. Type 1 models: TIMER-IMAGE; POLES. Type 2 models: projections from van Ruijven et al (2019). Type 3 models: AIM/CGE, GCAM. Type 4 models: TIAM WORLD GEM-E3. Type 5 models: ICES.

regarding the role of technological change and efficiency improvements compared to Type 3 models. Among the top-down simulation models relying on exogenous shifts, PE IAMs (Type 5) tend to project a higher median increment than GE IAMs (Type 2) and a higher median reduction. Type 2 models do not include the important effect of prices, which are also related to the net trading position on the international market (terms of trade effect). Higher prices would induce a partial reduction in demand.

Lower prices could induce a rebound effect, pushing further demand. GE effects also imply changes in the income available to households and in the cost structure of producers, which are further elements that can lead to differences between PE and GE effects. The intensity of future global warming exacerbates the differences across model type results. For instance, in the projections of the total incremental demand of buildings (Panel a), under RCP 4.5 (RCP 8.5), the median total demand of Type 2 models is two times (five times) higher than the median demand of Type 3 models. This pattern is consistent across end uses and sectors, and suggests that the specific choice over the climate variable and the functional form of climate shock may affect the projections more sharply than other modeling aspects. The differences across the projections of model types vary according to the specific sector and end use service. The gap between the projections is higher than for the cooling demand of the commercial sector (panel a) and for the heating demand of the residential sector (panel b). Top-down models based on sectoral-specific exogenous shift parameters project substantially higher increases in incremental commercial cooling demand. Energy demand for the residential sector projected by Type 2 top-down models [33] and by Type 3 models (GCAM by [26] and AIM/CGE by, [24]) under the SSP 2 and RCP 8.5 is comparable (8 EJ in the former study and 9–10 EJ in the two latter studies), while it differs remarkably when the commercial sector is considered (114 EJ in the former study and 4–22 EJ in the two latter studies). Therefore, the adoption of transmission mechanisms of climate on energy demand allowing for the sectoral characterization of the shocks can be identified as a key driver of heterogeneous results.

2.7 Discussion

This Chapter systematically reviews and compares quantitative projections of buildings energy demand that include the future energy use for heating and cooling needs at global and regional levels. Despite the huge number of scenarios generated by the IAM community, only 14 studies (leading to 69 energy scenarios and 19 macroeconomic scenarios, for a total of 88) that project energy demand under different socio-economic and climate scenarios and that account for the feedback from the climate into energy demand could be identified. The resulting studies are analyzed based on a classification that considers in detail the energy system, the relationship between the energy and the economy, and the technical representation of the specific demand for heating and cooling. Results show that projections underestimate the energy demand of the building sector when energy use is driven solely by income and population drivers and not by changing climatic conditions and subsequently by rising adaptation needs.

The analysis provides substantial evidence of an increase (decrease) in cooling (heating) demand across warming scenarios and over time. However, there are, depending on the combination of service, sectors, and RCP scenarios, important differences in the magnitude of the projections. Uncertainty increases over time, especially in relation to cooling demand and when commercial activities are included. Thermal adaptation in buildings due to climate change is projected to require additional energy, ranging from a median value of 0.01 EJ (16 EJ) under the RCP 1.9 to 8.5 EJ (61 EJ) under the RCP 8.5 in 2050 (2100), corresponding to a 2% (11%) increase under the RCP 1.9 and a 13% (70%) increase under the RCP 8.5, with respect to future demand under no climate change in 2050 (2100). The projected additional median demand in buildings required in 2100 under RCP 8.5 corresponds to a doubling with respect to total building demand in 2016. Models lacking extensive margin adjustments highly underestimate the additional cooling needs of the building sector. Two main archetypes of extensive margin modeling are identified, and they are either based on a weak empirical basis (the market penetration approach) or they only implicitly account for the future evolution of air-conditioning ownership (the exogenous shift approach). Recent country-specific studies have highlighted the amplification effect deriving from the growth in appliance ownership in Mexico [38] and in California [39], while [40, 41] show that the dynamics of air-conditioning are country-specific and relate to demographic and infrastructural characteristics, including education and housing conditions. IAMs have also typically paid scarce attention to the non-linear responses of energy demand and to impacts of extreme events, such as heat waves (Table 2).

Table 2: Feedback between energy demand and climate: frequency of different characteristics.

		N° of studies
Intensive margin modeling	Exogenous shift parameter	5
	Scaling Factor	9
Extensive margin modeling	Market penetration	8
	Exogenous shift parameters	5
	Not modeled	1
Functional form across sectors	Homogeneous	6
	Heterogeneous	1
	Only one sector considered	7
Functional form across world areas	Homogeneous	9
	Heterogeneous (e.g. temperate vs tropical countries; climate clusters)	5
Climate variable adopted	CDDs/HDDs	9
	Temperature	4
	Temperature bins	1
	Extreme events (e.g. heat waves)	0

One limitation of the approach presented in this Chapter is that some key aspects affecting cooling and heating demand, namely building characteristics (floor space, insulation properties), appliance characteristics (HVAC system type) and behavioral aspects (thermal comfort thresholds, energy saving behaviors), could not be investigated in detail. The IAMs incorporating bottom-up technology rich modules (building or energy system models) or flexible end-use functions (energy demand models) account for such drivers by including building characteristics (generally floor space) and HVAC system efficiencies (generally the energy efficiency ratio, or EER). Usually, the positive correlation between floor space and GDP is used to model the evolution of this variable over time. Some studies simulate different behaviors of people towards the use of AC by varying the temperature thresholds used to compute CDDs and HDDs across SSPs [23, 21, 24]. Even when building and behavioral characteristics are taken into account, the marginal contribution of such drivers is often hidden in model results and projections are presented in an aggregate way that does not permit a direct comparison between those different assumptions. Based on the results gathered, it was possible to elaborate only on the role of HVAC system efficiency by by relying on [16, 1], which investigate the extent to which the energy efficiency of heating and cooling appliances influence space cooling energy needs: higher appliance efficiency brings cooling energy demand down by 30% in 2050 [1] and by 45% in 2100 [16].

2.8 Closing remarks

Future research aimed at deepening the integration of climate impact feedback into the mitigation and energy scenario needs to address two challenges. First, how to use the new emerging evidence across multiple countries, regions, and sectors, often by means of different methods, to better represent the climate-energy feedback loop in IAMs in a consistent way and preventing double counting. Developing IAMs capable of characterizing the subnational and sectoral diversity of heating and cooling needs is certainly warranted. Second, to what extent the empirical basis concerning the adoption and use of energy-using durables providing thermal comfort, such as air-conditioning, will extend to countries where those dynamics have not been investigated.

The work developed in the succeeding Chapters aims to respond to some of the challenges identified. In particular, a novel methodological approach for the integration of adaptation-energy feedbacks in a IAM is proposed and adopted in Chapter 3. The approach allows to: i) integrate non-linear dynamics of the typical IAM climate-energy system by modeling the occurrence of extreme temperature days; ii) expand the projected impacts across different fuels (electricity, gas and oil) and sectors (residential, commercial and industrial); iii) quantify the implications on energy investments and costs, on the stringency of mitigation policies and on the co-benefits of mitigation on air pollution.

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3 An integrated assessment of the energy needs for adaptation

3.1 Preface

Despite the growing evidence indicating that adaptation-driven energy use will play an increasingly important role in future energy scenarios, as assessed in Chapter 2, the literature providing long-term projections of energy scenarios still fails to account for adaptation-driven energy demand. Yet, estimating the potential size of future energy needs for adaptation may have important implications for the transition towards sustainability and decarbonized economies. In the context of a rapid transformation and simultaneous occurrence of climate change impacts, it is important to examine how responses to climate change affect energy systems, and therefore the achievement of mitigation goals, as well as their economic costs.

The proceedings of this Chapter have been published as an Article in Nature Communications[4]. Motivated by the results of Chapter 2, Enrica De Cian and I posed the initial research questions. All authors developed the energy-adaptation feedback loop. In particular, I developed the statistical emulator and wrote the code introducing the new components in the model, in collaboration with Johannes Emmerling, Malcolm Mistry and Giacono Marangoni. I led the analyses of results and wrote the first draft of the manuscript, with all authors contributing to revising the final version.

3.2 Introduction

The sensitivity of energy demand to weather fluctuations has long been documented in economic and engineering studies [1, 2, 3, 4]. Yet, most energy scenarios and mitigation pathways do not include the adaptation-energy feedback [5], and only very few studies have used IAMs to conduct macroeconomic assessments at the global scale[6]. Global-scale contributions have relied on econometric simulations ([7, 8, 9]) to provide partial equilibrium projections of the potential, ex-ante changes in energy demand, without accounting for price-induced substitution and income effects that only macroeconomic approaches can describe. Although Computable General Equilibrium (CGE) models suggest that the global market economy can easily absorb

[4]The Chapter is derived from: Colelli, F.P., Emmerling, J., Marangoni, G. et al. Increased energy use for adaptation significantly impacts mitigation pathways. Nat Commun 13, 4964 (2022). https://doi.org/10.1038/s41467-022-32471-1

the costs associated with changes in energy use for adaptation [10, 11, 12, 13], we lack an overall understanding of the implications for the energy system in the context of ambitious mitigation policies.

This work provides evidence on the macroeconomic implications of climate change impacts and analyze how price-induced substitution and income effects, as well as technical change adjustments, affect global and regional mitigation pathways. The novel methodologies integrates an adaptation-energy feedback loop for all world regions, main fuels, and economic sectors into the IAM "World Induced Technical Change Hybrid model" (WITCH) [14]. The results indicate that adapting to climate change by means of the energy habits as we did in the past will increase the global demand for electricity by 7% (18%) and for fuels by 1% (2.5%) by 2050 (2100) under the current socioeconomic trends and mitigation policies. The increase in energy needs leads to more physical capital being locked into fossil fuels, for an additional 960 Gigawatt (GW) of new gas-fired capacity, 360 GW of new oil-fired capacity and 300 GW of new coal-fired capacity, cumulatively from 2020 to 2050 (corresponding to a yearly average increase in new fossil fuel-based capacity of 55 GW). Adaptation would also require more resources for grid investments, power generation, and, in some regions and sectors, for fuel consumption. The carbon price required to reach a certain carbon budget would need to increase, and the cost-effective allocation of emissions would also look different compared to a situation that does not account for the energy use for adaptation. Results show that when the energy requirements of adaptation are modeled, the gains from lower adaptation needs reduce the additional energy system costs associated with more ambitious mitigation goals. The study endogenously integrates the energy needs for adaptation into mitigation pathways, highlighting the implications for decarbonization and policy design.

3.3 Methods

IAMs couple human and climate system and quantitatively describe the inter-dependencies among socioeconomic, behavioral, technological, and physical drivers affecting future global and regional pathways. The WITCH model [14] is a process-detailed IAM that fully integrates into the optimization process a top-down representation of the economy, a bottom-up description of the energy system, and simplified dynamics of the climate system, and air pollution module (See Methods).

The adaptation-energy feedback loop is modeled in three steps summarized in Figure 5.

First, a reduced-form relationship between country-level annual average temperature and two extreme temperature indicators (ETIs), the annual occurrence of extreme cold (<12.5°C) and hot (>27.5°C) days is estimated based on an empirical model (Supplementary Methods). A cluster analysis is used to capture the heterogeneity in the reduced-form equation across countries with markedly different climates (four clusters shown in the top-left panel of Figure 5). The resulting statistical emulator makes it possible to directly project the future occurrence of days with extreme temperatures based on the regional annual temperature levels. Regional temperatures are also statistically related to the global change in annual mean temperature, the variable commonly included in the climate modules of IAMs (see the Supplementary Methods).

Second, the relationship between changes in the occurrence of extreme temperature days (ETIs) and the demand for electricity, gas, oil in the residential, commercial, and industrial sectors are included in the model, following the empirical estimates provided in [7] (see Methods and Supplementary Methods). This approach differs from analyses based on indicators of Cooling and Heating Degree Days (CDDs and HDDs) or average annual temperatures ([15, 16, 13, 17]) that tend to shrink the tails of the distribution of meteorological drivers, leading to an aggregation bias that can underestimation of the impacts on energy demand. A comparison between the two approaches is provided by [18], who show how modeling energy consumption with HDDs and CDDs does not make it possible to capture the non-linear increase in energy consumption at extremely high temperatures.

Third, changes in energy demand affect the economy, described by the model's production tree, through the productivity of energy inputs, which is now endogenous. The supply-side of the energy sector endogenously adjusts to meet the climate-induced changes in demand, leading to changes in the costs of power generation, grid infrastructure, fuel extractions and expenditures, including domestic extraction and imports.

I examine the implications of the adaptation energy feedback on mitigation policies (carbon pricing and cost-effective emission allocation) and their co-benefits in terms of air pollution in a cost-effective setting. The carbon budget is consistent with a predetermined climate target and implemented via a uniform global carbon price. I focus on climate policies that achieve the goal of keeping global average temperature increases either around 2.5°C or well-below 2°C compared to the pre-industrial level. Climate targets are therefore achieved in a cost-optimal way, with no international compensations nor carbon emission trading. In the current policy scenario, countries maintain the implemented climate policies until 2020 and a similar level

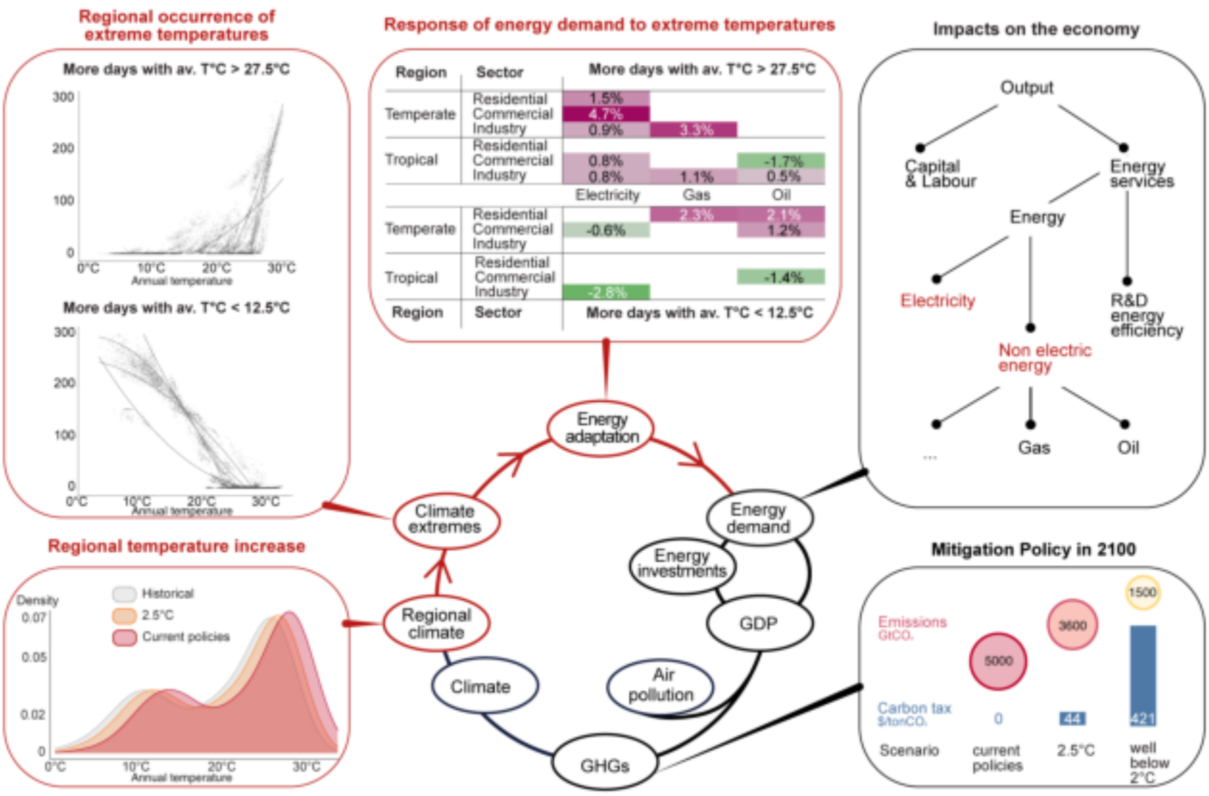

Figure 5. Integrated approach to the adaptation-energy feedback loop. The circle represents the integrated framework of the World Induced Technical Change Hybrid (WITCH) model, linking the economy, the energy system, and the climate system. Red lines indicate the components modified with new equations to model the adaptation-energy feedback loop. Top-left panel: eight clusters characterize the heterogeneity in the relationship between the Extreme Temperature Indicators (ETIs) and annual average temperature across world regions. Top-central panel: semi-elasticities as estimated in [7] representing the percentage change in energy demand for one additional day with average daily temperature (T) in the upper (T>27.5° C)/lower (T<12.5° C) bin, see [7]. A detailed description of each step and of the methodological advancements is presented in the Methods and Supplementary Methods. The WITCH model version used for the analysis (WITCH 5.0) is described in detail in [14].

of climate ambition is assumed afterwards. Socioeconomic trends of population and output growth follow the middle-of-the-road Shared Socioeconomic Pathway SSP2 [19], while results for other SSPs are presented as sensitivity analysis.

3.4 Results

3.4.1 Regional exposure to extreme temperatures

Under the current policy scenario, the annual count of warm days (>27.5°C) at around 2100 goes up substantially at the global level. The increase in the annual number of warm days, compared to the historical level, exceeds the decrease in the annual number of cold days (<12.5°C). Maps of future projections point at a large variation in regional exposure (Figure 6). The populations in Indonesia, South-East Asia and Sub-Saharan Africa are projected to experience, by the end of the century, more than 100 additional days with average temperatures above 27.5°C, with respect to the simulated exposure in the year 2005. The implications for temperate economies are also non-negligible: at around 2100, in the current policy scenario, the United States and China are projected to experience an annual number of warm days that matches the historical level experienced in Mexico. Europe, the Middle East and the United States experience the largest decrease in the number of cold days. Stringent mitigation policies drastically reduce the exposure to extreme warm days and, in the well below 2°C scenario, the projected median number of additional days above 27.5°C at around 2100 is about three times smaller compared to the current policy scenario.

3.4.2 Final energy demand for adaptation

Energy needs for adaptation increase over time and with the degree of global warming (Figure 7, Panel a). Adaptation-energy demand in buildings and industry rise considerably in the current policy scenario. Global electricity will increase by 18% (an additional 75 EJ) in 2100, compared to the projected demand in the same year but without adaptation. Final demand for liquids and gases increases by 2.5% (an additional 10 EJ in 2100). Table 3 presents the total and relative increase in the combined final energy demand for electricity and fuels due to adaptation, across policy scenarios and SSPs. The overall amount of energy required for adaptation in 2100 under the SSP2, current policy scenario is equal to 20% of the global final energy demand in 2019 [20]. Different assumptions on the baseline energy demand as implied by different socioeconomic pathways affect the quantification of the additional energy use for adaptation, that reaches over 100 EJ / year in 2100 in the SSP5 (see Table 3 and Supplementary Material).

Ambitious mitigation policies cut the energy use for adaptation by half in the moderate emissions scenario (2.5°C) and by more than 70% in the low emissions scenario (Well below 2°C). The demand for liquids and gases for adaptation would essentially reduce to zero. I find that the majority of the additional energy needs are met by using electricity in both residential and commercial buildings and industrial activities. The industrial sector accounts for 40% of the additional electricity requirements. Heating, ventilation, and air-conditioning (HVAC) systems

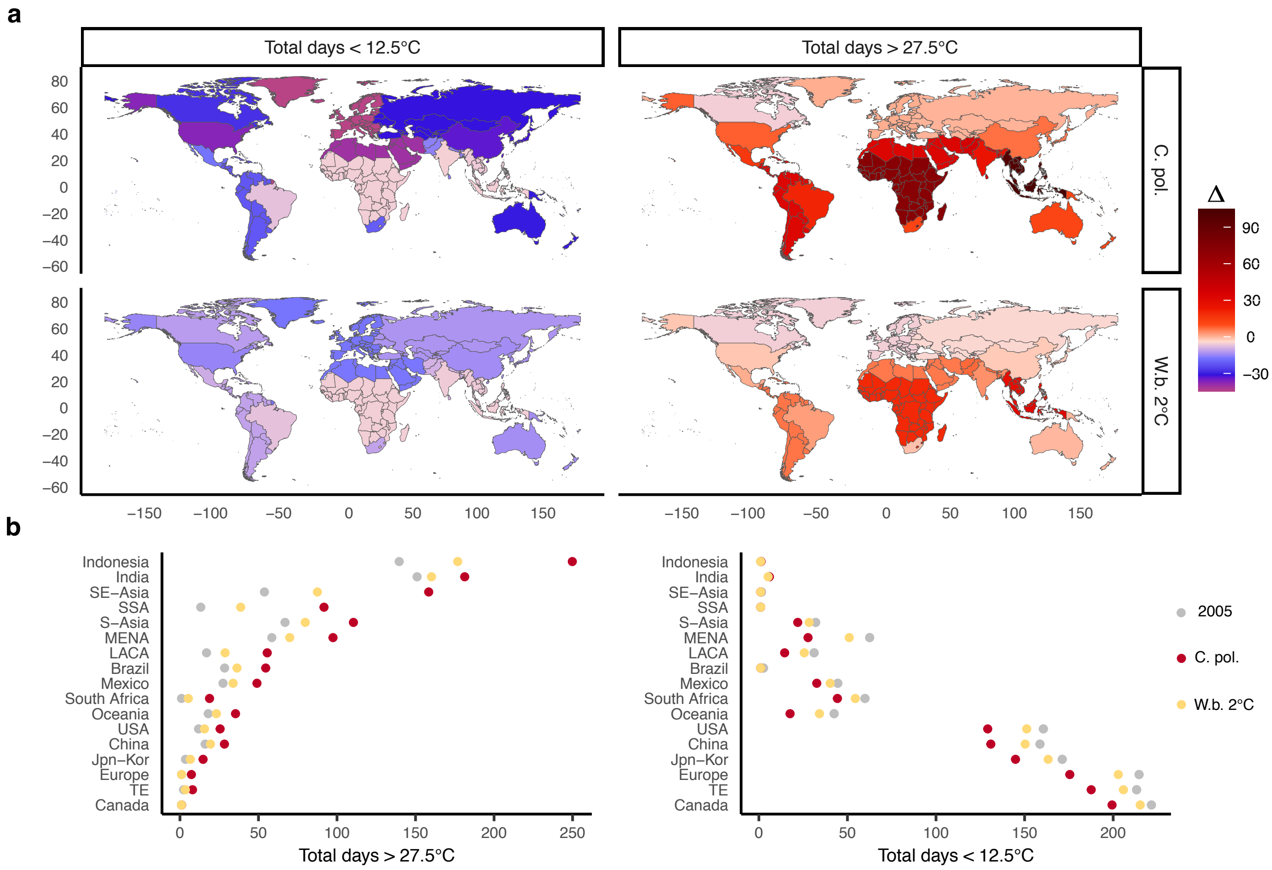

Figure 6. Future changes in the frequency of warm and cold days. ***a*** *Difference (Δ) between future (2090-2100) and historical (2005) annual number of days with average daily temperature (T) >27.5°C and T < 12.5°C.* ***b*** *Regional count of total days with T >27.5°C and T< 12.5°C in 2005 and in 2100 by policy scenario. Temperature indicators are constructed with population-weighted daily temperatures. Scenarios: Current policies (C.Pol) and Well below 2°C (W.b. 2°C).*

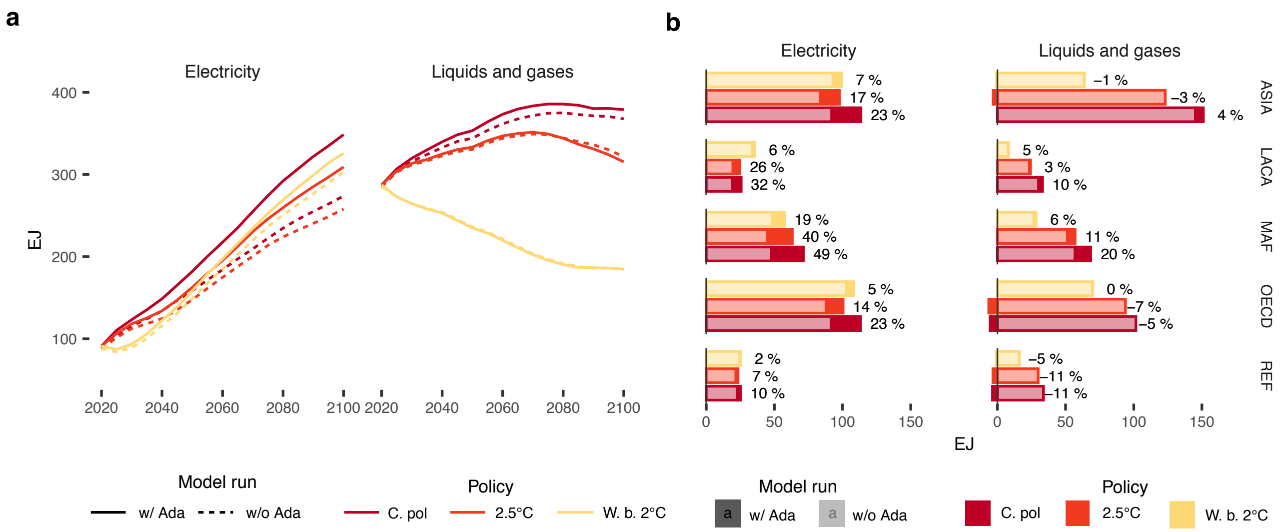

Figure 7. Projected electricity and fuel demand for adaptation under SSP 2 assumptions. ***a*** *Annual global average demand from 2020 to 2100 across the different scenarios excluding (dotted) and including (solid) the adaptation-energy feedback under the SSP2.* ***b*** *Regional final energy demand in 2100. Light bars show the value excluding the adaptation-energy feedback, while dark stacked bars show the positive or negative variation in energy demand induced by the adaptation-energy feedback. Labels in panel b show the regional percentage increase. Scenarios: Current policies (C.Pol), 2.5°C and Well below 2°C (W.b. 2°C).*

used by industries include comfort related energy use and continuous or process-related HVAC, the latter ensuring that the operation of manufacturing systems and production processes (e.g. food processing and storage industry) is not undermined by temperature variations [21].

The small increase in the final demand for liquids and gases masks heterogeneous responses across sectors. The reduction in fuel demand from lower heating requirements in residential and commercial buildings is compensated by the increase in industrial fuel demand as a response to more hot days. While space cooling in residential buildings is mostly delivered through electricity, industrial and commercial facilities can use fossil-fueled based cooling techniques, such as cooling absorption [22]. Variations in the consumption of fuels for cooling and heating purposes can also result from fuel-switching practices. For instance, the use of distributed petroleum-fired generators to satisfy final electricity demand may be particularly relevant in developing tropical economies characterized by unreliable electricity distribution systems.

Africa and the Middle East (MAF) will face the largest relative increase in final energy demand for adaptation (Figure 7, Panel b). These two regions account for roughly one fourth of the global additional increase in electricity demand, rising by almost 50% in the current policy scenario in 2100 relative to the no-adaptation case.

Table 3: Global final energy demand (EJ/year) in 2100 by scenario with (w Ada) and without adaptation (w/o Ada)

	Current policy		2.5°C		Well below 2°C	
	w/o Ada	w Ada	w/o Ada	w Ada	w/o Ada	w Ada
SSP2	641	727 (+13%)	579	624 (+8%)	486	510 (+5%)
SSP3	545	608 (+12%)	503	542 (+8%)	411	436 (+6%)
SSP5	771	889 (+15%)	688	748 (+9%)	610	647 (+6%)

3.4.3 New power capacity requirements

Additional new generation capacity is required to accommodate the increase in electricity use for adaptation. The mix of the additional generation capacity will be shaped by the ambitiousness and timing of mitigation policies (Figure 8, Panel a). In the next three decades (2020-2050), capacity additions in the current policy scenario will be still carbon-intensive, as mitigation policies start to re-direct power investments progressively over time. After 2050, new capacity mostly consists of renewable energy and storage.

Climate policy is key to avoid the negative feedback of the energy use for adaptation on mitigation objectives. If climate policy is not ambitious enough, adaptation needs can lead to additional lock-in into fossil-based generation (Figure 8, Panel b and Supplementary Material: in the current policy scenario, an additional 300 GW of new coal-fired capacity, 390 GW of new oil-fired capacity and 960 GW of new gas-fired capacity are installed cumulatively by 2050, as a result of the adaptation feedback, an average yearly addition of 55 GW for the three technologies combined. The additional oil-fired and coal-fired capacity required by the adaptation-energy feedback by 2050 falls by 50% to 90% from the current policy scenario, depending on the stringency of the climate policy. Additional gas-fired generation falls more progressively, and still 300 to 580 GW new capacity is installed to meet adaptation needs cumulatively by 2050, in the ambitious policy scenarios. Reduction in the additional investments in fossil fuel capacity in the climate policy scenarios results from the combination of lower electricity demand increases due to milder climate change as well as from the variation in the cost-optimal generation mix. The share of fossil-based generation in the total power mix does not change considerably when energy for adaptation is accounted for (see Table 4). Despite the non-negligible changes in the total carbon intensity of power generation in the current policy scenario, the overall total carbon intensity of the energy system does not change considerably in any scenario (see Table 4). The energy use for adaptation poses new challenges to the mitigation goals mostly through

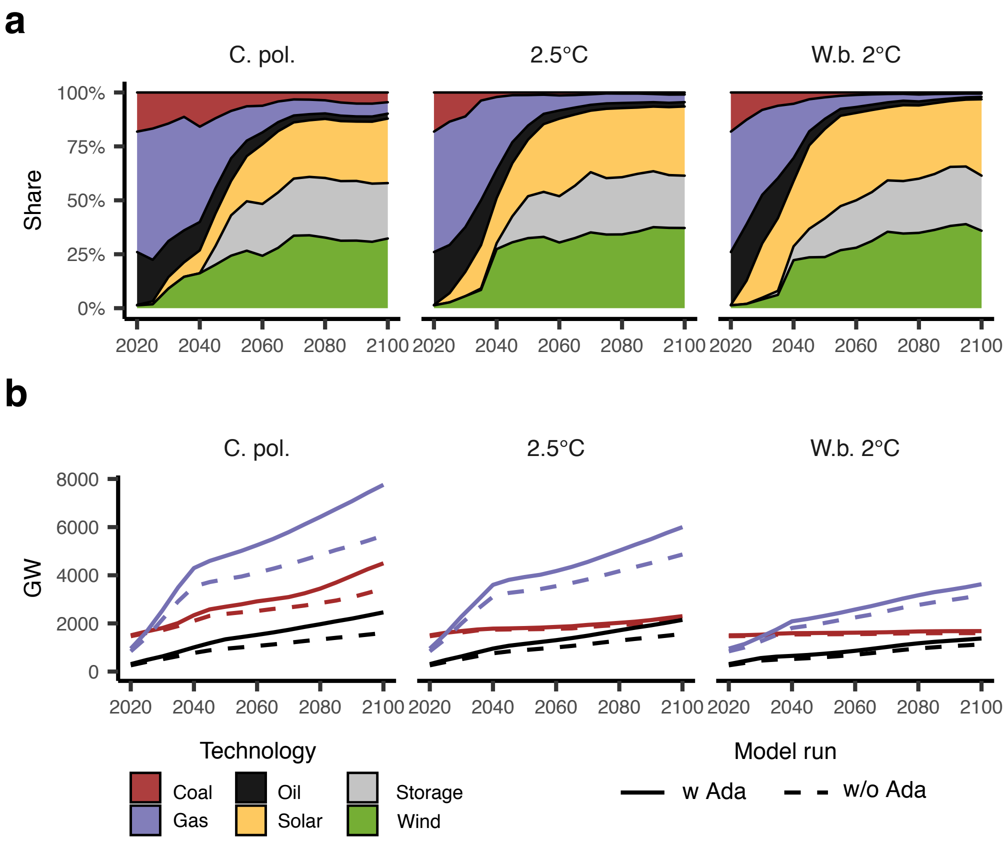

Figure 8. Additional power generation capacity. Technology mix of the additional average annual capacity to fulfill the additional energy for adaptation. ***b*** *Additional fossil-based new capacity installed cumulatively with (solid lines) and without (dotted lines) the adaptation-energy feedback. The additional new capacity installed cumulatively including also renewable sources is presented in the Supplementary Material. The technologies unaffected by the adaptation-energy feedback are not included. Scenarios: Current policies (C.Pol), 2.5°C and Well below 2°C (W.b. 2°C).*

the shift in demand, which increases in the energy intensity of the economy.

Table 4: Impact of energy use for adaptation on the power generation mix with (w Ada) and without adaptation (w/o Ada)

	Current policy		2.5°C		Well below 2°C	
	w/o Ada	w Ada	w/o Ada	w Ada	w/o Ada	w Ada
	Share of fossil fuels in the power generation mix					
2030	47%	49%	45%	47%	37%	38%
2050	23%	25%	17%	18%	12%	12%
2100	6%	7%	4%	4%	2%	2%
	Carbon intensity of power generation (gCO_2/kWh)					
2030	460	471	434	441	185	199
2050	306	325	171	169	≈0	≈0
2100	118	144	44	30	-121	-113

3.4.4 Variation in the energy system costs

The supply-side adjustments needed to meet additional energy for adaptation have non-negligible economic implications. The energy-adaptation feedback increases supply-side energy system costs (ESC), combining power and fuels costs, in all policy scenarios (Figure 9 Panel a). The increase is mostly driven by power system costs, including new investments in generation capacity, grid investments, and operating expenses from fuel consumption of traditional power plants. In the current policy scenario, global costs for electricity supply rise by 21% (Net Present Value incurred from 2020 to 2100), while total ESC increase by 4.5% (Table 5), due to both higher final energy demand and higher energy prices. The additional supply-side costs are passed on to consumers through increases in the price of electricity, growing by 2%-6% due to the adaptation-energy feedback, depending on the year, scenario and region.

Ambitious mitigation scenarios can cut the increase in the ESC induced by adaptation by more than half, depending on the stringency of the climate target. Most importantly, when the adaptation feedback is included, the gains from lower adaptation needs reduce considerably the additional power system costs required to reach ambitious mitigation targets (Figure 9 Panels b and c, and Table 5). Even ambitious mitigation ("Well below 2°C" scenario) can entail net gains in terms of power system costs, compared to the current policy scenario. The results underscore that ignoring the energy system costs attributable to rising energy use for adaptation results in an overestimation of the additional costs of mitigation policies (for the results across SSPs see the Supplementary Material).

The cost implications of the additional energy use for adaptation on households and economic activities are unequal between world regions. Annual per capita ESC will increase by 105 $/person on average across years and regions in the current policy scenario. The regions that will experience an increase in the per capita ESC above (below) the world average include the USA, MENA, South East Asia and Indonesia (Canada, China, India and Europe). A similar absolute increase in the per capita ESC has different implications between middle- and high-income countries. While in the US an increase of over 310 $/person accounts for a share of 0.4% of the regional per capita GDP, in the MENA region an increase of 250 $/person accounts for more than 0.7% of the regional per capita GDP.

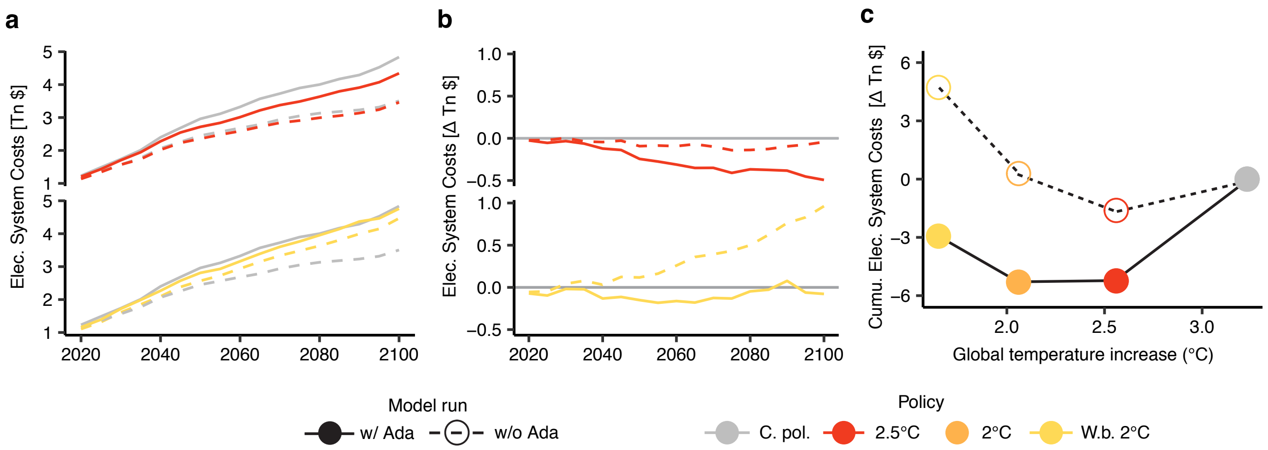

Figure 9. Annual electricity system costs by scenario. ***a*** *Total electricity system costs in trillion $, 2005 Purchasing Power Parity (PPP).* ***b*** *Additional electricity system costs in the mitigation scenarios with respect to the current policy, in trillion $(2005, PPP).* ***c*** *Variation in the cumulative electricity system costs associated to the more ambitious mitigation policy scenarios with respect to the current policy, in trillion $(2005, PPP). All projections are presented alternatively for the case with (solid lines) or without (dotted lines) adaptation. Operative fuel expenses for fossil-based power generation are included in the electricity system costs. Scenarios: Current policies (C.Pol), 2.5°C and Well below 2°C (W.b. 2°C). Results presented in panel a and b for the scenario 2°C are not shown to avoid clutter and can be fund in the Supplementary Material.*

Table 5: Energy System Costs (ESC) in Net Present Value ($ NPV, 3% discount rate) by policy scenario with (w/ Ada) and without adaptation (w/o Ada)

	Current policy		2.5°C		Well below 2°C	
	w/o Ada	w/ Ada	w/o Ada	w/ Ada	w/o Ada	w/ Ada
Electricity	66	80	65	74	71	77
Change (%)	-	-	-1 (-2%)	-5 (-6%)	5 (7%)	-3 (-4%)
Liquids and gases	297	299	291	290	271	271
Change (%)	-	-	-6 (-2%)	-9 (-3%)	-26 (-9%)	-28 (-9%)

3.4.5 Implications on emissions and global carbon prices

Energy needs for adaptation induce variations in the energy markets that ultimately result in a shift in global and regional greenhouse gas (GHG) emissions. In the current policy scenario, cumulative GHG adaptation-emissions reach 350 $GtCO_2eq$ by the end of the century, accounting for about 7% of the total cumulative GHG emissions from 2020 to 2100.

The regional distribution of emission in the current policy scenario reflects the the energy mix and the direct shocks on energy demand. In developing and tropical regions, the higher energy needs for adaptation are coupled with a slower energy transition and therefore additional cumulative emissions are larger than in developed temperate regions. Sub-Saharan Africa ("SSA") accounts for the highest additional cumulative emission increase due to energy for adaptation, but for a comparatively low level of additional cumulative emissions per capita. On the other hand, in regions such as South-East Asia ("SE-Asia") and Indonesia, the additional cumulative emissions are associated primarily with high emissions per capita. The US is the only OECD region where adaptation considerably increases global cumulative GHG emissions (Figure 10, Panel a) in the current policy scenario. Emissions are reduced in countries where the net reduction in energy demand prevails (Europe and Canada).

In the stringent mitigation scenarios, changes in regional emissions compensate each other by virtue of the constraint on the global carbon budget. When a global carbon tax is introduced, emissions are reduced the most in countries with relatively lower marginal abatement costs - e.g. China, Eastern Europe and Russia ("TE"), USA, Brazil, India. The magnitude of the reduction depends on the energy mix and on the extent of the abatement.

The lock-in of additional energy requirements into fossil-based generation, especially in the short-term, has direct consequences not only on GHG emissions, but also on air quality (see Figure 10, Panel b). A significant increase mainly in nitrogen oxides (NO_x), carbon monoxide (CO) and sulphur dioxide (SO_2), three of the key air pollutants related to the combustion of coal and oil [23, 24], is projected. Average annual emissions of air pollutants have their peak rise in Sub-Saharan Africa, South-East Asia and MENA, increasing by about 200 kton/year, 157 kton/year and 145 kton/year respectively. Although the high level of the spatial-temporal aggregation poses challenges to the identification of health impacts, the results suggest that people's exposure to high levels of pollution increases due to the adaptation-energy feedback, especially in low- to middle-income countries [25, 26]. The quantification of health costs related to the additional emissions of air pollutants and the analysis of how outcomes can be influenced

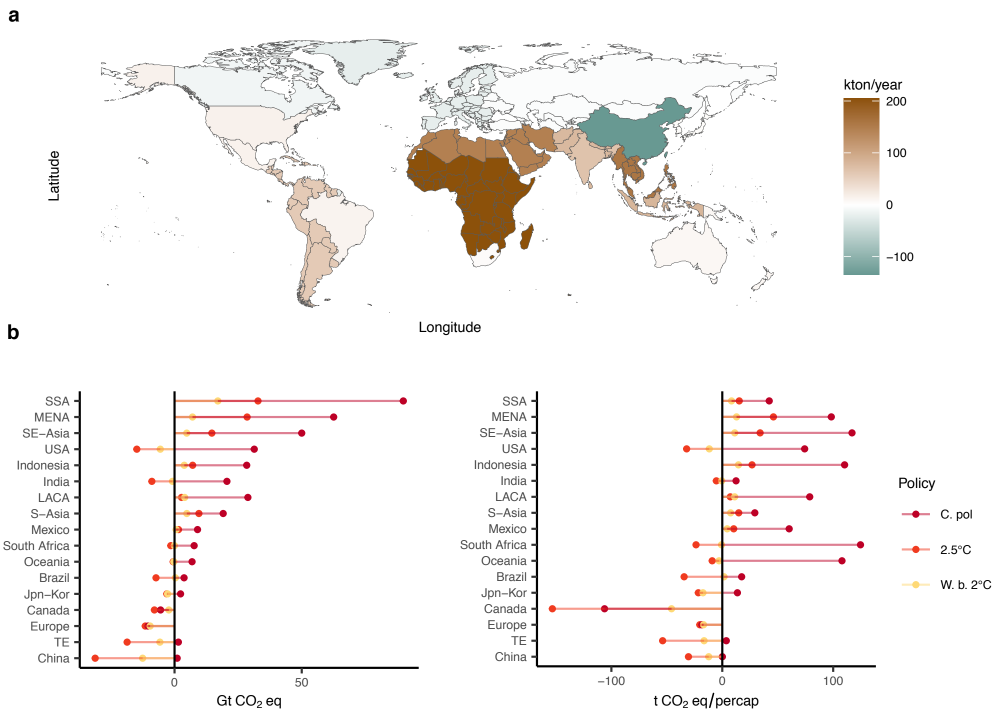

Figure 10. Regional variation in greenhouse gas (GHG) emissions and air-pollutants. ***a*** *Variation in air pollutants by region. Average total annual increase between 2020 and 2100 in the following air-pollutants: black carbon (BC), nitrogen oxides (NO_x), carbon monoxide (CO), sulphur dioxide (SO_2), organic compounds (OC), volatile organic compounds (VOC).* ***b*** *Additional cumulative GHG emissions for adaptation in 2100, total (left) and per capita (right). Scenarios: Current policies (C.Pol), 2.5°C and Well below 2°C (W.b. 2°C).*

by alternative narratives on technological change, efficiency improvements and policies directed at pollution control, is left for further research.

As a consequence of the variation in GHG emissions, the adaptation-energy feedback affects the level of the global carbon price needed to achieve the desired carbon budget (Table 6). The carbon price increase is highest in the least ambitious scenarios, as it grows by up to 30%, corresponding to a 5 to 8 (13 to 21) $/t$CO_2$eq increase in 2050 (2100), while it increases by 5% in the most ambitious mitigation scenarios ("Well below 2°C" scenario).

Table 6: Carbon tax ($/ton CO_2 eq.)

Year	2.5°C		W.B. 2°C	
	w/o Ada	w/ Ada	w/o Ada	w/ Ada
2030	8	10 (+31%)	74	78 (+5%)
2050	16	21 (+31%)	151	158 (+5%)
2100	44	57 (+30%)	422	443 (+5%)

3.5 Discussion

The simulated net increase in the global energy demand of residential and commercial buildings for adaptation confirms the literature's finding that energy demand of buildings is underestimated when IAMs rely solely on income and population drivers and disregard changing climatic conditions [5]. This Chapter shows that broadening the sectorial scope can provide relevant insights with respect to the assessments that focused on the buildings sector[5]. When the industrial sector is accounted for, the net additional energy needs for adaptation in 2100 under the current policy scenario are more than three times larger than when only buildings are considered (85 EJ/year and 25 EJ/year, respectively).
The supply-side impacts found in this study can be compared to a narrow set of model-based assessments conducted for the United States: a +5% increase in power generation, fuel, and grid costs is projected in the United States under the current policy scenario by 2050, in line with the estimates by [27], and a 20% increase in total installed capacity in 2050 under the current policy scenario, in line with the 16% increase found by [28] under the RCP 8.5. This work expands from the literature by quantifying the global additional investments required to transform the energy system to accommodate the energy use for adaptation. I find that the additional energy use for adaptation is largest in South-East Asia and Africa, highlighting the risk that existing vulnerabilities may be further exacerbated if power systems are poorly prepared to face the additional power demand for key services such as air-cooling.

If households and industries use more energy to cope with the ongoing and expected changes in climate conditions, the mitigation challenge can look inherently different. In a scenario where the ambition of mitigation policy does not rise rapidly, climate adaptation contributes to further exacerbate the risk of lock-in into polluting fossil-fuel-based generation in the next few decades. The additional final energy demand and the resulting energy costs are cut by 50% when aiming at the 2.5°C target and by up to 75% when reaching the target of Well Below 2°C. Nevertheless, even in the Well-Below 2°C target, an additional 10 EJ (20 EJ) of energy demand would be required annually by 2050 (2100). If power is not fully decarbonized, by 2050 adaptation could need an average annual addition of new fossil fuel capacity of about 55 GW, which corresponds to around 1% of the currently installed global fossil-based capacity and is comparable to the new coal capacity added yearly between 2017 and 2021 and to the global new investment decisions for gas-fired generation in 2019 [29, 20]). As a consequence, energy system costs and carbon prices increase because of adaptation.

While this Chapter has the ambition to shed light on one type of interaction between mitigation and adaptation at the global scale, several caveats remain. On the one hand, the way the responses of energy demand to meteorological conditions is characterized could actually lead to an overestimation of climate change impacts. This work implicitly assumes that energy demand does not significantly respond to daily temperatures between 12.5°C and 27.5°C. Accounting for the non-linear response of energy demand across the full distribution of daily temperatures would make it possible to factor in the attenuating impact of fewer moderate temperature days, reducing the energy demand shocks. In the same direction, behavioural changes related to the utilization of heating and cooling appliances [15] and new business practices, including greater consumer autonomy, digitalization, and new consumer-driven business models [30], could contribute to lowering the energy requirements of adaptation.

Conversely, adopting regional-specific thresholds in the computation of extreme climate indices, or accounting for the exacerbation in thermal-discomfort humidity, are aspects that could result in amplifying of the additional energy demand projected, especially in tropical regions [31]. Moreover, power system costs projected in this study can underestimate future impacts if peak electricity demand is more sensitive to extreme temperatures than total electricity demand [32]. New empirical evidence on the role that temperature extremes pose to the peak load, rather than on total electricity demand, would contribute to improving the estimation of the potential power system costs induced by climate change adaptation. Future work could explore the costs of an increase in the peak load due to more cooling needs at fine temporal scales by soft-linking a global Integrated Assessment Models to bottom-up power capacity expansion and optimal dispatch models. Power generation and transmissions are also vulnerable to climate change (see [33, 34] for a review), and therefore fully characterizing the interaction between mitigation and adaptation requires integrating demand-side and supply-side impacts.

3.6 Closing remarks

Integrating climate change impacts and adaptation in energy scenarios contributes to a more accurate understanding of mitigation scenarios and the energy transition [35]. This Chapter provided an account of how energy use for adaptation can endogenously affect mitigation goals and the design of cost-effective mitigation policies. Since the adaptation-energy feedback increases the energy system costs, this integrated framework captures mitigation's benefits in terms of reduced adaptation needs, reinforcing previous findings from aggregate, macroeconomic assessments [36]. Looking at the issue of energy demand for adaptation with novel lenses has provided a key indication: ignoring the energy system costs and the environmental implications attributable to rising adaptation needs in energy scenarios results in an underestimation of the benefits of mitigation policies.

Importantly, the feedback-loop included in the WITCH model is calibrated on the existing empirical evidence, but it relies on a modular and flexible structure that can be adapted and updated with the availability of new empirical evidence on how climate change affects energy use and energy supply. Chapter 4 will provide a range of new empirical results focusing on the electricity at a temporal frequency that is typically too desegregated for being represented in IAMs. Further novel modeling approaches that would advance the analysis conducted in this Chapter and develop scenarios in conjunction with the empirical evidence of Chapter 4 are presented in the discussion of Chapter 5.

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4 Adaptation-energy feedback: bridging models to new empirical evidence

4.1 Introduction

This Chapter, building upon the review conducted in Chapter 2 and the analysis of Chapter 3, provides an overview of how different modeling frameworks, including Integrated Assessment Models (IAMs), partial-equilibrium global energy models and Computable General Equilibirum Models (CGEs), can accommodate new empirical evidence improving the characterization of the energy-adaptation feedback. The overarching objective is to provide the modeling community of a general framework upon which to update models for the implementation of the energy-adaptation feedback. Specifically, I map out the inputs needed by models and assess the availability of existing empirical data and results serving such purpose.

As discusses in Chapter 2, there is large scope for improving the integration of the climate-induced shock in the aggregated energy demand function of IAMs, GCEs and global energy models. Most of the available models rely on a simple representation of the energy demand sensitivity to climate shifts (the "scaling factor"), which typically disregards both the long-term adjustments effects stemming from a change in energy-using appliance ownership and the non-linearities in the response to climate, for instance though a shift in the tails of temperature distribution rather than in the annual mean levels (see Chapter 2). Table 7 presents an overview of the features and components that enable to model the energy-adaptation feedback in 17 leading global models [5]: i) long-run energy demand shocks represented through aggregated energy demand elasticities ii) cooling demand shocks modeled though an explicit representation of appliances (e.g. AC) adoption; iii) climate-dependent high-frequency electricity demand shocks; iv) adaptation options on the energy supply side and on market operations; v) inclusion of sub-yearly climate shocks and weather extremes indicators. Most models have extensive potential for being updated in more than one of such aspects, provided a consistent availability of the empirical basis for calibration. First, all models can update their aggregated energy demand elasticities with the new empirical evidence capturing long-term adjustment effects to climate. More than haft of the IAMs reviewed and two out of three global energy models already include a detailed representation of the AC adoption functions, while the remaining

[5] Each feature can be either implemented with no modifications of the current model framework ("yes") or through a model integration with new modules/components of though linking with other models ("integration") or finally cannot be included due to the characteristics of the model ("no").

IAMs can implement end-use specific cooling shocks though new integrations (discussed in detail in section 4.3). The possibility to include adaptation impacts on high-frequency demand shocks in IAMs is less common, due to the limited availability of sub-annual and country-level representation of power dynamics in these models (see section ??). On the other hand, supply-side shocks related to adaptation and climate impacts could be implemented with smaller efforts in most cases, due to the detailed representation of the energy supply side in most IAMs, CGEs and global energy models. CGEs, especially if used in combination with energy models, can similarly provide new relevant contributions. Almost all models lack a detailed representation of sub-annual climate extremes unless new model integrations are performed. The next sections will turn to the detailed description of the existing empirical studies available to update models in each of the aspects identified, and on the scope for new research.

Table 7: Implementation of the adaptation-energy feedback

Model	**Model type**	**Energy demand elasticities**	**Explicit AC adoption**	**Hourly load elasticities**	**Energy supply-side shocks**	**Sub-annual climate extremes**
WITCH	IAM	Yes	Integration	Integration	Yes	Yes
REMIND	IAM	Yes	Yes	Yes	Yes	Integration
TIMER-IMAGE	IAM	Yes	Yes	Integration	Yes	Integration
COFFE-TEA	IAM	Yes	Integration	Integration	Yes	Integration
MESSAGEix	IAM	Yes	Yes	Yes	Yes	Integration
FUND	IAM	Yes	Integration	No	Integration	Integration
GCAM	IAM	Yes	Yes	Yes	Yes	Integration
AIM-Hub	IAM	Yes	Yes	Integration	Integration	Integration
DNE21+	IAM	Yes	Yes	Integration	Yes	Integration
E3ME-FTT	IAM	Yes	Integration	Integration	Yes	Integration
EPPA	IAM	Yes	Integration	Integration	Yes	Integration
ENVISAGE	CGE	Yes	No	No	No	Integration
GEM-E3	CGE	Yes	Integration	Integration	Yes	Integration
ICES	CGE	Yes	No	No	Yes	Integration
TIMES	PE-Energy	Yes	Integration	Yes	Yes	Integration
POLES	PE-Energy	Yes	Yes	Yes	Yes	Integration
PROMETHEUS	PE-Energy	Yes	Yes	Integration	Yes	Integration

4.2 Long-run energy demand elasticities

Empirical works studying aggregated energy statistics typically capture the elasticities of energy demand employing static models that constrain short-term elasticities to weather to be stable over time [1, 2, 3, 4, 5, 6, 7]. Yet, weather-dependent energy use in the short-term is expected to differ from the long-term response to a changing climate, because of the agent's ability to adjust energy-using durable stock over time. IAMs, global energy models and CGEs adopting energy demand elasticities derived from static econometric model may end up underestimating future energy requirements by failing to account for the rapid increase in energy-intensive durable goods (see Chapter 2).

Because data on the prevalence of AC appliances is often not available with the necessary spatio-temporal coverage of energy demand statistics, a set of empirical studies have adopted statistical workarounds to capture *implicitly* the effects of unobserved extensive margin adjustments. Exploiting billing-level information, [8] proposes a two-step approach based on the estimation of: i) the intensive margin temperature response functions using daily variation in weather and, ii) the variation in the slopes of the dose response functions across space as a function of climate. The requirement of billing data at the daily level constrains the applicability of such method at the global or multi regional scale, and as a consequence the inclusion of the estimated elasticities into global models. A growing group of studies is adopting dynamic econometric specifications, in particulat the Error Correction Model (ECM), to capture the effects of long-term adjustment between the dependent variable and its regressors. [9, 10] estimate an ECM panel with yearly observations and global coverage for demand of three different fuels, finding that the effects of temperature are greater over the long-term than in the short-term. The adjustments captured though the dynamic ECM equation can be considered as a proxy for the extensive margin because, over the long-term, agents have time to adopt the set of appliances that maximize their utility. Furthermore, as new appliances and cooling technologies become available, energy efficiency can also be improved, so that the overall impact on energy demand can be mitigated by the improved efficiency. These approach evaluates the hypothesis that the overall impact of the extensive margin drivers is reflected by the dynamic response of electricity demand to weather shock over the years, without the need to observe appliance prevalence rates and their energy efficiency. The ECM coefficient estimated by [11] have been adopted as model input in the analysis of Chapter 3, enabling to identify energy demand shocks implicitly including long-term adjustments. One shortcoming of the available empirical analysis such as [11] is that the long-run adjustment effects are estimated by treating economic growth as a control, rather than a modulating factor. The effect of socio-economic development, considered as a non-temperature confounder, is in fact typically removed through controls by most empirical studies estimating both short- and long-run elasticities [8, 11, 5, 12]. In doing so, past studies have disregarded the identification of a very relevant aspect on the response of energy demand to weather. Per capita income is, together with climate, the key driver affecting the diffusion of space conditioning durable capital stocks acquisition and usage [13]. Given that IAMs tipically identify energy demand trends over long time horizions (30 years), new empirical studies should provide a set of long-run elasticities identifying both the economic and the climatic effects on the extensive margin (see Chapter 5).

4.3 Explicit AC adoption

The models that include a detailed representation of end-use services and technologies can project the long-run extensive margin adjustments of energy demand directly, based on the explicit estimation of future appliances' ownership. The analysis conducted in Chapter 2 shows that the extensive margin of AC ownership has been modeled almost exclusively by relying on the empirical evidence derived from [14, 15]. As [15] use air-conditioning market saturation data for 39 US cities, studies that identify future AC adoption rates based on the study's estimates rely on the strong assumption that a functional relationship characterizing rich, industrialized and highly urbanized areas can be extended to very different socio-economic and climatic regions, such as emerging markets and tropical regions. Furthermore, the estimates of [14], used in combination with [15] to project the impact of socio-economic on AC ownership, are based on a cross-sectional model that suffers from limited controls for country- and time-specific confounding effects.

In the last two decade AC has been growing rapidly in both developed and developing regions [16], making of paramount importance to conduct novel and broader set of empirical analysis that shed light on the determinants of AC adoption across climatic, socio-economic and demographic conditions. Recent empirical studies have begun to expand the available evidence by exploiting survey-level micordata, improving with respect to the past literature both in terms of the set of determinants and controls considered and as for the geographic coverage. [13] provide a quantification of how income and climate drive air-conditioning adoption in Brazil, India, Indonesia, and Mexico, controlling for a comprehensive set of country-specific household characteristics. The authors show that in emerging economies the decision to purchase air-conditioning in response to warmer climatic conditions is country-specific and strongly dependent on household's socio-economic conditions and demographic characteristics, and that disregarding other characteristics of households, including education and housing conditions, can significantly bias the estimates of the marginal contribution of income and climate, which would appear larger. In Chapter 5 I contribute to this growing field by proposing a novel methodology that exploits country and sub-country panel data in two very different world regions, India and Europe, to provide a generalized functional relationship between AC market saturation, cooling degree days, per capita income and urbanization.

The AC adoption functions have so far been used in IAMs only for the direct estimation of cooling services' demand though bottom-up building demand modeling frameworks; top-down models that lack the representation of different end-use services have typically disregarded the inclusion of cooling demand shocks in their frameworks, or, alternatively, have adopted the *indirect* estimations deriving from the long-run energy demand elasticities described in section 4.2. The inability of including a *direct* estimation of the cooling energy in top-down models is constrained by the lack of empirical evidence providing in a unified framework a set of aggregated energy demand elasticities and the modulation effect on such elasticities from AC capital accumulation. [17]] is to the best of my knowledge the only study that has moved towards the estimation of an aggregated energy demand function dependent on AC ownership. Focusing on Mexican provinces, the study provides a cross-section comparison of energy demand responses exploiting the *current* heterogeneity in AC saturation levels. The responses in places currently having high AC saturation rates are used as proxies for the responses of places with current low AC saturation and that are expected to increase their prevalence of AC in a hotter future. The framework proposed by [17] sheds light on the mechanisms at play but cannot be directly adopted in global energy models, since it lacks a generalized equation describing the modulation effect of AC ownership on aggregated electricity demand (see Chapter 5).

4.4 Power system impacts

IAMs are the ideal tool to describe the pathways towards the energy transition and to inform international and regional climate policies because of their global, multi-decadal and multi-sectoral scope. Yet, IAM-based scenarios typically lack the spatial and temporal precision to inform power system planning [18]. [19] shows for instance that assuming unconstrained electricity flows inside large regional areas without internal network constraints causes an overestimation of the potential of variable renewables within IAMs. Considerable new model improvements have been implemented in recent years regarding power system in IAMs, typically with the aim of improving the representation of variable renewable energy technologies [20, 21, 22, 23, 24]. Power system models, differently from IAMs, can incorporate high spatio-temporal resolutions by design, but tend to have narrower sectoral and geographic scopes and shorter time horizons. Nevertheless, state of the art frameworks can simulate continental- or global-scale power system dynamics at high frequencies [25, 26]. Rather than relying on computationally-expensive internal IAM model improvements, the modeling community has suggested to enhance the temporal and spatial scope of IAMs though inter-model linkages with global-scale power system models, which can take the form of either soft- or hard- linking [27, 19]. Soft-linking is essentially based on the facilitation of data flows between models, allowing models to make separate and endogenous investment decisions while leading to a joint solution [28]. Though soft-linking scenario results from IAMs can be fed into independent model to assess given scenarios with enhanced modelling resolution. Results from these simulations can then be redirected to the IAM through iterative bi-directional soft-linking. Hard-linking on the other hand is based on an algorithm that communicates dynamically between both models and leads to a singular set of results [29]. While both methods require substantial data manipulations, the feasibility of hard-linking relies on several additional conditions: first, modelling tools computationally able to function in this setting, secondly, significant time and resources are needed to ensure that both models can reach a joint optimization [29]. For these reasons, soft-linking approaches have been more commonly adopted in recent years: proof of concept applications of a soft-linking between a detailed power system model and a IAM have achieved almost-full convergence both in terms of decision variables and (shadow) prices [30, 19].

The trade-off between scope and detail in most modeling frameworks has so far constrained the investigation on the interplay between climate change adaptation and key power system components (high-frequency demand, generation, transmission and distribution). Overcoming these limitations entails realizing three main objectives: i) enhance the empirical understanding of how power systems are affected by climate change, both due to demand-side adaptation responses and to physical impacts to key infrastructure (power grid, power generation plants); ii) accurately model the power sector transformation over long time horizons in terms of investment and dispatch; iii) expand the representation of sub-annual variation in the climate, allowing for the propagation of the empirical shocks (point i) into the detailed power system framework (point ii).

4.4.1 Hourly load elasticities

Long-term peak-load forecasts are critical for planning generation, transmission and distribution capacity additions and retirements several years in the future. Even with the incomplete representation of impacts though the yearly shocks developed in Chapter 3, the influence on power systems of demand-side shocks as populations adapt to climate change has appeared to be far from negligible.

The evidence stemming from Chapter 3 shows that the energy required to adapt to higher temperatures can result in significant additional generation capacity and higher emissions of greenhouse gases and local air pollutants, in turn affecting the ambition of mitigation policies.

Regional versions of leading IAMs have been coupled with regional power-system models with the aim of assessing climate change impacts on peak load and generation (GCAM-US). The example of CC shows that even if a fully endogenous global framework similar to the one presented in Chapter 3 cannot be represented, novel IAM-based works can provide insightful results though simpler implementations, i.e. assessing the impact of climate change on the hourly electrical load for a set of representative seasonal time-slices using alternative demand levels as exogenous inputs.

The complexities in coupling different energy models' are not the only factor preventing an accurate description of the impacts adaptation on the high-frequency fluctuations of the load. To date, the empirical works focusing on the estimation of the energy-temperature response function using high-frequency (hourly or daily) load and weather data have focused only on the short-term intensive margin adjustments [5, 8, 31, 12], disregarding instead the long-run extensive margin adjustments. How increases in the frequency and intensity of temperature extremes will amplify electricity demand to levels that exceeds current power systems capacity, when endogenous adoption of residential air-conditioning (AC) is accounted for, is a key blind spot on the quantification of impacts of climate change.

4.4.2 Impacts on energy supply and market operations

Weather-driven electricity demand peaks must be accommodated by exceptional ramp-up requirements of power generating units. In highly decarbonized power systems, such requirements can be accommodated by the synchronous variation in renewable technologies' generation, in particular solar PV. If such power requirements cannot be met through variable renewables sources, power systems must ramp-up flexible generation technologies, typically gas and coal fired generation, with important implications on emissions of GHG and local air pollutants. Dispatch models simulate the operations of regional power grids, in particular the ability to meet the net load (total loan minus renewable generation) by thermal generation units subject to operational constraints.

Climate change can impact power systems not only by pushing power demand to record highs, in turn requiring exceptional ramp-ups of power generators, buy also by [32]: ii) affecting the efficiency of thermal electricity generation (more risk-sensitive to heatwaves) and renewable technologies (more risk-sensitive to cold waves and other extreme events), iii) reducing transmission and distribution capacity, further challenging the operation of electricity grids. Section 4.4.1 discusses the opportunities and limits of including i) into IAMs. At present, the effects of climate change on i) and ii) are poorly understood, leaving the actors liable to ensure the system stability with limited evidence based on historical climate conditions.

Most of the literature has so far focused on how reduced water availability due to climate change can impair electricity generation of hydroelectric dams [33, 34, 35]. Yet, also coal and nuclear power plants, operating through steam-turbine processes, can be severely affected during droughts due to variations in streamflow levels and temperatures, affecting the availability of the cooling water needed to generate at full capacity [36]. Gas-fired power plants, that operate though combustion-turbine processes that require little or no water for cooling, can be affected by a reduction in the efficiency of turbines due to extreme temperatures, ultimately leading to capacity reductions [37]. Extreme weather events can also affect renewable generation, as photovoltaic solar cells can lose efficiency at high air temperatures [38]. Only a limited body of empirical studies estimated how climate change will affect thermoelectric power plants [39, 40]. New empirical studies should expand the understanding of power supply impairments due to extreme weather. Coupling such novel evidence to power dispatch and capacity expansion models can provide simulations of how power systems can respond to generation power outages or reduction in efficiency induced by extreme events through changes in the generation schedule of power plants, inter-regional market flows and investments in slack capacity (see also Chapter 6).

4.5 Non-linear climate shocks and weather extremes

Another important and long-debated limitation of IAMs is the complexity to include abrupt, irreversible, or catastrophic climate changes impacts in their frameworks ([41, 42]). In the context of the energy - adaptation feedback, IAMs have provided no indication so far on the responses of energy demand to extreme events such as heat waves (see Chapter 2). Also in this case, the major challenge derives from the different time scale between the variables that identify the occurrence of extreme weather events and models, which typically run with yearly time-steps [43].

The analysis conducted in Chapter 2 shows that the empirical and modeling literature has generally adopted two different climate variables: (i) temperature levels, or (ii) Thermal Degree Days. Heating Degree Days (HDDs) measure the number of daily units (usually in°C) that are registered below the thermal comfort threshold, referred to as base temperature, while Cooling Degree Days (CDDs) measure the number of daily units that surpass the thermal comfort threshold. Changes in HDDs and CDDs have often been adopted in the studies dealing with residential demand of space heating and cooling [6]. Notwithstanding their wide adoption in literature, Thermal Degree Days have the drawback of depending on the threshold values chosen for computing thermal discomfort. On the other hand, direct temperature variations can be represented in the empirical framework, either as the mean temperature [44, 45], or as the exposure to different intervals ("bins") of temperature [3, 4, 10]. In the former, potential non-linear responses of energy consumption can be captured by including higher-order terms, typically the quadratic temperature term. In the latter, a more complex variable is constructed by creating a series of temperature bins covering the full range of possible temperatures and, subsequently, by counting the number of days within each bin in a given period (often years). [3], that provide the only known comprehensive comparison between the two approaches, find evidence supporting the hypothesis that the standard approach of modeling energy consumption with HDDs and CDDs does not make it possible to capture the non-linear increase in energy consumption at extremely high temperatures. Similar conclusions stem from the comparison between alternative weather variables adopted for the estimation of the monthly electricity demand ECM developed in Chapter 5.

The availability to update IAMs with new global-level non-linear energy demand response functions is constrained, as the only recent example providing non-linear response estimates the short-run intensive margin component (see section 4.2), while available estimates accounting for the long-run adjustment effects are provided only for aggregated hot ($> 27.5°C$) and cold ($< 12.5°C$) temperatures. Novel empirical studies should therefore both focus on long-run extensive margin elasticities while accounting for the non-linear response of energy demand across the full distribution of temperatures.

In order to effectively capture the impacts of future extremes, new empirical studies would need to adopt datasets that are rich in terms of spatial and temporal resolution, with weather observations and energy data processed and aggregated in a way that preserves information regarding the tails of the weather distribution and its geographical specificity. Unless the short-term elasticities of demand are calculated at the same temporal and spatial scale as the IAM simulations into which they will be incorporated, the aggregation of short-term elasticities for the adoption in IAM is an important methodological limitation [46]. Stochastic modeling techniques and model-integration would need to be used in order to capture extreme events, an approach adopted so far mostly at the regional level [47, 48]. One of the possible solutions is the development of statistical emulators that allow the computation of annual weather extreme indices in the IAM, based on the endogenous average annual temperature projections, as proposed in Chapter 3. Another way to surmount the structural limitations of models is to perform quantitatively parts of the scenarios outside the confines of the model itself, as proposed by [49] and implemented by [50].

4.6 Closing remarks

This Chapter has drawn several lines connecting model capabilities and requirements for the representation of the energy-adaptation feedback, identifying diverse and often overlapping new research opportunities.

On the one hand, there are several opportunities for updating the energy demand functions of existing models with limited additional effort, both in terms of the aggregated energy demand elasticites and as for the AC adoption functions. The most pressing bottleneck in this regard appears to be the availability of novel empirical studies that capture extensive margin adjustments, either by identifying long-run energy demand shocks when no explicit information on appliances' adoption exists or by providing a generalized framework estimating the response of energy demand conditional on future AC prevalence rates. On the other hand, an integrated assessment of key aspects such as climate change impacts on hourly and peak load profiles, power generation and the power grid require in most cases a combination of both modeling advancements and novel empirical evidence. Substantial potential lies in soft-linking results from IAMs into more detailed global power system models, to assess given scenarios with enhanced modelling resolution, and allowing to evaluate such solutions in the IAM through iterative bi-directional soft-linking. Finally, improving the representation of extreme events in all model types is a precondition to a detailed evaluation of the adaptation-energy feedbacks.

In Chapter 5 I develop a suite of alternative empirical methods that aim to address some of the aspects identified. First, given the importance of identifying long-run energy demand shocks when no explicit information on appliances' adoption exists (as discussed in section 4.2), I propose a methodological approach that exploits variations in climate in a panel framework, providing a set of extensive margin elasticities of electricity demand that are modulated by the level of per capita income. Furthermore, in section 5.3, I present the results of a novel method based on an ECM framework exploiting monthly energy statistics and weather-income interaction component. Second, I address the lack of updated empirical estimations on the drivers of AC ownership and of a generalized empirical framework that estimates the effect of AC prevalence on electricity demand (as discussed in section 4.3). I show that future co-variation between load and temperature is greatly underestimated unless the impacts of extreme heat exposures is made conditional on electricity consumers' adjusting the stock of energy-using durable goods in the long-run. Finally, Chapter 5 expands the empirical literature on power systems impacts (section 4.4.1), as I focus on the analysis of electricity demand at fine temporal scale, exploiting a novel data-set of daily and hourly peak load demand across over 50 states in Europe and India.

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5 Empirical investigations of the adaptation-mitigation trade-offs

5.1 Preface

Empirical projections of electricity demand increases as populations adapt to climate change generally lack the spatial and temporal precision to inform power system planning [1, 2, 3]. As a result, operational forecasts tend to reflect the assumption that historically-observed weather patterns will persist over the panning horizon [4, 5]. The burgeoning availability of high-frequency (hourly or daily) load and weather data can potentially address this disconnect, but thus far climate change impacts have primarily been inferred from regional-scale geographic level variation over comparatively short ($\lesssim$ 10y) time scales [6, 7, 8, 9].

In the first part of this chapter (sections 5.2) I propose two alternative methodologies that improve operational forecasts with features from empirical projections, in order to better address long-term forecast for investments planning. I show that fine temporal scale co-variation between load and temperature can empirically identify the impacts of transient extreme heat exposures, conditional on electricity consumers' adjusting their utilization of stocks of energy-using durable goods that are fixed in the short run (adaptation on the intensive margin [10]). The challenge addressed is the identification of simultaneous extensive margin adaptation: consumers' responses to average weather conditions experienced over many years, consisting of new technology adoption or adjustment of stocks of appliances with varying energy efficiencies, which are only rarely directly observed [compare 11, 12].

The proceedings of section 5.2 are being prepared for two distinct submissions, one to Nature Scientific Reports and one to the Journal of Environmental Economics and Management (JEEM). The manuscripts are co-authored by Enrica De Cian and Ian Sue Wing. Baring few minor changes to the figures and text, adapted in order to perform a comparison between the methodologies adopted in the two papers, this chapter is mostly unchanged from the versions under preparation. I designed and performed the research, analyzed the data and wrote the paper. Enrica De Cian and Ian Sue Wing provided scientific input. All co-authors are involved in the revision of the final text.

In section 5.3 I propose an alternative methodology for the estimation of long-term adaptation adjustments of electricity demand when no information on the diffusion of cooling and heating appliances is available. The analysis is complementary to the high-frequency empirical frameworks developed in the previous sections in many regards, as in this case the analysis: i) is based on a dynamic econometric model that captures the relationship between weather variations and electricity consumption towards equilibrium, when agents have time to adjust; ii) focuses on a rapidly growing tropical economy, Brazil; iii) exploits monthly level energy and climate statistics. Importantly, I test the hypothesis that per capita income modulates the long-term relationship between electricity demand and weather, an effect which is reinforces the results obtained in section 5.2. I find that evolving socio-economic dynamics considerably increase the projected impact of climate change in the tropical and developing region, a common finding throughout Chapter 5. The proceedings of this section have been published as an analysis in Energy and Climate Change [6]. The work is co-authored by Malcolm Mistry. I developed the econometric analysis and wrote the first draft. Malcolm Mistry processed the climate data and revised the final version of the manuscript.

Finally, in section 5.4 I expand the methodology developed in 5.2 and test if the decomposition of weather observations into climatic moving averages and weather anomalies can identify statistically different effects than estimations based on contemporaneous weather, when using aggregated data at the year-country level and fixed effect panel models. Past works have relied on the covariation between economic outcomes and weather to estimate long-run climate impacts because of the presumption that we cannot observe meaningful climatic variation within units in the econometric framework. In this section I argue that exploiting over 60 years of records in meteorological and climatic variations within and between countries, this assumption can be relaxed. I compare empirical estimates alternatively based on weather and climatic exposure, finding statistically significant and non-negligibly higher impacts in the latter case. Furthermore, I find evidence that: i) per capita capital stock modulates the response of energy demand to climatic exposure; ii) per capita energy demand modulates the response of income growth to climatic exposure. In the second part of the analysis I use the estimated damage functions to identify the resulting long-run responses of energy demand and income to temperature changes around mid-century. The analysis elucidates the potential: i) energy demand requirements for climate change adaptation; ii) economic losses due to climate change; iii) (partial) attenuation of economic losses from adaptation through higher energy consumption induced by adaptation. The proceedings of section 5.4 are being prepared for submission

[6] Francesco Pietro Colelli, Malcolm N. Mistry, Income-dependent expansion of electricity demand for climate change adaptation in Brazil, Energy and Climate Change, Volume 3, 2022, 100071, ISSN 2666-2787, https://doi.org/10.1016/j.egycc.2022.100071.

to Nature Energy. The manuscript is co-authored by Ian Sue Wing. I designed and performed the research, analyzed the data and wrote the paper. Ian Sue Wing provided scientific input and was involved in the revision of the final text.

5.2 Estimation of extensive margin adjustments using high-frequency data

5.2.1 Introduction

Electric power systems' generation capacity, transmission and storage are designed to meet peak load, the maximum quantity of electricity instantaneously demanded by grid-connected residential, commercial and industrial customers. Electricity demand is highly weather sensitive [13]. air-conditioning (AC) to provide cooling during hot weather accounts for 30% of peak demand in temperate and industrialized countries such as the US and 10%-15% in growing and tropical regions such as India, Indonesia and Mexico [14]. A major concern that climate change-driven increases in the frequency and intensity of extreme temperatures, both heatwaves and cold spells, will adversely affect electricity grids' ability to reliably deliver power by pushing demand to levels that exceed system capacity. It is likely that the potential for such impacts to arise will grow with the prevalence of air-conditioning, which itself responds positively to higher temperatures and increases in per-capita income [15, 16, 17, 18]. Key uncertainties are the extent to which system capacity and utilization will increase in an attempt to adapt to these transitory shocks, and what the implications might be for electricity demand and power sector emissions, particularly in emerging economies [19].

Prior approaches that rely on contemporaneous weather realizations [7, 6, 9] or use dynamic proxies for the effects of energy-using capital goods accumulation [3, 12] are ill-suited for providing an indication of the long-term implications on high-frequency power demand due to climate change. There are several reasons why coefficients estimated exploiting weather variations may not be directly applicable to estimating the impacts of climate change over the medium or long term [20]: adaptation (adjusting among a set of technological opportunities but also through technological change), general equilibrium effects (adjustment of prices and factor reallocations) and intensification of climate effects. Measuring adaptive behaviours when assessing the relationship between energy demand and thermal comfort is of key importance: adaptation shapes agents' use of energy-intensive durable stock in responses to transitory temperature shocks ("intensive margin") and agents' new adoption of energy-intensive durable stock in response to the permanent shifts in climate ("extensive margin") [10]. Adaptation though the extensive margin takes time to influence energy demand because, given the fixity of capital goods in the short-term, actors are constrained in their response to unanticipated weather shocks.

The empirical frameworks that have been adopted in order to estimate how actors adapt to climate change can be divided broadly into three groups (for a review see [20, 21]): i) cross-section studies ii) panel models linear in weather; iii) hybrid approaches. On the one hand, the cross-section approach measures long-term adaptation by estimating the response function across geographic areas characterized by different climate conditions, assuming that in order to maximize their welfare agents will have fully adjusted technology deployment, capital investments and practices under the climate they face [22, 23]. The drawback of this approach is the inability to control for time-invariant factors that are correlated with both the climate and the outcome variable, resulting in potential omitted variables' biases. To the best of my knowledge, no study has so far adopted a purely cross-section approach in order to identify the response of energy demand to climate. On the other hand, panel models rely on the deviations of weather realizations from the location-specific average of weather over time, while the differences in climate, constant over time, are captured by the location fixed-effect [1, 24]. The main advantage of this approach is the ability to control for time-invariant variation across space though the inclusion of fixed-effects. A large number of studies have investigated how residential energy demand responds to temperature by using the panel fixed-effect framework [1, 2, 7, 6]. A relevant drawback of this approach is that the unit-specific climate effects, constant over time, cannot be identified because they are perfectly collinear with the unit fixed effect. Since the estimation relies only on unexpected weather shocks, the identification of adaptive behaviour becomes challenging [21]. In the context of energy demand, the estimation of elasticities based on this framework provides an adequate measure of short-term movements of energy demand, i.e. of the changes along the intensive margin, but fail to account for the responsiveness of energy demand to slowly moving adjustments along the extensive margin.

A growing number of alternative hybrid approaches aiming to identify the impact of climate impacts, rather than weather, are emerging in the literature. The main advantage of these approaches is to estimate climate change effects while still controlling for unobservable confounding variables. Different methods have been adopted to this aim [21]: i) non-linear specifications in weather allow for varying marginal effects of warming, but imply that the estimated effects are

a mix of long- and short-term responses [24]; ii) two-stage approaches estimate in a first step the response to weather linearly and across time for any given location, and in a second step relate the value of the estimated weather coefficients to climate, based on cross-sectional regressions [25, 26]; iii) long-differences' panel regression, based on multiple periods of medium-term change in the same unit; iv) dynamic models estimating an error correction component that captures the long-term adjustments of energy demand [3]; v) panel studies partitioning the variation in both weather and climate, using the two to jointly estimate the effects of short- and long-term variation respectively [27, 28]. To the best of my knowledge, these innovative approaches have rarely been adopted for the estimation of the energy demand's long-term relation with climate, with the exception of error correction models based on macro-data panels [3] and two-stage models based on billing micro-data [12].
Fine temporal scale co-variation between load and temperature can empirically identify the impacts of transient extreme heat exposures, conditional on electricity consumers' adjusting their utilization of stocks of energy-using durable goods that are fixed in the short run. This is adaptation on the so-called "intensive margin" [10]. The challenge is to identify simultaneous "extensive margin" adaptation: consumers' responses to average weather conditions experienced over many years, consisting of new technology adoption or adjustment of stocks of appliances with varying energy efficiencies—which are only rarely directly observed [compare 11, 12] (see Figure 11). The analyses developed in this Chapter innovates with respect to the available literature by providing a direct quantification of how climate and income affect consumers' responses to weather shocks, by determining their low-frequency adjustment of energy-using capital goods like appliances and air conditioners, and the high-frequency intensity of utilization of those durables.

I disentangle the effects of extensive-margin adaptation and intensive-margin responses of electricity demand to temperature in two very different regions, Europe and India, covering roughly one fourth of global population and 20% of global electricity consumption. Two alternative methodologies are developed in order to identify the interplay between intensive and extensive margins using high-frequency power market data. The first methodology exploits regional-level data on AC prevalence, derived from micro-level survey data, and is therefore based on a direct observation of capital stock variations over time. The second methodology evaluates if intensive and extensive margins can be identified even with no direct information on AC prevalence, though the low-filter variations of income and climate. The latter methodology

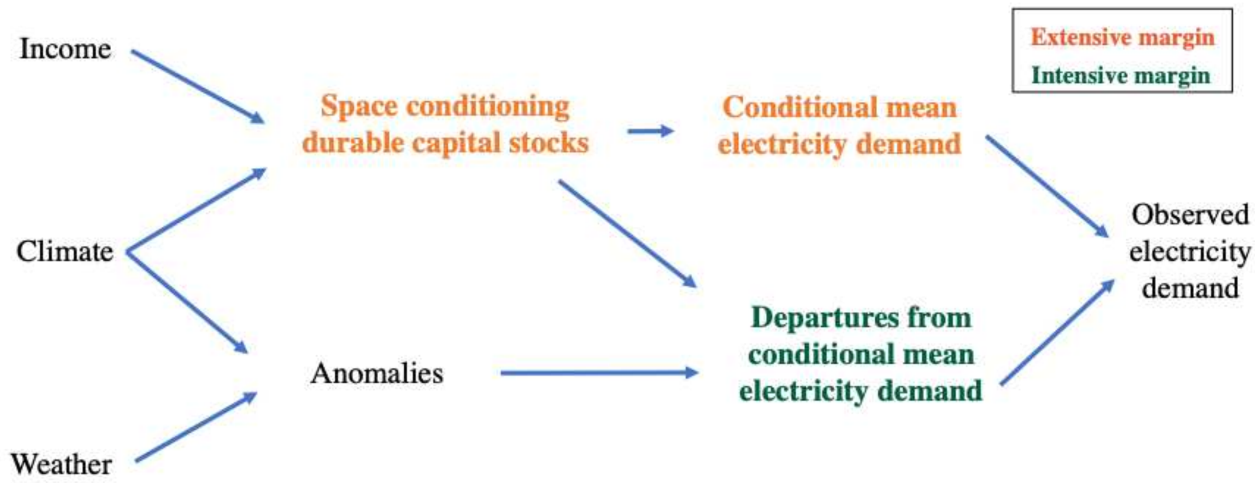

Figure 11. Conceptual framework of the intensive and extensive margin. Own elaboration.

is evaluateed because it can be applied to a larger number of world regions than the former, due to lack of AC ownership data at the required scale (regional and multi-annual) is rarely available in countries other than Europe and India (with the exception of the United States).

The first methodology ("Weather and AC ownership") proceeds in three stages [11, 15, 18]. First, I empirically analyze the high-frequency intensive margin component of electricity demand, captured by the day-by-day co-variation between peak and total load and maximum daily temperature at different levels of regional AC prevalence. The second step is to empirically characterize adjustment on the extensive margin, modeling the adoption of AC across regions and years in response to spatial and temporal differences in integrated heat exposure and income. I exploit the low-frequency year-on-year adjustments of AC ownership in a dataset of 17 European countries and 30 Indian states that differ markedly in their climate characteristics and income levels.

The second methodology ("Climate and income model") is inspired by the work of [12], and it distinguishes between the responses of peak load to high-frequency transitory departures of daily maximum temperatures from their climatic normal values that reflect changes in appliance utilization, and low-frequency year-to-year evolution of decadal average daily maximum temperatures and per-capita income that reflect the growth, and/or improvements in the efficiency of, appliance stocks.

In both cases, the final step consists in coupling the reduced form adaptation responses with projections of mid-century changes in daily maximum temperatures simulated by 29 global climate models (GCMs), in order to elucidate the separate extensive- and intensive-margin contributions to, and joint amplifying effect on, peak and total electricity consumption.

5.2.2 Methods

Data: For the empirical analyses I assemble two longitudinal datasets: a dataset of annual rates of AC ownership covering 17 European countries over the period 1990-2019 [29] and 30 Indian states over the period 2013-2019 [30], as well as a dataset of daily peak and total electric load covering 16 European countries over the period 2015-2019 [31] and 28 Indian states over the period 2013-2019 [32]. Each dataset is matched to population-weighted temperature exposures, computed from ERA5 0.25° hourly 2m temperature series [33], as well as annual real per capita GDP in 2015 US dollars [34, 35]. The first low-frequency dataset is used to empirically model the drivers of AC adoption across an inter-regional gradient of income and climatically-determined heat exposure. To match the time-step of the outcome variable, diurnal average temperatures are computed and aggregated over the course of each year to construct population-weighted CDD24s as a measure of integrated heat exposure. I use the second set of high-frequency data to analyze the contemporaneous effect of heat on the per-capita demand for electricity, conditional on the prevalence of AC. To that end, daily peak and average electric load are matched to diurnal maximum temperatures and annually-varying GDP and AC prevalence (Supplementary Methods and Supplementary Tab. 1).

For the projection component of the analysis, I use future estimates of global population and GDP downscaled to X-Y° grids from [36] and [37], respectively, developed in accordance with the shared socioeconomic pathway (SSP) scenarios. Shift in CDDs and daily maximum temperatures from current to mid-century climates are estimated using the outputs of 29 global climate models (GCMs) participating in the Coupled Model Intercomparison Project, Phase VI (CMIP6) [38]. Specifically, I use GCM-simulated daily temperature fields for moderate (SSP245) and vigorous (SSP585) warming scenarios that are bias corrected and downscaled to a 0.25° grid, from the from the NASA NEX-GDDP-CMIP6 dataset [39, 40, 41] (Further details are provided in the Supplementary Material.)

For the estimation of future CO_2 emissions from electricity generation I use technology-specific power generation data recorded on a daily time-step for European countries [31] and on a monthly time-step for India's five electricity dispatch regions [35], over the period 2017-2020. I couple power generation statistics with carbon intensity associated to the operation of power plants available at the country level for Europe [42] and at the national level for India [43].

Weather and AC ownership

In the framework exploiting weather and AC ownership information, the extensive margin is modeled as follows: in each location (i) and year (t), the probability of AC ownership is approximated by the share of households with AC (s), which I model as a function of the 10-year moving average CDD24s ($\mathcal{C}$), the logarithm of the 10-year moving average annual per capita income (y) and the logarithm of the 10-year moving average annual urbanization rate (u). The dependent variable is continuous on [0,1]. The empirical specification is a cross section-time series OLS regression with a logit link function [44]:

$$\begin{aligned}\mathrm{logit}(s_{i,t}) &= \log\left(\frac{s_{i,t}}{1-s_{i,t}}\right) = \boldsymbol{Z\alpha} \\ &= \alpha_i^0 + \alpha^Y y_{i,t} + \alpha^C \mathcal{C}_{i,t} + \alpha^{YC}(y_{i,t}\cdot\mathcal{C}_{i,t}) + \alpha^U u_{i,t} \qquad (4)\end{aligned}$$

with location fixed effects α^0, and estimated parameters α^Y and α^C that capture the direct effects of income and heat exposure, and α^{YC} that captures their interaction. The functional form yields nonlinear effects of the linear predictors, governed by the logistic transformation:

$$\widehat{s} = \mathrm{logit}^{-1}\left(\boldsymbol{Z}\widehat{\boldsymbol{\alpha}}\right) = \frac{\exp\left(\boldsymbol{Z}\widehat{\boldsymbol{\alpha}}\right)}{1+\exp\left(\boldsymbol{Z}\widehat{\boldsymbol{\alpha}}\right)} \qquad (5)$$

The intensive margin is instead captured by the responses of European and Indian peak and total electricity demand to high temperature exposure on a daily time step. I bin population-weighted diurnal maximum temperatures into k intervals of 3°C width, $B_k = [\underline{T}_k, \overline{T}_k)$, and construct a k-vector of indicators that track whether each day's maximum temperature falls within a given interval:

$$\mathcal{T}_k = 1\cdot\{T \in B_k\} + 0\cdot\{\text{Otherwise}\}$$

Bins are differentiated by macro-region to account for the latter's large climatic differences—Europe: $\{<0, 0-3, ..., 30-33, >33\}$, India: $\{<12, 12-15, ..., 33-36, >36\}$. The resulting indicator variables are employed as high-frequency covariates in regionally-stratified linear fixed effects models of per capita daily electric load, q_v, where the subscript $v = \{\text{Peak, Total}\}$ indexes peak or total demand [1, 7, 3, 6]. Suppressing location and time subscripts, the empirical specifications are:

$$\mathbb{E}[\ln q_v] = \sum_k \beta^T_{k,v} \mathcal{T}_k + \beta^Y_v y + \text{controls} \tag{6}$$

$$\mathbb{E}[\ln q_v] = \sum_k \beta^T_{k,v} \mathcal{T}_k + \sum_k \beta^{TAC}_{k,v} \left(\mathcal{T}_k \cdot s\right) + \beta^Y_v y + \text{controls} \tag{7}$$

where controls include state or country fixed effects that absorb variation associated with unobserved temporally-invariant confounders, and day-of-week, season and year fixed effects that control for idiosyncratic time-varying influences that are unrelated to temperature. Both models are estimated by OLS, with standard errors robust to heteroscedasticity and serial correlation and clustered at the state level. (See the Summpelentary Material for additional details.)

Specification (6) follows the empirical approach in prior literature, in which the parameters are identified based on contemporaneous co-variation between electricity demand and realizations of weather [6, 7]. In particular, $\boldsymbol{\beta}^T$ is identified off the deviations of observed daily load and binned temperature exposures from their local average values—shocks which are informative of the average short-run response across locations. The elements of $\boldsymbol{\beta}^T$ trace out the intensive margin response of energy demand to temperature, not accounting for consumers' adjustments of stocks of energy-using durables. The potential amplification of demand due to latter [15, 18] is explicitly captured in the preferred specification, (7), by the vector of interaction coefficients, $\boldsymbol{\beta}^{TAC}$. The fitted coefficient vectors $\widehat{\boldsymbol{\beta}}^T$ and $\widehat{\boldsymbol{\beta}}^{TAC}$ provide flexible piece-wise linear spline representations of macro-regions' distinct nonlinear temperature response functions.

Finally, climate change impact projections are computed by combining the estimated parameters $\widehat{\boldsymbol{\alpha}}$ and $\widehat{\boldsymbol{\beta}}$ with climate change projections to estimate the impacts of mid-century temperature increases on peak and total electricity demands, conditional on the future level of AC ownership. I use representative 5-year periods from the current (2010-2014) and mid-century (2055-2059) epochs. Within each epoch I compute at the grid cell level, for each year, the 10-year moving average CDDs, $\overline{\mathcal{C}}^{Cur}$ and $\overline{\mathcal{C}}^{Fut}$, and, for each day, the contemporaneous maximum temperature interval, $\overline{\mathcal{T}}_k^{Cur}$ and $\overline{\mathcal{T}}_k^{Fut}$. Following [45], climate change-driven temperature shifts were estimated by calculating the differences between simulated 10y average annual CDDs and daily maximum temperatures over the historical and future epochs, and adding these "deltas" to the corresponding series of historical observations recorded by ERA5. The resulting synthetic series for the current and future epochs, $\widetilde{\mathcal{C}}^{Cur}$, $\widetilde{\mathcal{T}}_k^{Cur}$ and $\widetilde{\mathcal{C}}^{Fut}$, $\widetilde{\mathcal{T}}_k^{Fut}$, are then used to project future AC prevalence in conjunction with eq. (5):

$$\widetilde{s}^{Fut} = \frac{\text{logit}^{-1}\left[\widehat{\alpha}^0 + \widehat{\alpha}^Y \widetilde{y}^{Fut} + \widehat{\alpha}^C \widetilde{\mathcal{C}}^{Fut} + \widehat{\alpha}^{YC}(\widetilde{y}^{Fut} \cdot \widetilde{\mathcal{C}}^{Fut}) + \widehat{\alpha}^U \overline{u}\right]}{\text{logit}^{-1}\left[\widehat{\alpha}^0 + \widehat{\alpha}^Y \widetilde{y}^{Cur} + \widehat{\alpha}^C \widetilde{\mathcal{C}}^{Cur} + \widehat{\alpha}^{YC}(\widetilde{y}^{Cur} \cdot \widetilde{\mathcal{C}}^{Cur}) + \widehat{\alpha}^U \overline{u}\right]} \widetilde{s}^{Cur} \tag{8}$$

and the concomitant impact on daily peak and total per capita load in conjunction with eq. (7):

$$\psi_v = \frac{\exp\left[\sum_k \widehat{\beta}^T_{k,v} \widetilde{\mathcal{T}}^{Fut}_k + \sum_k \widehat{\beta}^{TAC}_{k,v}\left(\widetilde{\mathcal{T}}^{Fut}_k \cdot \widetilde{s}^{Fut}\right) + \widehat{\beta}^Y_v \widetilde{y}^{Fut}\right]}{\exp\left[\sum_k \widehat{\beta}^T_{k,v} \widetilde{\mathcal{T}}^{Cur}_k + \sum_k \widehat{\beta}^{TAC}_{k,v}\left(\widetilde{\mathcal{T}}^{Cur}_k \cdot \widetilde{s}^{Cur}\right) + \widehat{\beta}^Y_v \widetilde{y}^{Cur}\right]} \tag{9}$$

Eqs. (8) and (9) are computed using each GCM's simulated output at the grid cell level (g) for the 5y epoch and constitutent days (d), respectively. I leverage The observations of historical average per capita demand for i European countries and Indian states to aggregate the shocks using future (SSP2 and SSP5) gridded population, $\widetilde{n}^{Fut}$, as follows:

$$\Psi_{v,i} = \frac{\sum_{g(i)} \sum_d \psi_{v,d} \overline{q}_{v,i,d} \widetilde{n}^{Fut}_g}{\sum_{g(i)} \sum_d \overline{q}_{v,i,d} \widetilde{n}^{Fut}_g} \tag{10}$$

I decompose the impact metric into the fractional effect of each driver: i) the variation in people's propensity to use their current endowment of appliances under a changed climate ($\widetilde{\mathcal{T}}^{Fut}_k$); ii) the variation in people's endowment of AC appliances due to the shift from current to future per capita income ($\widetilde{y}^{Fut}$), under the historical climate; iii) the variation in people's endowment of AC appliances due to climate change ($\widetilde{\mathcal{C}}^{Fut}$), under the historical per capita income; iv) the interaction effects due to the non-linearity of the co-occurring climate and income effects measured in stages i - iii; v) the scaling effect of future per capita income (i.e. vertical shifts of the nadir due to economic growth).

Climate and income model

The following section describes the empirical framework of the "Climate and income model", while more detail on the theoretical framework and on the identification strategy can be found in the Supplementary Material. This empirical approach relies on two key elements. The first is the decomposition of the meteorological variable, daily maximum temperatures T, into two components: long-run climate normals and weather anomalies, the latter defined as deviations from those norms. I measure the climate normals ($\overline{C}_{i,d}$) as the 30-year moving average of the daily maximum temperature. For every day in the sample $\overline{C}_{i,d}$ combines the information of the weather realizations of the previous 30 years in that same calendar day [7]. The adoption of a moving average derives from the assumption that individuals and firms respond to information on climatic variation they have observed and processed over the years [8]. The weather anomaly (ω_d) is computed as the deviation of daily maximum temperature from the 30-year average of maximum temperature. Weather shocks are computed as the difference between the observed weather exposure and the exposure expected by economic agents in each specific calendar day in the year. While the meteorological anomalies recall most of the literature relying solely on the exposure to weather with a fixed-effect, time-demeaning, specification, the variation over time of the long-term climate norm is new in the setting of the analysis of electricity demand.

$$\mathbb{E}(T_{i,d}|C_i) = \overline{C}_{i,d} = \frac{\sum_{n=j-31}^{j-1} T_{i,d}}{30} \tag{11}$$

$$\omega_{i,d} = T_{i,d} - \overline{C}_{i,d} \tag{12}$$

where: i indexes the State, d indexes the day, j indexes the year.

The second key element of the empirical approach is the estimation of the intensive and extensive margin components in the same equation. The appealing features of the estimation strategy I propose are twofold: i) exploit variation that evolves slowly over time in each location to identify the average impact of long-term climatic changes, while controlling for time-invariant and time-specific observable variables though the fixed-effects; ii) retain the high frequency nature of the load-weather co-variation, enabling to capture not only shocks evolving slowly over time but also fast responses of peak load to unexpected weather anomalies.

I characterize the response of per capita daily peak load to climate and weather anomalies by estimating a fixed-effect panel model in each of the two macro-regions, Europe and India. Variables are observed in State i and day d. For the clarity of notation, equations below omit regional and the time indices.

I evaluate a first "naive" model specification including as main interest variable the observed

[7] In an alternative specification I construct a monthly average of the 30-year moving average of daily maximum temperatures, in order to evaluate if the inter-annual variation of The climate variable at different frequencies (daily or, alternatively, monthly) could affect the results. I find similar results for both specifications (see Supplementary Table 4 and 7), and therefore rely on the more general specification using a day-specific climate variable.

[8] I evaluate alternative measure relying, respectively, on 10 and 20 years moving averages, finding negligible differences in the econometric model.

daily maximum temperature exposure, binned into jth intervals (T_j). Temperature bins are a semi-parametric function that is widely adopted in order to capture non-linearities in the response through the inclusion of linear parameters (as in [1, 7, 3, 6]). Regressions employing bins flexibly trace out piece-wise linear splines. The aggregated response is, however, non-linear, broadly representing a parsimonious regression specification with a quadratic term (see [46] for further details). This specification frames the identification strategy in the same way than previous high-frequency panel studies, that is relying entirely on contemporaneous weather realizations [6, 7]. The effect on electricity demand in measured exclusively by the deviation of observed temperature from its local average value, and therefore β_j identifies shocks which are informative of the average short-run response across locations. Controls include per capita GDP and a matrix N including time and unit fixed-effects and a set of calendar dummies, see equation 13a.

In the preferred specification the two sets of covariates of interest are: i) the 30-year moving average of daily maximum temperature exposure binned into kth 3°C intervals, denoted by the dummy indicators $D_{k,i,d}$; ii) the daily departure from these long-term averages, captured by the positive and negative temperature anomalies, $\omega^{+}_{i,d}$ and $\omega^{-}_{i,d}$, respectively[9]. I sort each daily observation into bins with a specific equidistant cut off of 3°C [10]

The effect of the weather anomalies from the climate is conditional on the temperature level: a given anomaly (e.g. +/- 1°C) in a day with a hot climate norm (e.g. 28°C) affects the response of the load demand differently than the same anomaly in a day with a cold climate norm (e.g. 12°C). Therefore, weather anomalies are included in the equation through an interaction term with the climate variable, providing a flexible and asymmetric modulation of the linear piece-wise response of the load. In order to reduce the number of variables included in the model, I evaluate two alternative specifications: one in which weather anomalies are interacted with all climate bins k and one in which weather anomalies are interacted with two aggregated bins p capturing only the exposure to climatic norms below 15°C and above 24°C for Europe and

[9] An alternative specification uses month- ($D_{k,i,d}$) rather than calendar day-specific ($D_{k,i,m}$) variations in average climate. As I find no substantial differences between the two specifications, results are presented for the higher-frequency daily variable

[10] I conduct a set of robustness tests by adopting different cutoffs, ranging from 1.5°C to 5°C. I also test the reference temperature bin representing thermal comfort, by excluding from the regression equation alternatively the bins of the interval 15°C-18°C, 18°C-21°C and 21°C-24°C. I evaluate the performance of the different alternatives based on standard performance metrics (AIC, BIC) and find that the specification based on 3°C is the one obtaining the best scores. The selected thermal comfort interval for Europe is 18°C-21°C while for India is 21°C-24°C.

below 15°C and above 27°C for India[11]. The results of all specifications are provided in the Supplementary Material (see the Supplementary Tables 1 - 7). The preferred model does not include un-interacted terms for $\omega_{i,d}^{+}$ and $\omega_{i,d}^{-}$, because they provide no additional information with respect to the interacted terms.

In a set of alternative specifications I evaluate three ways in which per capita income, measured by the logarithm of per capita GDP in the previous year, y, affects the response of electricity demand to the climate and weather anomalies. In the equation 13b, income has no effect on the shape of the temperature response: it is simply a non-linear control that captures the adjustment of consumers' low-frequency conditional mean level of demand. In the equation 13c per capita income is assumed to interact only with the response of demand to climatically determined diurnal temperature maxima. This captures the situation in which the normal temperature regime induces agents to invest in stocks of energy-using space conditioning durable, but the extent to which agents respond through actual stock adjustments and average utilization levels is constrained by their income (as in the equation 59). The final specification includes a further interaction term between income and weather (equation 13d), allowing to evaluate the hypotheses that agents' ability to afford a more intensive use of existing energy-using stocks under a positive or negative temperature anomaly depends on their income (as in the equation 61).

$$q = \sum_k \gamma_k^T D_k^T + \beta^Y y + \mathbf{N}\beta^{\mathbf{N}} + \varepsilon_1 \tag{13a}$$

$$q = \sum_k \left(\gamma_k^C\right) D_k^C + \sum_{p(k)} D_{p(k)}^C \left[(\gamma_{p(k)}^w) w\right] + \beta^Y y + \beta^{YY} y^2 + \mathbf{N}\beta^{\mathbf{N}} + \varepsilon_2 \tag{13b}$$

$$q = \sum_k \left(\gamma_k^C + \beta_k^C y\right) D_k^C + \sum_{p(k)} D_{p(k)}^C \left[(\gamma_{p(k)}^w) w\right] + \beta^Y y + \beta^{YY} y^2 + \mathbf{N}\beta^{\mathbf{N}} + \varepsilon_3 \tag{13c}$$

$$q = \sum_k (\gamma_k^C + \beta_k^C y) D_k^C + \sum_{p(k)} D_{p(k)}^C \left[(\gamma_{p(k)}^w + \beta_{p(k)}^w y) w\right] + \beta^Y y + \beta^{YY} y^2 + \mathbf{N}\beta^{\mathbf{N}} + \varepsilon_4 \tag{13d}$$

where

$$D_k^C = \not{\Vdash}[T_k \in (\underline{\mathrm{T_k}}\overline{\mathrm{T_k}})]$$

[11] As both specifications lead to very similar results (see the Supplementary Table 3 - 6), I rely on the latter specification, providing a more aggregated but sufficiently flexible response function to weather anomalies.

$$k^{Europe} \in \{< 0, 0-3, ..., 27-30, > 30\}, k^{India} \in \{< 12, 12-15, ..., 30-33, > 33\}$$

$$D^{C}_{p(k)} = \mathbb{1}[T_{p(k)} \in (\underline{\mathrm{T}}_{p(k)}, \overline{\mathrm{T}}_{p(k)})], p(k) \in \{< 12, > 24\}$$

$$\omega \in \{w^{-}_{i,d}, w^{+}_{i,d}\}$$

$$w^{+}_{i,d} = \begin{cases} T_{i,d} - \overline{\mathrm{C}}_{i,d}, & T > \overline{\mathrm{C}}_{i,d} \\ 0 & \text{otherwise} \end{cases}$$

$$w^{-}_{i,d} = \begin{cases} \overline{\mathrm{C}}_{i,d} - T_{i,d}, & T < \overline{\mathrm{C}}_{i,d} \\ 0 & \text{otherwise} \end{cases}$$

The coefficients γ^{C}_{k} capture the potentially nonlinear peak load response to climatically determined daily maximum temperature, while the coefficients δ^{+}_{p} and δ^{-}_{p} capture the potentially asymmetric response of peak load to differences between each day's maximum temperature and the long-term normal maximum. The modulation of per capita income on the effects of climate and weather anomalies is estimated though the interaction coefficients β^{C}_{k}, β^{+}_{p} and β^{-}_{p}. The matrix N includes time and unit fixed effect, controlling, respectively, for unobserved unit-invariant and time-invariant confounders, as well as day-of-the-year, weekly, monthly and yearly fixed effects, to control for calendar and seasonal effects unrelated to temperature variations. Equations are estimated by OLS using White standard error robust to heteroscedasticity and, alternatively, Newey–West standard errors accounting for serial correlation.

5.2.3 Results

Weather and AC ownership

Peak load temperature response conditional on AC: The responses of per capita daily peak load to maximum daily temperature (Figure 12) exhibit the non-linear U-shape previously found for mid-latitude locations [2, 7, 6, 9]. The minimum of the curve corresponds to the non-weather sensitive per capita peak load of 0.65 kWh in Europe and 0.12 kWh in India. The response to maximum temperatures, obtained without accounting for the AC prevalence modulation (green line in Figure 12), rises from a +10% increase at 24°C-27°C to a +25% increase when temperature is above 33°C in both marco-regions. The benchmark response falls within the range of AC-dependent responses identified though the interaction effect. AC prevalence non-linearly amplifies the response of the peak load to temperatures above 24°C (Figure 12 panel a and Methods). The amplification for a >33°C day in a State with a 70% AC prevalence rate (i.e. above 95th percentile of the two regions' distributions) is more than two times as large as the response under the mean AC prevalence in Europe (20%) and India (13%) (from +14% to +36% in Europe and from +21% to +49% in India). The amplification effect of AC is much larger in the >33°C range than around 24°C-27°C, suggesting that the intensity of utilization of cooling equipment increases disproportionately with extreme high temperatures. Given the two- to three-fold increase in the mean AC prevalence level projected in the two macro-regions circa 2050, I identify AC growth as a potential driver of large amplifications in the hourly peak electricity consumption. Weather-driven peak load fluctuations that today characterize mostly the regions with high AC prevalence will be experienced throughout larger portions of Europe and India.

Interestingly, at low rates of AC prevalence (1%), a > 30°C day is associated with an average increase above the minimum of 6% in Europe, but 20% in India. This result suggests that India's population, lacking access to AC, may rely heavily other electricity-using appliances (e.g., fans) as a substitute cooling technology to adapt to that country's intense heat exposure, varying in the region from 230-1370 annual CDD24 (5% - 95% quantiles) [18]. When the residual effect of energy-intensive durable goods other than AC is filtered out, peak load shocks for a given exposure to hot temperatures and AC ownership rate are very similar across the two marco-regions (vertical segments in Figure 12). The responsiveness of the peak load to maximum temperatures begins to saturate only above 36°C (separate observations of the 33°C-36°C and >36°C bins could be identified only for in India).

Air-conditioning prevalence and its drivers: I empirically model the cross-regional, time-varying dynamics of air-conditioning prevalence in India and Europe. I measure the probability of an average household living in any of the 47 sub-national regions across India and Europe to own air-conditioning with the fraction of regional population having access to central or room AC. AC adoption responds non-linearly to per capita income and the historical exposure to cooling degree days, the annual sum of daily average temperature exceedances above a 24°C threshold - CDD24, see Methods. AC prevalence increases rapidly in locations with warm climates (CDD24 >250) and annual per capita income of above $20k, reaching rates as high as 50%-70%, but in areas with cool climates (CDD24 <15) saturates at 15%-25%, irrespective

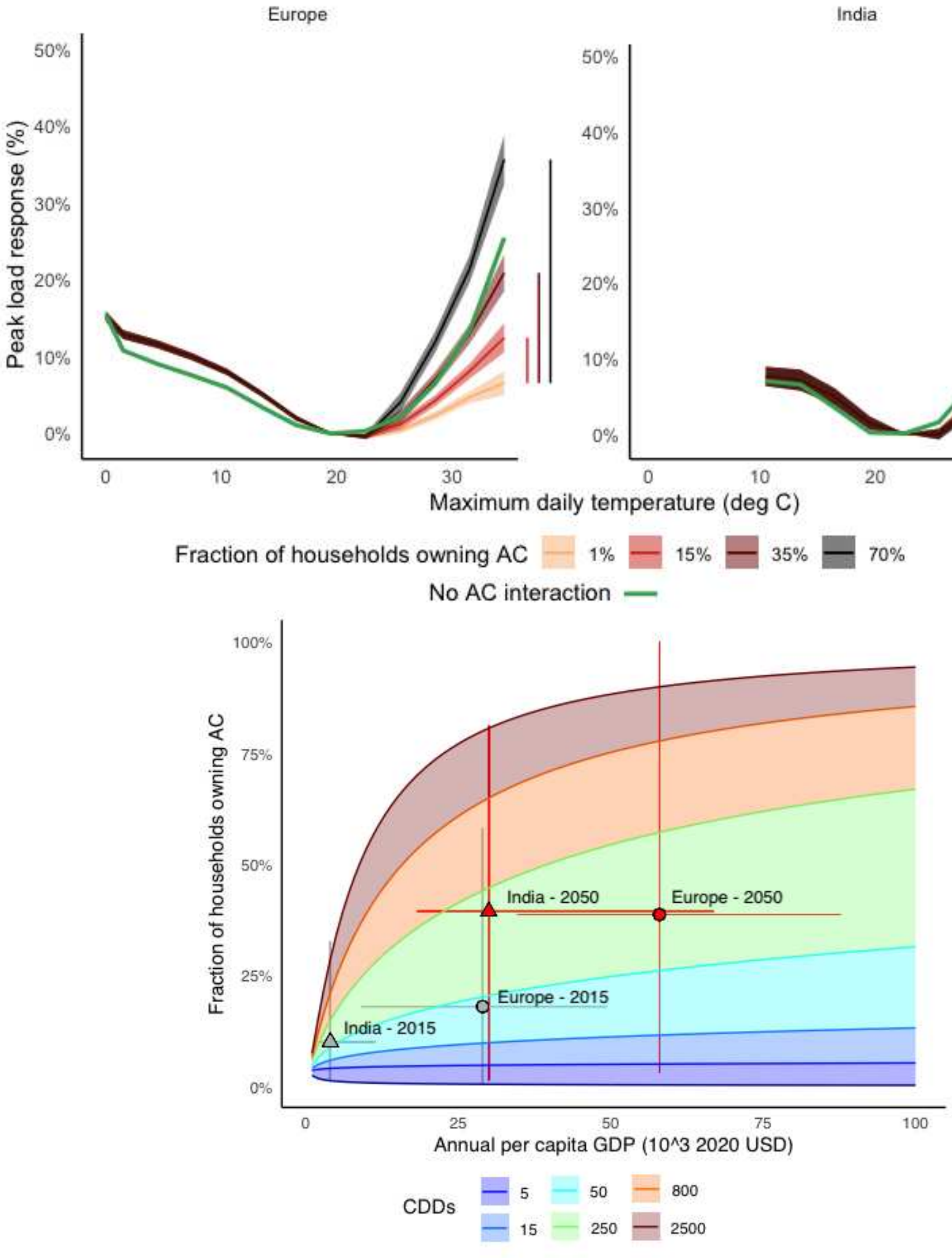

Figure 12. Intensive and extensive margin response functions. ***a****: Response of per capita daily peak load to maximum daily temperatures (and 95% C.I.) based on Equation 7. Vertical bars show the difference between the estimated response when AC >0% and when AC ≈0% for a >33°C (>36°C) day in Europe (India).* ***b****: AC ownership adoption function. Color ranges represent the income-AC curves at different levels of exposure to CDDs under the median urbanization level. Scatters represent the observed macro-regional AC ownership rates, as well as the prediction at mid-century under RCP 8.5 and SSP 5. Segments present the 10th-90th quantile of per capita income (horizontal) and AC prevalence (vertical) across the States in the two macro regions in 2015 and circa 2050.*

of per capita income. Urbanization further amplifies prevalence, independently of income and temperature (See Methods and Supplementary Material). The empirical AC adoption model suggests that Europe's current per capita income is already high enough to support widespread adoption of AC, but the historically low exposure to extreme heat has contributed to keep prevalence low.

Conversely, India's low per capita income constrains households' ability to acquire air conditioners, despite the high historical exposure to thermal discomfort. Thus, AC growth will respond relatively strongly to temperature in Europe's richer temperate member states, and to income in India's poorer hotter states. By coupling the adoption model with projections of CDD24s, income and population circa 2050, impacts of future temperature increases in Europe are inferred from a synthetic richer current India—causing AC prevalence to more than double from 19% to 41%, and effects of future economic development in India are inferred from a synthetic hotter current Europe—causing AC prevalence to increase four-fold from 10% to 40% (see Figure 12 panel b and Supplementary Material).

The current gap between developed and developing countries in the vulnerability to climate change is not eliminated in the future despite the convergence in the endowment of air-conditioning: the 900 million Indian households that lack AC circa 2050 will be exposed to substantially higher temperatures than their European counterparts (see section **??**).

Climate and income model

I find evidence of a statistically significant, U-shaped, relationship between peak electricity demand and the slowly varying climate exposure to maximum temperatures (see Supplementary Tables 1-7 in the Supplementary Material). The spline function resulting from the combination of the coefficients of the climate intervals (γ_k) increases more sharply in the temperature range for cooling services (around 24°C and above) than for heating services (around 12°C and below) both in Europe and India. The long-run response of the peak load to a shift in the climate from the reference interval to maximum temperatures above 30°C is considerably higher in Europe (a 30% increase) than in India (an 11%-18% increase respectively in the intervals 30°C - 33°C and above 33°C), when per capita income is fixed at the median level. In both Europe and India the long-run exposure to cold temperatures increases the peak by around 8% - 10%. In India the left-arm of the response derives from the exposure to mild temperatures around 10°C - 15°C, suggesting that the underlying end-uses driving the shock are unrelated to residential heating services and may derive from seasonal shifts in the power consumption of the agricultural and industrial activities that could not be captured though the fixed effects (such as the usage of ground water irrigation through electric pumps [47]).

In the preferred specification the long-term spline function is modulated by the short-run adjustment effect triggered by weather anomalies through the coefficients δ_p^+ and δ_p^-. The peak load response associated to any given maximum temperature realization T is not unique, but it depends on the underlying combination of the expected climate c and weather anomalies w. Keeping the maximum temperature realization constant, I find that the magnitude of the peak load shock when no weather anomaly occurs, i.e. when the expected exposure c equals the observed exposure T (*long-run* response), differs from the peak load shock when a temperature anomaly occurs, i.e. when the maximum temperature realization T equals $c + w$ (*short-run* response), see Equation 57. In particular, for any given $T > 24°C$ the *long-run* response lies above the set of *short-run* responses (coloured scatters in Figure 13): in other words, when the peak load is allowed to adjust in the long-run though the extensive margin, its sensitivity to hot temperatures increases. This result suggests that increasing air-cooling appliances' adoption is the driving underlying adaptation strategy to cope with an hotter climate. On the other hand, for any given $T < 15°C$ the *long-run* response lies within the set of *short-run* responses, suggesting that the sensitivity of peak electricity demand to heating needs may be reduced over time. Variations over time in the energy efficiency of appliances and better home insulation may be factors that contribute to such effect [12]. Furthermore, I find that per capita income modulates both the long-run response of the peak load across the full set of bins k, and the short-run response to positive weather anomalies occurring above 24°C for Europe and 27°C for India. Hence, the modulation effect of per capita income alters significantly both the *short-run* and *long-run* responses (Figure 13): the shocks associated with maximum temperatures above 30°C in Europe and above 33°C in India more than double when per capita income shifts from the 25th quantile (12.000 USD/year for Europe and 1.100 USD/year for India) to the 75th quantile (37.000 USD/year for Europe and 2.700 USD/year for India). I find that the high-income response of India approaches the low-income response of Europe, despite the large differences in nominal income per capita between the two regions.

Response function comparison across alternative methods

[12]The set of *short-run* responses is computed for each maximum temperature bins T_q (with a 1°C interval width) by taking into account any combinations of C and ω observed in the sample that would result in a value within T_q. In other words, the distribution of the observed C and ω in the sample is used to construct the distribution of possible *short-run* responses for any given T_q.

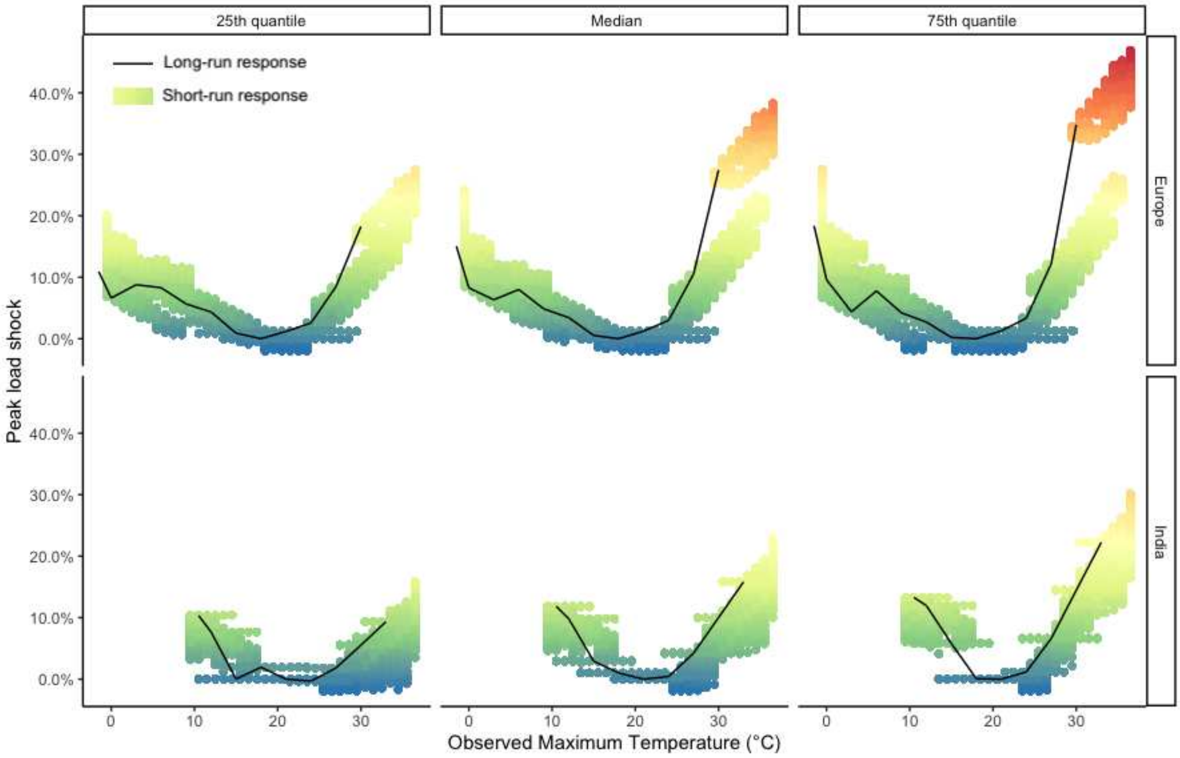

Figure 13. Long- and short-run adaptation responses to maximum temperature exposure by per capita income quantiles. The long-run adaptation response (black line) is presented next to the short-run response for each 1°C bin of maximum temperature exposure (coloured scatters). The range of short-run responses is computed, for each 1°C bin of maximum temperature exposure, from the distribution of the weather anomalies and climate norms in the two regions' samples.

The set of coefficients provided by the response functions of the two alternative methods can be compared in order to investigate how the different methodologies perform with respect to one another. Figure 14 shows the value of the peak load shock, i.e. the estimated coefficient representing the percentage increase in the peak load with respect to the mean level at the reference thermal comfort interval, based on the "Weather and AC ownership" (panel a) and the "Climate and income model" (panel b). In the first case (panel a), the peak load shock is defined for any given weather exposure interval, across the range of AC prevalence observed in India (1-70%) and in Europe (1-85%). In the second case (panel b), the peak load shock is defined for any given climate exposure interval (ranging from 24-27°C to >33°C) across the range of per capita income in India (1-8k USD/year) and Europe (14-44k USD/year). While the former set of shocks is linear across AC prevalence rates, the latter set of shocks is non-linear in income, with a saturation effect more evident in Europe than in India. The difference in the response function is driven by the underlying non-linear relation between per income per capita and AC prevalence across climate exposure levels. The value of the "Climate and income model" shocks in India is comparable to the value in Europe, despite the large differences in the regions' per capita income, because in India the exposure to a hotter climate results in similar high levels of capital stock accumulation as in Europe, and effect that is captured directly with the former model and indirectly with the latter. Furthermore, the value of the shock in each region is comparable between the two models: the shock associated the highest AC prevalence and maximum temperature bin based on weather observations (36-36°C for Europe and >36°C for India) is comparable to the shock associated the highest per capita income and maximum temperature bin based on climate (30-33°C for Europe and >33°C for India).

Climate change impacts on the peak load circa 2050

Both methodologies point to a substantial amplification of peak load circa 2050 in response to climate change. At mid-century, the amplitude of daily peak load variations over the course of the year can be greatly increased by hotter daily maximum temperatures in conjunction with expansion in the prevalence of AC (see Figure 15, left panel) or of per-capita income (see Figure 15, right panel). European impacts on the peak load exhibit a strong North-South gradient previously found by [6]. In northern regions with mild summers, AC prevalence remains low, with higher warm season temperatures contributing to slight (5%) increases in summer peak demand that do not offset winter peak declines that accompany decreased heating requirements. Conversely, in Southern regions daily summer peak demands increase by 20% - 30%.

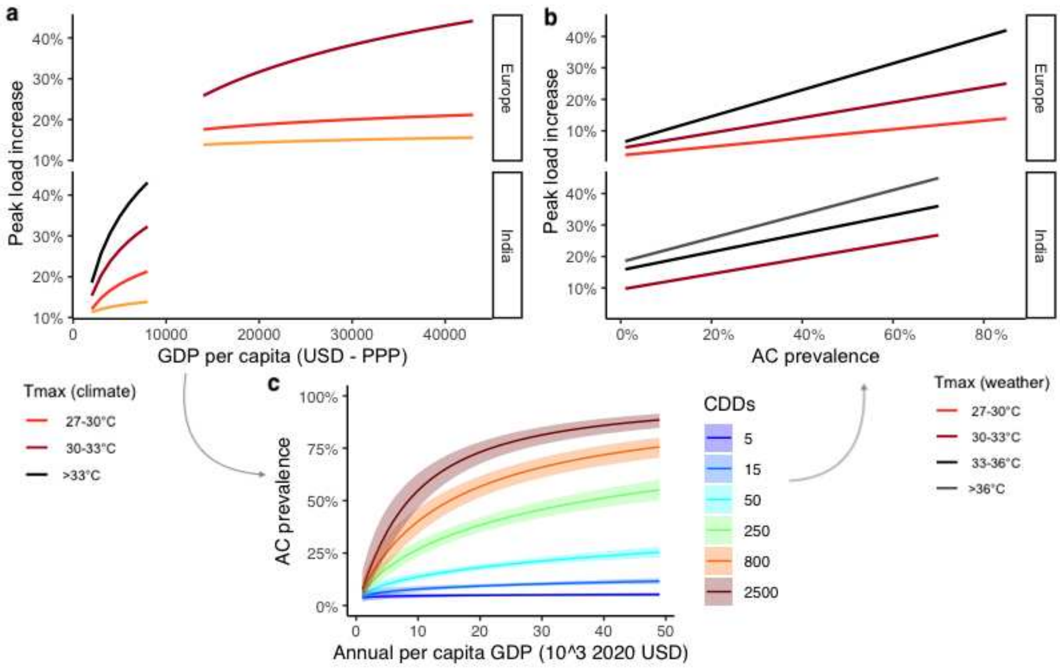

Figure 14. Response function comparison across alternative methods.

Substantial additional peak generation capacity is required circa 2050 in order to accommodate the additional cooling demand in Southern European states, Italy (+13 GW) and Spain (+10 GW), and in the Indian states of Punjab, Uttar Pradesh and Maharashtra (+ 4 GW). A weaker latitudinal gradient arises in India, where seasonal impact patterns are broadly similar across the majority of states. Except for the December-March dry season, fraction increases in peak demand are higher than in Europe, with uniform relative increases above 35% in North-Western India, where the amplifications of maximum daily temperatures is coupled with high future AC prevalence induced by income growth (approaching 100% in Punjab, Haryana and Chandigarh, see Supplementary Material). This divergence arises from the interaction of the different climates and temperature-load responses in the two macro-regions. Low-latitude Indian states are characterized by a near-monotonic demand response, where the diurnal maximum temperature range (24-40°C) corresponds to the portion of Figure 12 to the right of the nadir, while temperate Indian states and European countries exhibit the typical U-shaped response over a diurnal maximum temperature distribution with a lower support (0-33°C). This result provides further evidence against a latitudinal gradient of climate change impacts on energy demand that extends all the way to the equator [9].

Total annual electricity demand in Europe increases by roughly 33 TWh, or 2% from today's consumption, since the additional annual consumption of 40 TWh in Southern states is balanced

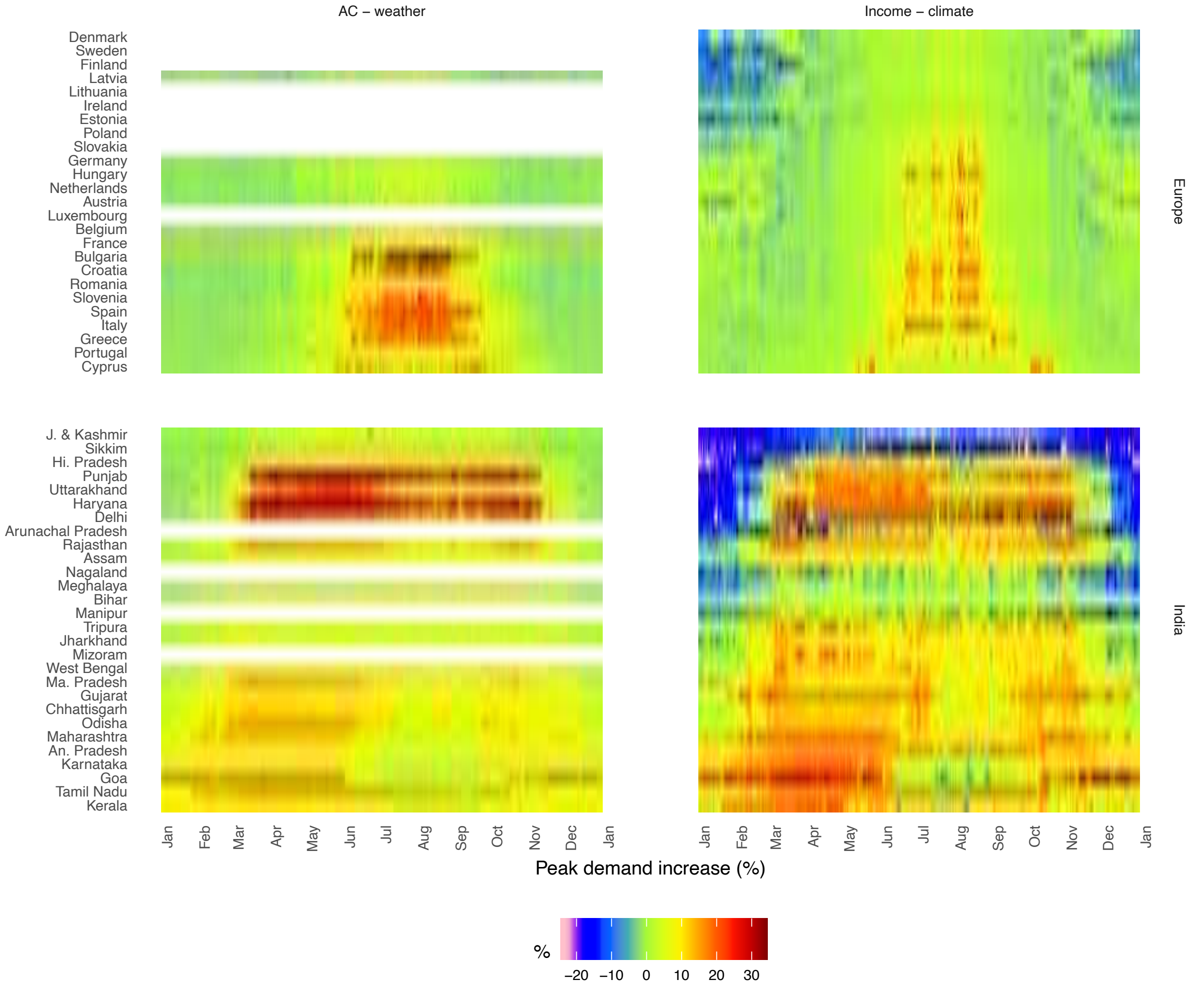

Figure 15. Comparison of climate change impacts on the peak load circa 2050. Relative increase in the daily peak load, median of 29 GCMs circa 2050 under RCP 8.5 and SSP 5, obtained from two alternative methods.

by mild decreases in consumption in Northern states. On the other hand, annual electricity demand in India grows by as much as 188 TWh, or 17% from today's consumption. The uncertainty around mid-century climate change projections, as inspected from the distribution of the impacts across 29 GCMs, does not affect considerably the projections (see the Supplementary Material).

Adaptation-mitigation tradeoffs

I evaluate the additional carbon emissions resulting from the growth in electricity demand for cooling simultaneously to the benefits of growing AC prevalence, namely the reduction in the number of people exposed to heat stress. I measure the trade-off between mitigation and

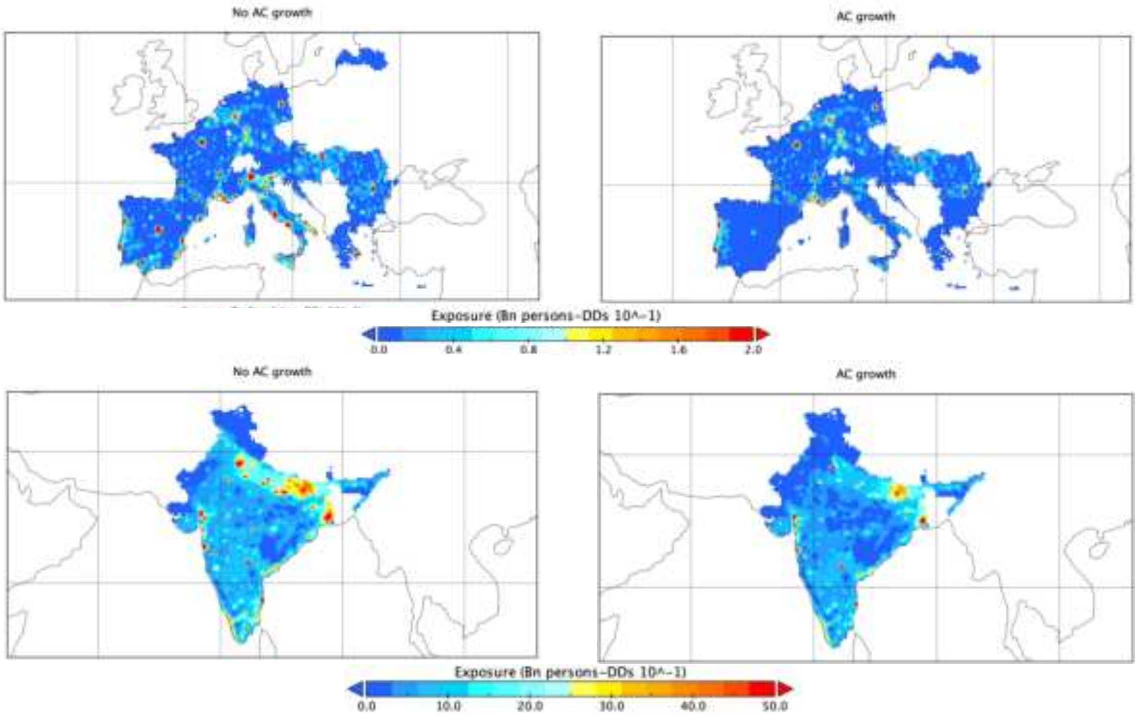

Figure 16. Maps of population exposure by AC growth scenario. Number of person-degree days (billion) in India and Europe by scenario, with or without the growth in AC from the historical level. Values in the color-palette are rescaled to 10^-1 *for easing visual inspection of the most exposed areas.*

adaptation by computing the state-level variations induced by climate change circa 2050 in: i) the annual CO_2 emissions from the additional electricity generation associated with AC use, assuming the current power generation mix (see Methods); ii) the daily average number of people that circa 2050 will be exposed to maximum temperatures above 24°C and have no AC in their homes, measured by the count of person-degree days (DDs). I compare two cases: one where population exposed to a hotter climate does not increase the AC prevalence with respect to today ("no AC growth"), but responds to a hotter climate by increasing the utilization of the current stock (i.e. though intensive margin only), and one where extensive margin adjustments allow to increase AC prevalence up to the level estimated based on Eq. 8 under SSP 5-8.5 (i.e. "AC growth", see also Figure 2, panel a).

I find that if AC prevalence increases in response to socio-economic and climate drivers, all states experience a reduction in the number of exposed people (downward shift) and, at the same time, an increase in the annual CO_2 emissions (rightward shift), with respect to the case in which AC prevalence is fixed at the historical level. Therefore, the benefit from the reduced exposure of population comes with a costs in terms of the increased challenge to reduce emissions.

The increase in carbon emissions from a unitary reduction in person-degree day exposure represents the extent of the tradeoff between adaptation and mitigation (Figure **??**, panel b). I compare the magnitude of the tradeoff in each 0.25x0.25 grid-cell in order to investigate patters of variations across regions and areas with different levels of development, proxied by the average per capita income in the grid-cell. On average, a decrease in heat exposures by one person-degree day results in 4 times lower electricity demand and 56% lower carbon emissions in India than in Europe, as a result of the higher carbon-intensity of power generation in India. Differences in the tradeoff are reflected also within each region across per capita income levels: I find that the median electricity consumption and carbon emissions per person-degree day increases when moving from poorer areas (per capita income below 25th quartile) to richer areas (per capita income above 75th quartile) both in India and Europe. Only in the richest European areas I identify an inversion in the tend, as the emissions per person-degree day with respect to the previous income per capita quartile decline due to a reduction in the carbon intensity of the power mix in those areas.

At the macro-regional level, the growth in AC prevalence circa 2050 results in an increase of the annual additional CO_2 emissions from 38 Mton CO_2 to 160 Mton CO_2 in India and from 7 Mton CO_2 to 17 Mton CO_2 in Europe and, at the same time, it reduces the number of average daily heat exposures to maximum temperatures above 24°C from 11.1 billion to 7.3 billion person-degree days in India and from 430 million to 265 million person-degree days in Europe. Even after accounting for AC growth, I project that each day circa 2050 on average in India roughly ten times more people than in Europe will be exposed to maximum temperatures above 24°C and have no ACs in their homes. Additional emissions associated with the growth in AC prevalence are non negligible: in India and Europe they correspond to 15% and 2% of the estimated historical emissions from power generation.

5.2.4 Discussion

While there is no comparable study providing evidence of the impact of extensive margin adjustments to climate change on peak electricity demand, a small number of studies indicate how the peak load of developed countries responds to intensive margin adjustments [7, 6]. The range of shocks provided for the European countries in [6] are in line with the projections

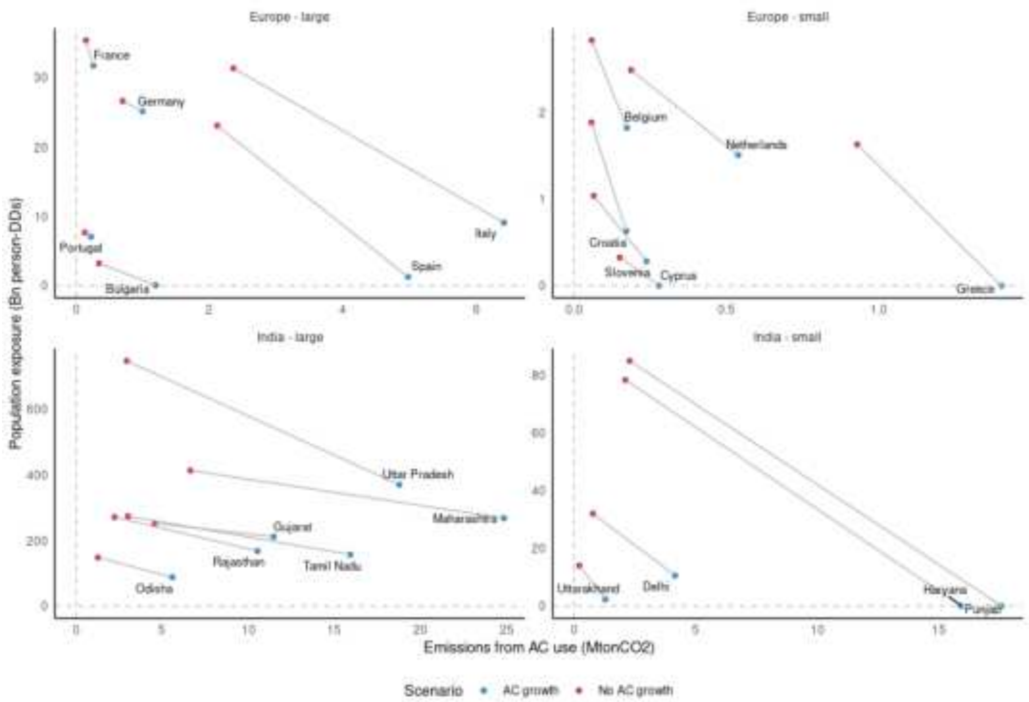

Figure 17. Annual exposed population and carbon emissions under alternative AC prevalence scenarios circa 2050. State-level variations induced by climate change circa 2050 in the annual CO_2 emissions from power generation and annual count of person-degree days exposed to daily maximum temperatures above $24°C$, respectively with (blue) and without (red) the projected growth in AC prevalence. States are grouped into different panels depending on the size of the population exposed. The states with the smallest population counts have been removed to avoid clutter, the figure showing all states is shown in the Supplementary Material.

based solely on the amplification effect of temperatures circa 2050 and current AC prevalence. The preferred model specification provides substantially higher relative changes in peak demand already around 2050, due to the long-run adjustments of AC ownership on top of the short-term adjustments of AC use.

Furthermore, the projections are inclusive of the amplification effect of per capita income and climate change on the extensive margin, an effect that has so far been identified only by studies exploiting annual-level cross-sectional variation between households [12, 11]). Finally, the non-linear structure of the response function based on temperature bins calls into questions findings of studies which rely only on response functions limited to extreme temperatures (such as [48]). Overall, this paper reinforces the argument that changes in electricity demand due to climate change adaptation are going to be driven by movements along both the extensive and intensive margin, with large differences between developed and developing regions [10].

Although I project a two- to four-fold increase in the macro-regional AC ownership rate of households in Europe and India respectively, I find that as the climate warms, almost 640 million people across India and 60 million across Europe remain exposed to heat stress with no AC in their homes on an average day of the year. Despite being lower than the average exposure under historical climate and AC prevalence (990 million people in India), the projected number of exposed people in the future identifies how adaptation through the use of energy-intensive appliances, remaining not affordable for many under the socio-economic assumptions of SSP5 and SSP2 (see Supplementary Material), may require alternative adaptation options or policy intervention to account for the needs of the most exposed and poorest parts of society. The regional variation in the incidence of the two components, intensive and extensive margin, within EU and Indian regions, suggests that differentiated policy interventions might be more effective.

Here I draw the conclusions on the mitigation-adaptation tradeoff with a measurement of population exposures assuming that only the presence of AC in the household shields people from heat stress. The number of exposed people tends to be overestimated when lacking to account for forms of adaptation alternative to AC, such as fans or efficient building insulation, that can reduce thermal stress. On the other hand, the method presented tends to underestimate exposures as I do not account for the exposure of population owing an AC occurring during the time spent outdoors for commuting, work or leisure activities.

While the main impact metrics are constructed taking the median across 29 GCMs, I also report the individual models' impacts and analyse how the uncertainty around climate warming affects the results (see Supplementary Material). Recent evidence focusing on the outputs of the Coupled Model Intercomparison Project, phase 6 (CMIP6) has shown that relying on multi-model ensemble medians may lead to higher projections of warming than the IPCC's assessed-warming averages [49]. In the sensitivity analysis I rely on the recent classification of GCMs proposed by [49], that based on the metrics of equilibrium climate sensitivity and transient climate response identifies the GCMs providing reasonable projections of warming consistent with the IPCC AR6, and those characterized by high-sensitivity resulting in "too hot" projections. While we find only one clear outlier on the high end, we also identify a 10%-18% difference between the impacts relying on the ensemble median of the "consistent" vs "hot" models groups, depending on the region (see Supplementary Material). The results provide new evidence on the significance of model selection in impact assessments.

I leave for future work the adoption of a weather variable accounting for humidity (i.e. daily maximum wet-bulb temperature), which may be a more accurate explanatory variable when aiming to identify the energy used by appliances to provide thermal comfort in tropical regions [18]. A further improvement would be accounting for differences in the temperature-load response function across sectors, as the available evidence based on more aggregated energy demand statistics shows considerable heterogeneity between the residential, commercial and industrial users [3, 50].

5.3 Income-dependent climate shocks in an dynamic error correction model

5.3.1 Introduction

In this section I investigate how climate change will shape the mid-century electricity demand of a large tropical country, Brazil, by adopting a dynamic econometric model based on sub-national data. I aim to identify the long-term relationship between electricity demand and weather conditions in Brazil, a rapidly growing tropical economy. Iassemble a panel dataset of monthly electricity demand of 27 Brazilian Federal States across four different sectors: residential, commercial, industrial, and rural. Icouple energy statistics with high resolution weather data, thus enabling us to retain detailed information from the weather distribution and its geographical specificity. Itest the adequacy of alternative econometric specifications and thermal discomfort measures as robustness checks. Finally, by building on the estimated response function, Iquantify the mid-21st century (2041-2060) amplification of electricity demand due to moderate (RCP2 4.5) and severe (RCP 8.5) warming scenarios [51].

Though previous studies have investigated the impacts of climate change on Brazilian power demand [52], the estimation of such impacts at finer spatiotemporal scales, while also accounting for the adjustments of appliance penetration over time, is lacking. Furthermore, the empirical works evaluating the sensitivity of energy demand to weather conditions have in general not expanded the analysis beyond the residential and commercial sector [53, 54]. While aggregate industrial energy demand is typically considered non-sensitive to weather variations because of the strong composition effects [53], recent empirical investigations show that the energy demand of the industrial as well as the agricultural and transport sectors, could be remarkably affected by climate adaptation [3]. The sectoral disaggregation of electricity demand adopted in this study is therefore an important methodological contribution to the literature. Furthermore, similarly to [1], I test the adequacy of alternative weather variables to capture the variation of monthly electricity demand.

5.3.2 Methods

Data: I assemble a panel dataset of monthly observations for the 2004-2017 period, for all 27 Brazilian Federal States, comprising of: (i) per capita electricity consumption disaggregated by sector (residential, commercial, industrial, public and rural); (ii) socio-economic drivers (GDP per capita, sectoral electricity prices) and, (iii) weather variables measuring thermal discomfort (I adopt alternatively monthly temperature bins in the main specification and Degree Days as a robustness check). Electricity consumption is obtained from the Resenha Mensal do Mercado de Energia Elétrica [55], while average monthly electricity prices by the Agência Nacional de Energia Elétrica, ANEEL [56]. State-level monthly GDP and population are calculated by a linear interpolation of the yearly regional GDP available from the Instituto Brasileiro de Geografia e Estatistica, IBGE [57]. Hourly near-surface air temperature and relative humidity data (aggregated to daily averages) used for computing the thermal discomfort indices are derived from the ERA5-Land reanalysis data made available by the European Center for Medium Range Weather Forecasting, ECMWF [39], at 0.1° gridded resolution (see SI). Using the input meteorological variables, I assemble two thermal measurements of CDDs: dry-bulb (CDDsdry) and wet-bulb temperatures (CDDswet). CDDswet make it possible to account for relative humidity, in addition to temperature [18, 58]. Monthly CDDsdry are computed by using a threshold of 24°C, which is the value typically associated with the thermal comfort of tropical countries [18]. by definition are lower in magnitude compared to , and equal when rh=100%, i.e., when both dry- and wet-bulb temperature are equal (see [59] for further details). For this reason, I adopt two alternative thresholds, 18°C and 24°C, for computing monthly CDDswet. HDDs are computed by utilizing the commonly adopted threshold of 18°C, and an alternative threshold of 15°C is used as a robustness check. As an alternative thermal discomfort measure, I adopt the monthly count of days in which the daily mean temperature falls in a set of intervals (henceforth "temperature bins"). Also in this case, I test the adequacy of both dry-bulb and wet-bulb temperature, leading to two alternative measurements of the temperature bins. I adopt the temperature bins to capture the potential non-linear effect of days with extreme temperatures in Brazil, a country where many areas exhibit relatively low variability of daily temperatures [58]. I sort each daily observation into bins with a specific equidistant cut off of 3°C[3]. Regressions employing bins flexibly trace out piecewise linear splines. The aggregated response is, however, non-linear, broadly representing a parsimonious regression specification with a quadratic term (see [59] for further details). All meteorological variables are computed at the grid cell level and are subsequently aggregated to the state-level using gridded population data from the Center for International Earth Science Information Network.

Concerning projections for future climate change scenarios, changes in weather exposures are assembled utilizing the NASA Earth Exchange Global Daily Downscaled climate Projections (NEX-GDDP) dataset [39]. The hindcast period, representing the current climate, ranges from 1986-2005[5], while mid-21st century future climates are drawn from the models' output for 2041-2060, under both RCP 4.5 and 8.5 scenarios.

Econometric model

I estimate a dynamic ECM, building on the work by [3, 60]. The statistical tests validating the adequacy of the ECM to the panel data, based on [61, 62], are presented in the the Supplementary Material. The fixed effect specification described below, makes it possible to check for both the presence of unit-specific unobserved factors which do not change over time, and the time-specific unobserved factors that affect all units equally in each time period. The unit fixed effect in the ECM captures the influence of unobserved time-invariant country-specific factors on the average growth rate of electricity demand, while the time fixed effect captures the influence of unobserved unit-invariant time-specific factors on the average growth rate of electricity demand [62]. The equation partitions the influence of the covariates into short-term and long-term effects, captured by the terms in square and curly braces, respectively (Eq. 14). If the ECM approach is appropriate, then -1 $< \gamma <$ 0, while β and η estimate the long-term effect, that of a unit increase in thermal discomfort (h), GDP per capita (gdp) and prices (p) have on y. These long-term effects will be distributed over future time periods according to the rate of error correction γ (Eq. 15). The specification assumes homogeneous short- and long-term coefficients, as well as the speed of adjustment within the group of 27 Federal States.

$$\begin{aligned} \Delta y_{i,t} = +\alpha V_i + \theta Z_t + [\sigma \Delta gdp_{i,t} + \iota \Delta h_{i,t} + \theta \Delta p_{i,t}] + \gamma y_{i,t-1} \\ -(\eta gdp_{i,t-1} + \beta h_{i,t-1} + \zeta p_{i,t-1}) + \varepsilon_{i,t} \end{aligned} \tag{14}$$

$$\begin{aligned} \beta^{long-run} &= -(\beta/\gamma) \\ \eta^{long-run} &= -(\eta/\gamma) \end{aligned} \tag{15}$$

$$\beta h_{i,t-1} = \sum_{T=binj}^{T=bini} \beta T_{i,t-1} \vee \beta CDD_{i,t-1}^{dry} \vee CDD_{i,t-1}^{wet} \tag{16}$$

With: i: Federal State t: month (Jan 2004 to Dec 2017) y: natural logarithm of per capita monthly electricity consumption h: thermal discomfort indicator selected in the model, alternatively set to temperature bins ($T_{i,t}$), drybulb CDDs ($CDDs_{i,t}^{dry}$) or wetbulb CDDs ($CDDs_{i,t}^{wet}$) gdpi: natural logarithm of gdp per capita p: natural logarithm of electricity prices V: vector of state-specific dummies Z: vector of time-specific dummies $\varepsilon : randomerrors.$

In a second model specification (Eq. 17), I investigate whether the level of income, captured by the monthly GDP per capita, modulates the response of electricity consumption to thermal discomfort in equilibrium. The hypothesis tested here is whether higher levels of per capita GDP amplify the optimal response of electricity consumption to thermal discomfort. This amplification would result from an increase in the optimal level of stock penetration of durables in households characterized by higher average income [45]. Other factors that could affect the aggregate impact of per capita income on the weather response function, include a variation in the propensity to use ACs, and a variation in the tolerance for heat of households.

The interaction effect captures the aggregated impact of all possible drivers contributing to identifying the income modulation effect. I test this hypothesis by having the level of GDP per capita interact with the lagged thermal discomfort variables included in the dynamic ECM. The resulting specification is the following:

$$\begin{aligned}\Delta y_{i,t} = &+\alpha V_i + \theta Z_t + [\sigma \Delta gdp_{i,t} + \iota \Delta h_{i,t} + \theta \Delta p_{i,t}] + \gamma y_{i,t-1} \\ &-(\eta gdp_{i,t-1} + \beta h_{i,t-1} + \beta h_{i,t-1} \cdot gdp_{i,t-1} + \zeta p_{i,t-1}) + \varepsilon_{i,t}\end{aligned} \tag{17}$$

I estimate Eq. 14 and 17 for each sector and alternative thermal discomfort variables, using ordinary least squares (OLS) fitting criterion. The results of the tests on the presence of cross-sectional heterogeneity, serial correlation and multicollinearity among the variables are presented in the Supplementary Material. Finally, in order to identify which model specification better represents the evolution of electricity over time, I compute multiple performance metrics as described in the Supplementary Material.

In the second stage of the analysis, I combine econometrically estimated long-term elasticities with socioeconomic and climate change scenarios in order to project the future magnitude of sectoral electricity demands around mid-21st century. First, GDP and population projections around the year 2050 drive projections of baseline electricity demand. I use the downscaled shared socioeconomic pathways (SSPs) projections of population and GDP, available for the SSPs 1-3 [63]. Next, climate change impacts on electricity demand are developed by forcing the fitted empirical response functions with the distributions of the derived thermal discomfort indicators under future climate warming. The plausible future (2041-2060) spread of thermal discomfort during the baseline historical period (1986-2005) is estimated by utilizing the NEX-GDDP multi-model minimum, maximum and median measurements of the monthly thermal discomfort variables. I use, alternatively, the RCPs 4.5 and 8.5 scenarios, which yield a global average temperature increase, respectively, of 1.5°C and 2°C at around the year 2050. The climate change impact metric is derived from the computation of the differences in exposure between each GCM's simulated current and future climates, rather than on the direct comparison of simulated future exposures against their observed counterparts, since climate model simulations generally do not reproduce observed high frequency weather extremes and may therefore exhibit biases relative to current climate [64, 65]. This approach is achieved by adopting the the 'delta' change method [66]:

$$\Psi_{i,h,s,2050} = [\frac{exp(\widehat{\beta}_s^h \cdot 1/n \cdot \sum_{t=1}^{n} \widetilde{h}_{i,t}^{Fut})}{exp(\widehat{\beta}_s^h \cdot 1/m \cdot \sum_{t=1}^{m} \widetilde{h}_{i,t}^{Hist})} - 1] * 100 \tag{18}$$

$\Psi_{i,h,s,2050}$ represents the change in electricity demand determined by future climate, relative to what is historically computed for each thermal discomfort variable (h) in each Federal State (i), at any given month (t), and for any given sector (s). More details on the delta change method are presented in the Supplementary Material. The composite effect of socio-demographic and climatic components yields the projected electricity demand. Note that this approach takes into account urbanization dynamics in two ways: implicitly, as future state-level temperature shocks are derived from population-weighted gridded fields, and directly, as I derive total state-level demand by multiplying the projected per capita electricity consumption by the population count, which varies between and within regions across SSPs.

5.3.3 Results

Income per capita modulates the long-term adjustments to weather shocks: Across all specifications, the ECM coefficients , β and η (see Eq. 14) are statistically significant ($p < 0.05$) and have the expected sign (see the Supplementary Tables S7-S9 in the Supplementary Material). In accordance with part of the literature [7], I find no evidence of a significant relationship between electricity and weather exclusively for the industrial sector. The model based on the temperature bins performs better than the models based on the Degree Days across all sectors (see the the Supplementary Material). This result underscores the importance of allowing for the non-linear impact of temperatures on electricity demand, a characteristic well captured by the specification employing temperature bins. Furthermore, the specification that includes the interaction between per capita GDP and the long-term effect of weather (Eq. 14) performs better than the specification with no interactions (Eq. 17). Finally, I find that the model based on dry-bulb temperature bins performs better than the model based on wet-bulb temperature bins (see Supplementary Tables S9-S10 in the Supplementary Material). I therefore base the projections of future shocks of electricity demand on the non-linear dry-bulb temperature response function, which allows for the modulating effect of per capita GDP. Figure 18 shows the long-term coefficients (β long-term) estimated from Eq. 15. Each $\beta^{long-term}$ element captures the marginal effect of an additional day of exposure within the corresponding interval (e.g., the average effect of one more day in the 24°C-27°C bin, versus the reference comfort level, the bin 18°C-21°C dropped in the regression11). Only intervals >24°C are characterized by a significant interaction coefficient with income (see the Supplementary Tables S7 - S9 in the Supplementary Material). The magnitude of the long-term semi-elasticities indicates that electricity consumption tends to increase with higher thermal discomfort. I find a strong non-linear behavior, as the coefficient associated with an increase in the frequency of days with average temperature >30°C is roughly two times larger than the same coefficient of the 27°C-30°C interval, and four times larger than the 24°C-27°C interval. Furthermore, sectoral differences are non-negligible: residential demand exhibits the highest response, followed by the commercial sector and lastly by the public and rural sector. The level of regional per capita GDP greatly affects the magnitude of the long-term adjustment: the coefficient associated to temperatures >30°C in the highest income decile is almost four times higher than the one in the lowest income decile in the residential sector (a 4% increase in demand versus a 1% increase), and almost three times higher in the commercial sector (a 2.5% increase versus a 0.8% increase), while for the public and rural sectors the difference is negligible. I find no evidence of a statistically significant response of power demand to low temperatures, suggesting that heating requirements may be primarily met through other fuels' consumption.

The long-term response is greater than the short-term one by roughly 20%-30%, depending on the specification (see the Supplementary Tables S7-S9 in the Supplementary Material). This result validates the distinction between the intensive- and extensive-margin adjustments in this empirical setting, as it confirms that both income and contemporaneous weather shocks exert persistent effects on electricity demand. The error-correction coefficients are uniformly significant, ranging between -0.35 and -0.45 depending on the sector, implying that at each time period, a share of 35%-45% of the remaining gap is corrected. Electricity demand re-equilibrates after a shock so that a full equilibrium is reached within one year across the three sectors. The service sector is characterized by the most rapid response for closing the disequilibrium gap (eight months), suggesting that the propensity of replacement and penetration of energy-using appliances by commercial and public agents under disequilibrium conditions is slightly higher than the propensity of households (12 months).

Turning to the effects of socio-economic growth on the levels of electricity demand captured by the long-term coefficients of per capita GDP, I find that the residential sector's long-term adjustments are 40% higher than those of the commercial, public and rural sectors. The results

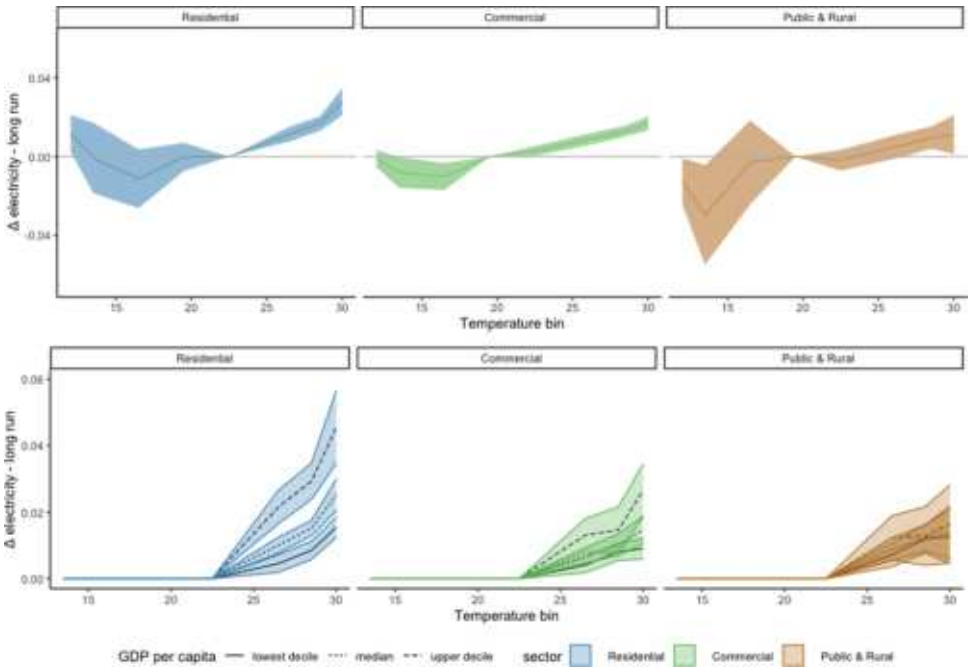

Figure 18. Sector-specific long-run response of the electricity demand to temperature in Brazil. The long-term coefficients of the temperature bins based on the 14 and 17 are reported. The 95% confidence intervals (shaded regions) are based on standard errors robust to heteroskedasticity, cross-sectional and auto-correlation. Panel b presents the heterogeneous coefficients based on the interaction with income per capita in different deciles (lower, middle and upper deciles).

are within the range estimated by previous studies [19, 59, 63] (see the Supplementary Table S12 in the Supplementary Material). The coefficients associated to the price of electricity are significant but with a counterintuitive, positive sign. An inspection of the time series of prices and GDP per capita suggests that the two are highly correlated, since the former has been evolving in the wake of increased per capita GDP over the years (see the Supplementary Material). The relationship may further be biased by the imperfection of the market due to the subsidies applied to low-income households [61,62]. I drop electricity prices in the final specification in order to provide unbiased estimates of the GDP per capita coefficient.

Economic growth amplifies the relative impact of adaptation.

The long-term elasticities identified through the ECM model are applied to project the sectoral future electricity demand around mid 21st-century under different socioeconomic and climatic conditions. Baseline future sectoral electricity demand, i.e., demand without climate change, varies greatly depending on the SSP (see Supplementary Table S11): total demand in 2050 is projected to increase from 20% under the SSP 3 to 85% under the SSP 1, with respect to the 2017 level. Per capita electricity consumption grows at a faster pace, respectively between

35% and 110%, depending on the SSP. The residential sector fuels most of the increase, since the demand of households in SSP 1 are more than two times larger than demand in 2017 (from 134 TWh to 164-298 TWh, depending on the SSP).

Climate change exerts an additional influence on electricity demand, deriving from the increase in thermal stress. This shock is driven by a significant shift in the number of days from the mid-temperature bins (24°C-27°C) to the high-temperature bins (27°C-30°C and >30°C), affecting in particular the North, East and Centre-West of Brazil (see the Supplementary Material). Higher thermal stress triggers a response of the electricity demand, computed as the ratio of sectoral electricity demand in a future climate relative to the electricity demand under the historical climate (Ψ, see Eq. 18). Figure 19 shows the value of the shock by Federal State and month under the RCP 4.5 (the total shock for the RCP 8.5 is presented in the Supplementary Material). The shocks of all sectors affected (residential, commercial, public and rural, and excluding industrial) are combined into a unique building demand shock. The projections excluding an interaction effect between weather and per capita income point to an increase in the monthly per capita electricity demand of buildings ranging between 10% and 20%, depending on the state and the period of the year ("No income effect" panel). Regional differences in thermal stress exacerbation result in heterogeneous effects across Federal States and seasons, as the percentage increases in total electricity demand are lowest in the South and highest in the North and Centre-West[13].

Markedly higher adaptation requirements originate when the amplification effect caused by economic growth is taken into account, as per capita monthly electricity demand is projected to increase by up to 30% - 45% in SSP1, 25% - 40% in SSP2 and 20% - 30% in SSP3, depending on the state. In other words, I find that when the rise in thermal stress is combined with the higher sensitivity to weather shocks of a richer economy, the relative increase in electricity demand from adaptation more than doubles in magnitude, with large differences across states and SSPs. The residential and commercial sectors are affected the most, while the combined public and rural sector is characterized by lower shocks due to the lack of a modulating effect of per capita income.

Climate change and population growth fuel large additional electricity require-

[13]North: Acre, Amapa, Amazonas, Para, Rondonia, Roraima, and Tocantins; North East: Alagoas, Bahia, Ceara, Maranhao, Paraiba, Pernambuco, Piaui, Rio Grande Norte, Sergipe; Centre-West: Distrito Federal, Goias, Mato Grosso, Mato Grosso do Sul; South: Parana, Rio Grande do Sul, Santa Catarina; South-West: Espirito Santo, Minas Gerais, Rio de Janeiro, Sao Paulo

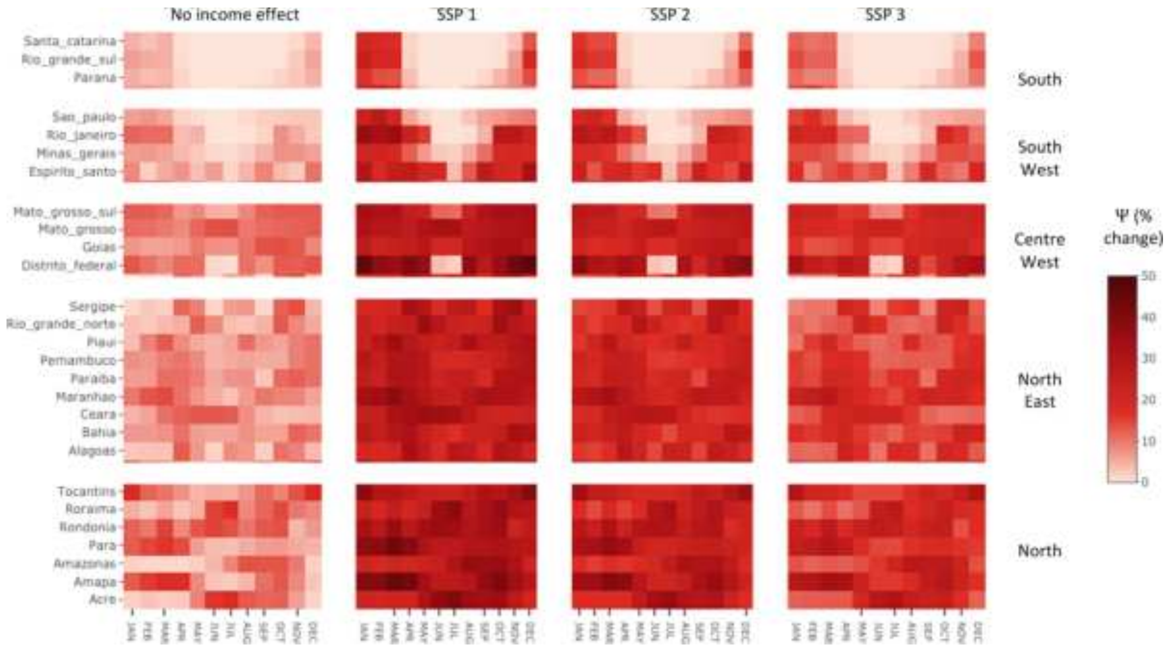

Figure 19. Delta change shock across months and Federal States under the RCP 4.5.

ments

I combine baseline per capita electricity demand with the climate-driven shock and population projections by SSPs to quantify the total additional electricity required to adapt under the alternative socioeconomic and climate projections (Figure 20). Under the RCP 4.5 (RCP 8.5), adaptation increases the electricity demand of Brazilian buildings circa 2050 by up to 20-25% (25%-30%) during summer months, and up to 9%-14% (12%-18%) yearly, depending on the SSPs. This increase corresponds to additional requirements of up to 40-94 TWh (51-117 TWh) per year under the RCP 4.5 (RCP 8.5), up to one third of the total demand of buildings in 2017, equal to 300 TWh (Supplementary Table S13). This result suggests that income has a comparatively more important role than climatic exacerbation in expanding weather-dependent energy requirements. The residential and commercial sectors drive more than 80% of the total increase (Figure 20, panel b). The differences across the possible socio-economic pathways are greater than the differences across RCPs' and GCMs' projections. Importantly, the projections allowing for the modulation effect of income per capita results in almost three-times greater energy requirements than the projections excluding this effect (see Supplementary Table S13).

I find a remarkable heterogeneity in the increase of power demand across Federal States (Figure 21). States in the North (Acre, Amapa, Amazonas, Para, Rondonia, Roraima, and Tocantins), and Centre-West (Distrito Federal, Goias, Mato Grosso, Mato Grosso do Sul)

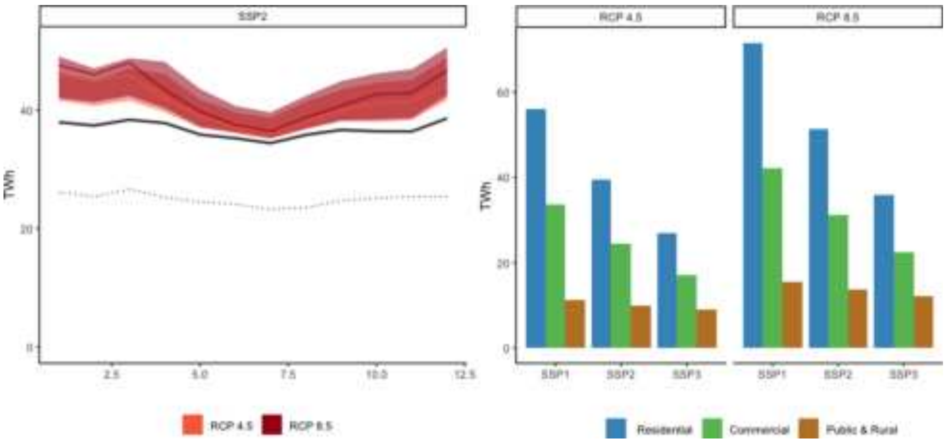

Figure 20. National electricity demand circa 2050. Monthly electricity demand (residential, commercial public and rural sectors) in 2017 (dotted line), and in 2050 baseline (black line) and including the climate change amplification (shaded regions), under the SSP 2. Panel b: Additional yearly electricity demand circa 2050 by sector, RCP and SSP. Shaded regions in Panel a depict the GCMs' projection range (minimum, median and maximum). All projections are based on Eq. 4a and exclude the power demand in the industrial sector.

experience the highest increases in the per capita yearly demand, with a median value across states ranging from 600 kWh/person to 1200 kWh/person, depending on the SSP and RCP. The highly populous states in the South-West (Espirito Santo, Minas Gerais, Rio de Janeiro, Sao Paulo) account for the largest share of the additional yearly demand, despite the relatively low additional per capita demand. The states of Rio de Janeiro and Sao Paulo in particular experience a remarkable increase in the total electricity requirements due to rising thermal discomfort and population growth, ranging from roughly 9 to 21 TWh in the former, and from 11 to 25 TWh in the latter, depending on the scenario. The amplification of demand is equal to roughly 30%-70% and 13%-30% of the power demand of buildings in 2017 in the two states, respectively.

The possibility of comparing the results with the literature is limited to the small number of studies that directly investigate future power needs in a changing climate, and either focus on Brazil at a country level [14,25,26], or report regionally disaggregated global projections [6,63,64]. The projected additional demand required for climate change adaptation is larger than previous country-level assessments based on static econometric models [14,25,26], while is in line with the results of Integrated Assessment Models [6,63,64], wherein cooling needs are estimated based on bottom-up energy demand models which allow for an increase in the penetration of cooling appliances.

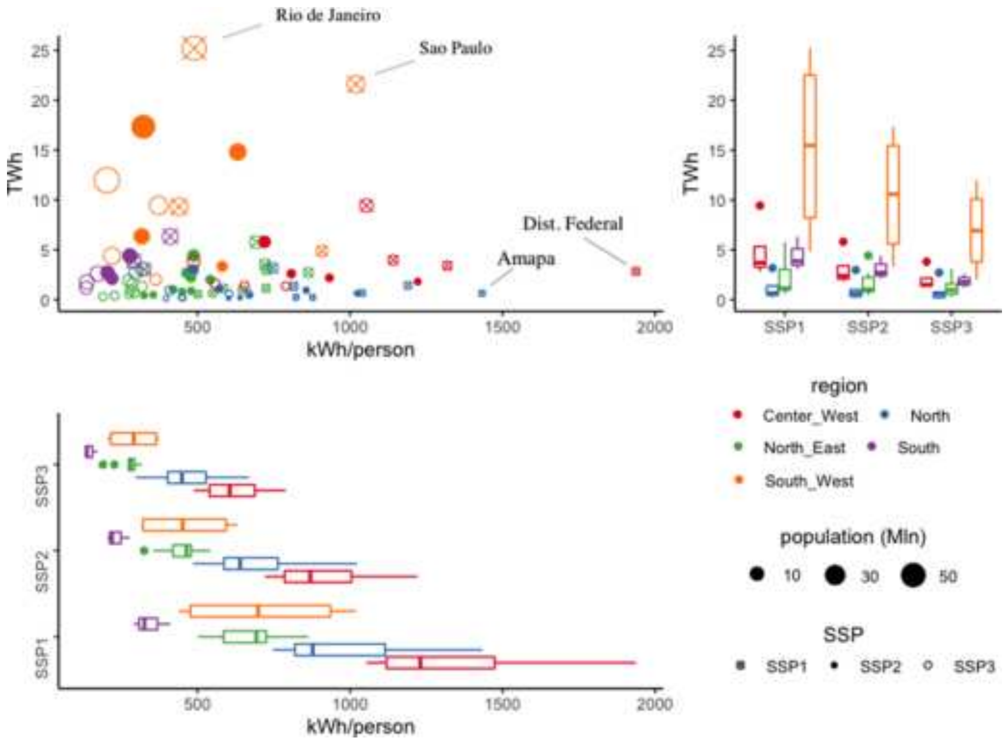

Figure 21. Additional yearly electricity demand by Federal State. Increase of electricity demand per capita (kWh/person) and total (TWh) circa 2050 in RCP 4.5. The shape of the points represents the different SSPs, the size represents the population in each state and the colour the regional classification. Boxplots represent the variables' variability within each regional group, by SSP. Values are computed based on the GCMs' ensemble median.

5.3.4 Discussion

The approach presented in this Chapter provides a novel, empirically grounded method to quantify how socioeconomic developments modulate the response of a population's power demand for climate change adaptation, on top of the extent to which they scale up climate-independent demand. The dynamic econometric specification makes it possible to investigate the extent to which power demand may evolve in the future depending on the ability of agents to adjust their energy-using durable stock according to different levels of per capita income. The income amplification effect results in thermal adaptation requirements three times larger than in the case where no interaction is included. As a result, I find that income growth has a comparatively more important role than climatic exacerbations in the expansion of electricity demand for cooling. As the amplification of the shock due to per capita income growth can plausibly characterize other world areas, expanding this analysis to other rapidly growing tropical economies would be of great importance. This aspect is underscored by recent micro-level evidence on the determinants of future air-conditioning adoption in tropical economies [16]. Pavanello et al., [16], focusing on Brazil, India, Indonesia, and Mexico, find that these countries have a vast unmet demand for air-conditioning, and that appliance ownership is highly uneven across income deciles. Their results in line with the evidence presented in this Chapter, as indicate that a household's ability to adapt to climate change through the use of energy is linked to its socio-economic condition.

Benefits of early mitigation, expressed by the reduction in the additional electricity required to adapt under the RCP 4.5 with respect to the RCP 8.5, are non-negligible. In the pathway characterized by the largest GDP per capita and population growth among the three SSPs evaluated (SSP 1), the avoided increase in electricity demand associated with early mitigation totals 24 TWh per year, equal to one-fourth of the electricity demand of Brazil's buildings in 2017. The benefits of early mitigation are lower under the SSP 2 (middle-of-the road) and SSP 3 (regional rivalry) pathways, respectively 17 TWh and 12 TWh per year. The difference derives from the smaller GDP and population growth projected under these pathways. The projections therefore provide quantification of a trade-off between economic growth and sectoral adaptation costs. It is important to underscore that the long-term adjustment effects captured empirically though the error correction model are based on the business-as-usual practices over the last decades. Therefore, the projections depend on the assumption that the historical evolution of the extensive margin, including appliances' diffusion and energy efficiency, can be an appropriate measure of the evolution of the extensive margin in the future. The adoption of energy efficient appliances at a rate higher than the historical one, let alone breakthrough technological changes, can reduce the large adaptation needs projected under the "sustainability" storyline of SSP 1. The future adoption of energy efficient appliances will be a key modulating factor because currently the average efficiency of ACs sold in Brazil is well below the efficiency of the best-performing models on the market [14]. In addition to appliance efficiency, consumer energy-saving behavior will affect the intensity of appliance use, contributing to modulate the energy consumption necessary for adapting to climate change. The purchase of a more efficient appliance may for instance increase the propensity of households to use it (i.e., would increase the intensive short-term margin shock), resulting in a rebound effect.

The adoption of more stringent energy policies can contribute to reducing the increase in energy needs for adaptation: energy standards can foster the adoption of efficient appliances, while the reduction of energy consumption subsidies would contribute to passing on to households correct market signals and reducing unnecessary electricity use. Furthermore, currently untapped alternative adaptation measures may be deployed in buildings through the mid 21st-century. Applying a combination of passive design strategies can neutralize the increases in the thermal discomfort hours and the cooling energy usage of Brazil's residential buildings due to the effects of climate change [67]. A decarbonized energy mix will limit GHG emissions associated with the additional electricity demand required for adaptation, making it possible to avoid a risky, vicious, and positive feedback between the economy and the climate [66]. Although Brazil's power generation mix has a relatively low carbon intensity due to its high share of hydropower, model-based projections of the decarbonization efforts of Brazil's energy system by mid-century suggest that in the scenarios unconstrained by climate policies carbon intensity may substantially rise as a result of a growing penetration of gas- and coal-fired generation [67,68]. The interaction between adaptation and mitigation policies at the regional and global level is investigated in more detail in Chapter 3.

The results call for a new set of integrated evaluations of demand shocks and supply side-vulnerabilities due to climate change, an approach rarely adopted [13]. Several new lines of research can broaden the identification of adaptation impacts on the energy sector. First, the quantification of the additional electricity demand is a sector shock that precedes any market adjustment. Mechanisms internal to the power market such as price signals and rebound effects could result in different market-based ex-post demand shocks. Second, implications of climate change adaptation should consider the corresponding supply-side effects of an increase in the frequency of extreme temperatures: energy system models have projected a reduction of up to 50-70 TWh per year of hydropower (around 10% of future total hydropower capacity) due to climate change adaptation by 2050 [68]. Furthermore, the surge in the use of air-conditioners can increase not only overall power needs but also the peak demand, affecting in turn the requirements for generation capacity and distribution systems, thus placing further stress on the power system. The lack of a high-frequency power market in Brazil has constrained the analysis to an evaluation of monthly-level total demand fluctuations. As I focus only on electricity demand, the work disregards the future variation in the energy demand of fuels such as gas and oil, that can be used by households to heat their homes in the winter. Nevertheless, the available evidence suggests that consumption of fuel for heating purposes constitutes only a small part of budlings' energy demand in Brazil [67]. Finally, the trivial effect of weather shocks on industrial electricity demand, which may derive from the confounding aggregation of heterogeneous industrial processes, points to a need to conduct further assessments with higher sectoral detail.

5.4 Climate change impacts on energy demand and economic growth: short- vs long-term effects in a global macro panel

5.4.1 Introduction

Several works have relied on the intensive margin to estimate long-run climate impacts because of the presumption that one cannot observe meaningful climatic variation within units in the econometric framework: a few example being [69, 70] as for economic growth and [71, 6, 7] as for energy demand. In this work I separate the effect of weather shocks and climatic variations over time in each location, identifying in the same equation, respectively, the causal impact of short- and long-term adaptation. I partially follow the model developed by [28] to study economic agents' adaptation to Ozone-concentration levels, and argue that exploiting over 60 years of records in meteorological and climatic variations within and between countries, the assumption that one cannot observe meaningful climatic variation within units in the econometric framework can be relaxed.

5.4.2 Methodological framework

Weather

The simplest panel fixed-effects (FE) approach to empirically model the impacts of climate change estimates the following equation:

$$y_{i,t} = \beta_1 T_{i,t} + \beta_2 x_{i,t} + \varpi_i + \varepsilon_{i,t} \tag{19}$$

Here i and t index cross-sectional units and time periods of observation, the variables y, T and x denote the outcome of interest, the driving meteorological variable of interest—often temperature, and other spatially and temporally varying predictive factors, and ϖ indicates fixed effects that account for idiosyncratic time-invariant influences on the outcome at each cross-sectional units.

The impact response parameter, β_1 is identified by the partial covariation between the time-demeaned values of the outcome and weather variables:

$$y_{i,t} - \overline{y}_i = \beta_1(T_{i,t} - \overline{T}_i) + \beta_2(x_{i,t} - \overline{x}_i) = \beta_1 \mathcal{A}(T_{i,t}) + \beta_2 \mathcal{A}(x_{i,t}) \tag{20}$$

where, for any cross-sectionally and temporally varying variable v, the anomaly operator $\mathcal{A}(v_{i,t}) = v_{i,t} - \overline{v}_i$ records an observation's deviation from its local long-run mean. Eq. 59 makes clear that β_1 thus captures the meteorological, rather than climatological, impact response.

Attempts move beyond Eq. 19 allow outcome–temperature responses to vary conditional on modulating factors that may be time-invariant, z, time-varying, x as before, or both:

$$y_{i,t} =$$

$$T_{i,t}(\beta_1 + \beta_2 z_i) + \mu_i + \varepsilon_{i,t} \tag{21}$$

$$T_{i,t}(\beta_1 + \beta_2 x_{i,t}) + \beta_3 x_{i,t} + \mu_i + \varepsilon_{i,t} \tag{22}$$

$$T_{i,t}(\beta_1 + \beta_2 z_i + \beta_3 x_{i,t}) + \beta_4 x_{i,t} + \mu_i + \varepsilon_{i,t} \tag{23}$$

Time-demeaning these expressions yields, with some rearrangement (see Supplementary

Methods):

$$
\begin{aligned}
&y_{i,t} - \overline{y}_i = \\
&\mathcal{A}(T_{i,t}) \cdot (\beta_1 + \beta_2 z_i) && (24)\\
&\mathcal{A}(T_{i,t}) \cdot (\beta_1 + \beta_2 \overline{x_i} + \beta_2 \mathcal{A}(x_{i,t})) - \beta_2 \overline{\mathcal{A}}(T_{i,t}) \overline{\mathcal{A}}(x_{i,t}) + \overline{T}_i \cdot (\beta_2 \mathcal{A}(x_{i,t})) && (25)\\
&\mathcal{A}(T_{i,t}) \cdot (\beta_1 + \beta_2 z_i + \beta_3 \overline{x}_i + \beta_3 \mathcal{A}(x_{i,t})) - \beta_3 \overline{\mathcal{A}}(T_{i,t}) \overline{\mathcal{A}}(x_{i,t}) + \overline{T}_i \cdot (\beta_3 \mathcal{A}(x_{i,t})) && (26)
\end{aligned}
$$

In Eq. 24 the weather response exhibits an affine relationship with the level of the cross-sectionally varying factor. In particular, suppose that for this purpose one utilizes time-invariant climate exposures, $\overline{C}_i$. It is important to understand that in such settings, $\beta_1 + \beta_2 \overline{C}_i$ does not capture the impact of climate. Rather, this term captures the variation in the impacts of transitory weather shocks with climatic differences. By contrast, eqs. 25 and 26 do capture the impacts of climate through the coefficient on mean weather, $\beta_3 \mathcal{A}(x_{i,t})$, while embodying more complicated expressions for the impacts of weather anomalies. Both effects vary over cross-sectional units and time periods, and depend on the deviation of the time-varying factor from its local mean.

Applications of 26 have been adopted by [69] when the variable of interest y is per capita and by [71] when y is energy demand. Importantly, in both cases the the effect of weather is being modulated by both cross-sectionally varying factors: [69] stratifies the temperature-income relation by income per-capita classes, while [71] by cross-sectional climate exposures and spatially and temporally varying per capita income, $m_{i,t}$.

The justification for this approach is that the variation in long-run climate over the historical period of their sample is not sufficiently large to allow within unit variation to be exploited for the purposes of identification.

This exercise yields deeper insights into the partial effect of temperature traced out as a response in Rode et al Fig. 1. For countries grouped by climate (χ) and income (μ), they plot, for the combination $\gamma\langle\chi, \mu\rangle$, the product of temperature and the fitted coefficient of (23), evaluated at the group mean

$$
\text{Impact}(T, \gamma) = T(\widehat{\beta}_1 + \widehat{\beta}_2 \overline{C}(\gamma) + \widehat{\beta}_3 \overline{m}(\gamma))
$$

But, by (26), the limitation of this calculation is that it merely gives a group-wise stratification of the effect of weather, but indeed only a component of the true effect. In the next section I propose a method that extracts the correct response to the anomaly and climate.

Climate and weather anomalies

The empirical approach relies on the decomposition of the meteorological variable, daily maximum temperatures T, into two components: long-run climate normals and weather anomalies, the latter defined as deviations from those norms. I measure the climate normals ($\mathcal{C}_{i,t}$) as the 10-year moving average of the yearly CDDs. For every i,t in the sample $\mathcal{C}_{i,t}$ combines the information of the weather realizations of the previous 10 years. The weather anomaly ($\mathcal{A}_{i,t}$) is computed as the deviation of observed yearly CDDs from $\mathcal{C}_{i,t}$. While the meteorological anomalies recall most of the literature relying solely on the exposure to weather with a fixed-effect, time-demeaning, specification, the variation over time of the long-term climate norm is new in the setting of the analysis of energy demand.

$$T_{i,t} = \mathcal{C}_{i,t} + \mathcal{W}_{i,t} \tag{27}$$

Where:

$$\mathbb{E}(T_{i,t}|C_i) = \mathcal{C}_{i,t} = \frac{\sum_{n=j-11}^{j-1} T_{i,t}}{10} \tag{28}$$

Substituting equation 27 into equation 22 leads to the following empirical specification:

$$y_{i,t} = \alpha + \beta_1 \mathcal{W}_{i,t} + \beta_2 \mathcal{C}_{i,t} + \beta_3 x_{i,t} + \beta_4 \mathcal{W}_{i,t} x_{i,t} + \beta_5 \mathcal{C}_{i,t} x_{i,t} + \mu_i + \varepsilon_{i,t} \tag{29}$$

Where β_1 captures the effect on y of contemporaneous shocks from the expected climate. β_2 captures the effect of slowly-changing climatic exposure, and β_4 and β_5 capture the modulation of a time-varying variable $x_{i,t}$ on the time-varying climate exposure and anomalies, respectively.

Applying time-demeaning to equation 29 and rearranging terms, I find that the FE estimation is based on:

$$\begin{aligned} y_{i,t} - \overline{q}_i = & \overline{\mathcal{W}_i} \cdot \beta_4 \mathcal{A}(x_{i,t}) + \\ & \mathcal{A}(\mathcal{W}_{i,t}) \cdot (\beta_1 + \beta_4 \overline{x}_i + \beta_4 \mathcal{A}(x_{i,t})) - \beta_4 \overline{\mathcal{A}}(\mathcal{W}_{i,t}) \overline{\mathcal{A}}(x_{i,t}) + \\ & \overline{C_i} \cdot \beta_5 \mathcal{A}(x_{i,t}) + \\ & \mathcal{A}(C_{i,t}) \cdot \big(\beta_2 + \beta_5 \overline{x}_i + \beta_5 \mathcal{A}(\mathbf{x}_{i,t})) - \beta_4 \overline{\mathcal{A}}(\mathcal{C}_{i,t}) \overline{\mathcal{A}}(x_{i,t}\big) \end{aligned} \tag{30}$$

In this specification, the terms i) and ii) capture transitory fluctuations in y due to weather anomalies from the expected climate, conditional on the modulating factor $x_{i,t}$ level and anomalies; in term iii) the effect of cross-sectional fixed climate on y is modulated by within-unit anomalies in x; in term iv) the effect of variations in climate - i.e. unit-specific exposure to climate change - on y is isolated though the coefficient β_3 and modulated by both $x_{i,t}$ level and anomalies.

5.4.3 Empirical framework

Data I assemble a panel dataset covering 134 countries and 60 years (1960-2019), comprising: i) population-weighted annual average temperatures, annual Cooling Degree Days (CDDs, with thresholds alternatively 18°C and 24°C) and Heating Degree Days (HDDs, with thresholds alternatively 15°C and 18°C) from gridded ERA5 data; ii) per capita energy consumption ($q^{m,j}$) in five sectors (m: resiential, commercial, industrial, agriculture, transport) and for two energy carriers (j: electricity and fossil fuels); iii) economy-wide and sector-specific per capita GDP ($x_{i,t,m}$) and total capital stock per capita ($k_{i,t}$) from the OECD and the IMF datasets.

For the projections I use future estimates of gridded global population and GDP from [36] and [37], respectively, developed in accordance with the shared socioeconomic pathway (SSP) scenarios. Shifts in DDs and annual mean temperatures from current to mid-century climates are estimated using the outputs of 8 global climate models (GCMs) participating in the Coupled Model Intercomparison Project, Phase VI (CMIP6) [38]. Specifically, I use GCM-simulated daily temperature fields for moderate (SSP245) and vigorous (SSP585) warming scenarios that are bias corrected and downscaled to a 0.25° grid, from the from the NASA NEX-GDDP-CMIP6 dataset [39, 40, 41].

Climate and anomalies decomposition

The empirical approach relies on one key element: the decomposition of the meteorological variable into two components: long-run climate normals and weather anomalies, the latter defined as deviations from those norms. I measure the climate normals ($\overline{C}_{i,t}$) as the 10-year moving average of the variable of interest, with the later being alternatively: i) annual mean temperatures; ii) Cooling Degree Days (computed alternatively with a cutoff of 18°C and 24°C); Heating Degree Days (computed alternatively with a cutoff of 15°C and 18°C). For every year in the sample $\overline{C}_{i,t}$ combines the information of the weather realizations of the previous 10 years in that same location[14]. The adoption of a moving average derives from the assumption that individuals and firms respond to information on climatic variation they have observed and processed over the years. The weather anomaly (ω_d) is computed as the difference between the observed weather exposure and the exposure expected by economic agents $\overline{C}_{i,t}$. While the meteorological anomalies recall most of the literature relying solely on the exposure to weather with a fixed-effect, time-demeaning, specification, the variation over time of the long-term climate norm is new in the setting of the analysis of both energy demand and income growth. I use Eq. 27 - 28 to estimate climate and anomalies. More in detail, I compute the vector of weather anomalies $\mathbf{AT} \in \{aT^-_{i,t}, aT^+_{i,t}\}$ in the case of annual mean temperatures and $\mathbf{ADD} \in \{aCDD^-_{i,t}, aCDD^+_{i,t}, aHDD^-_{i,t}, aHDD^+_{i,t}\}$ in the case of Degree Days:

$$\mathrm{aT}^+_{i,t} = \begin{cases} T_{i,t} - \overline{T}_{i,t}, & T > \overline{T} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{aT}^-_{i,t} = \begin{cases} \overline{T}_{i,t} - T_{i,t}, & T < \overline{T} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{aCDD}^+_{i,t} = \begin{cases} CDD_{i,t} - \overline{CDD}_{i,t}, & CDD > \overline{CDD} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{aCDD}^-_{i,t} = \begin{cases} \overline{CDD}_{i,t} - CDD_{i,t}, & CDD < \overline{CDD} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{aHDD}^+_{i,t} = \begin{cases} HDD_{i,t} - \overline{HDD}_{i,t}, & HDD > \overline{HDD} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{aHDD}^-_{i,t} = \begin{cases} \overline{HDD}_{i,t} - HDD_{i,t}, & HDD < \overline{HDD} \\ 0 & \text{otherwise} \end{cases}$$

Figure 22 shows the degree of unit-specific variation in the climate variables, focusing on CDDs (24°C) and HDDs (15°C). I identify substantial variation in the variables, justifying the adoption of *climatic* DDs and annual temperatures for the empirical estimations.

[14]I test alternative measure relying, respectively, on 20 and 30 years moving averages, finding negligible differences in the econometric model.

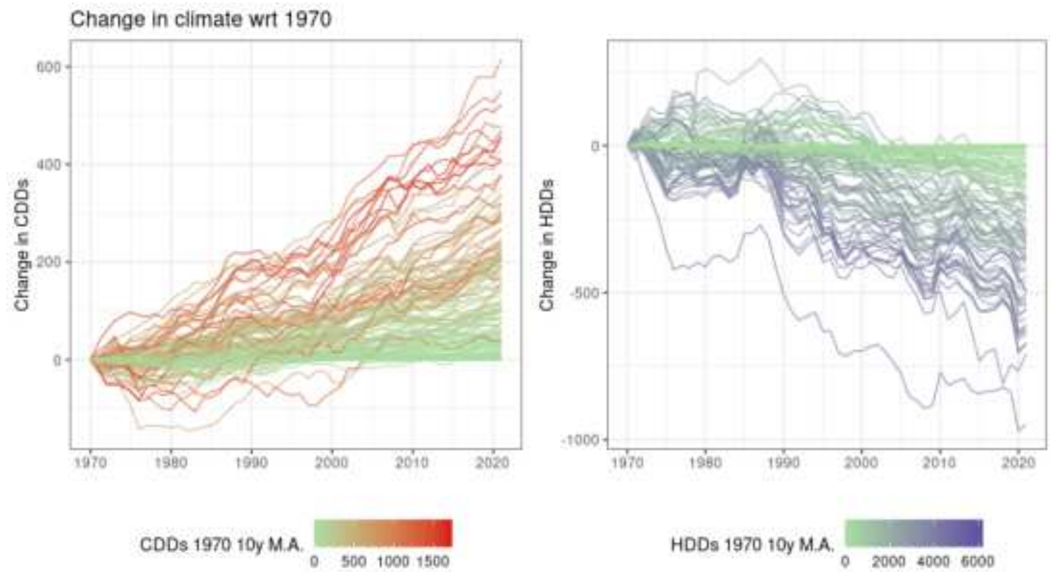

Figure 22. Annual level change in the 10-year moving average of CDDs (24°C) and HDDs (15°C) with respect to the moving average level in 1970. Colours of the lines is based on the climatic CDDs-HDDs level in 1970..

Energy demand

I estimate a set of fixed-effects (FE) models where the dependent variable is the sector-specific natural logarithm of per capita final energy demand. I first test a set of equations based on the standard weather-based specifications:

$$q_{i,t}^{m,j} = \beta_1^{m,j}\mathcal{CDD}_{i,t} + \beta_2^{m,j}\mathcal{HDD}_{i,t} + \beta_3^{m,j}x_{i,t,m} + \mu_i^{m,j} + \lambda_t^{m,j} + \varepsilon_{i,t}^{m,j} \tag{32}$$

Location (μ_i) and time (λ_t) fixed effects flexibly control for unit-specific time-invariant and year-specific global unobservable effects.

Secondly, I test a set of models where the weather exposure (CDD and HDD) is replaced by the climate exposure ($CCDD$ and $CHDD$) and the vector of hot and cold anomalies ($\mathbf{ADD}^l$), based on the proposed specification of Eq. 29:

$$q_{i,t}^{m,j} = \beta_1^{m,j}\mathcal{CCDD}_{i,t} + \beta_2^{m,j}\mathcal{CHDD}_{i,t} + \beta_3^{m,j}x_{i,t,m} + \beta^{m,j,l}\mathbf{ADD}_{i,t}^l + \mu_i^{m,j} + \lambda_t^{m,j} + \varepsilon_{i,t}^{m,j} \tag{33}$$

Finally, I expand Eq. 32 and Eq. 33 by testing if the level of capital accumulation, measured as the lagged natural logarithm of per capita capital stock $k_{i,t-1}$, affects the influence of weather or climatic exposure on energy demand. I resort to the logged value of k, rather than the contemporaneous level, in order to reduce the risk that endogeneity between capital accumulation and energy demand biases the results, leading to the final specifications:

$$q_{i,t}^{m,j} = \mathcal{CDD}_{i,t} \cdot (\beta_1^{m,j} + \delta_1^{m,j} k_{i,t}) + \mathcal{HDD}_{i,t} \cdot (\beta_2^{m,j} + \delta_2^{m,j} k_{i,t}) + \beta_3^{m,j} x_{i,t,m} + \mu_i^{m,j} + \lambda_t^{m,j} + \varepsilon_{i,t}^{m,j} \tag{34}$$

$$q_{i,t}^{m,j} = \mathcal{ACDD}_{i,t} \cdot (\beta_1^{m,j} + \delta_1^{m,j} k_{i,t}) + \mathcal{AHDD}_{i,t} \cdot (\beta_2^{m,j} + +\delta_2^{m,j} k_{i,t}) + \beta_3^{m,j} x_{i,t,m} + \beta^{m,j,l} \mathbf{ADD}_{i,t}^{l} + \mu_i^{m,j} + \lambda_t^{m,j} + \varepsilon_{i,t}^{m,j} \tag{35}$$

Comparing Eq. 32 - 34 to Eq. 33 - 35 allows to test the hypothesis that unit-specific time-varying climatic changes around the mean climatic exposure have a different effects on energy demand than weather changes around the mean weather exposure.

Economic growth

In the second part of the empirical analysis I test if economic growth is affected by average annual temperatures, and if te adoption of a weather versus a climatic indicator results in different impacts on y. I estimate a set of FE models where the dependent variable is the first difference in the natural logarithm of annual real (inflation-adjusted) gross domestic product per capita, that can be interpreted as the per-period growth rates in income.

I first test the specification based on weather exposures, replicating the analysis of [69], where income growth is associated to linear and quadratic terms of mean annual temperature and precipitation. I sequentially add a set of controls including: the lagged growth rate of y, country fixed effects and country specific linear or quadratic time trends. Controls allow to flexibly account for time invariant country-specific factors affecting growth rates, as well as on the country-specific path of economic development. The specification including all control variables is:

$$\Delta y_{i,t} = \lambda_1 \mathcal{T}_{i,t} + \lambda_2 \mathcal{T}_{i,t}^2 + \zeta_1 \mathcal{P}_{i,t} + \zeta_2 \mathcal{P}_{i,t}^2 + \eta_1 \Delta y_{i,t-1} + \mu_i + \rho_i t_{i,t} + \varepsilon_{i,t} \tag{36}$$

In order to test the hypothesis laid in Section 2, I test a model that is based on the decomposition of weather exposure between climatic moving averages of annual mean temperatures ($CT_{i,t}$) and the vectors of positive and negative weather anomalies from that averages ($\mathbf{AT}_{i,t}$), resuting in the following specification:

$$\Delta y_{i,t} = \lambda_1 \mathcal{CT}_{i,t} + \lambda_2 \mathcal{CT}_{i,t}^2 + \lambda_p \mathbf{AT}_{i,t}^p + \zeta_1 \mathcal{P}_{i,t} + \zeta_2 \mathcal{P}_{i,t}^2 + \eta_1 \Delta y_{i,t-1} + \mu_i + \rho_i t_{i,t} + \varepsilon_{i,t} \tag{37}$$

Finally, I test if the level of per capita energy demand can influence the relationship between temperatures and income growth, by including an interaction term between the linear and quadratic temperature terms and the lagged natural logaritm of per capita final energy demand $q_{i,t-1}$. I resort to the logged value of q in order to reduce the risk that endogeneity between energy demand and income biases the results. The final specifications, depending on the temperature model adopted, is:

$$\begin{aligned} \Delta y_{i,t} = & \\ & \mathcal{T}_{i,t} \cdot (\lambda_1 + \omega_1 q_{i,t-1}) + \mathcal{T}_{i,t}^2 \cdot (\lambda_2 + \omega_2 q_{i,t-1}) + \\ & \zeta_1 \mathcal{P}_{i,t} + \zeta_2 \mathcal{P}_{i,t}^2 + \eta_1 \Delta y_{i,t-1} + \mu_i + \rho_i t_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{38}$$

$$\begin{aligned} \Delta y_{i,t} = & \\ & \mathcal{CT}_{i,t} \cdot (\lambda_1 + \omega_1 q_{i,t-1}) + \mathcal{CT}_{i,t}^2 \cdot (\lambda_2 + \omega_2 q_{i,t-1}) + \lambda_p \mathbf{AT}_{i,t}^p + \\ & \zeta_1 \mathcal{P}_{i,t} + \zeta_2 \mathcal{P}_{i,t}^2 + \eta_1 \Delta y_{i,t-1} + \mu_i + \rho_i t_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{39}$$

5.4.4 Results

Energy demand response functions

I estimate the energy demand response to CDDs and HDDs for the combination of 10 cases (5 sector by 2 fuels) and 4 specifications (with weather-based or climate-based Degree Days and with/without an interaction effect of capital stock). Only the coefficients related to the thermal exposure of the main variables (weather and climatic DDs) are shown in Table 1, while full results can be found in the Supplementary Material. The impact on per capita final energy demand of thermal exposure of CDDs and HDDs is significant in all sectors and fuels, excluding a few exceptions as for the residential sector sensitivity of electricity demand to cold temperatures and of fossil fuel demand to hot temperatures. Importantly, in all cases the interaction term between CDDs and long-run per capita capital stock is positive, pointing to the exacerbation of the sensitivity of both electric and fossil fuels consumption under hot temperatures with an increasing capital accumulation. The results as for the interaction between fossil demand and long-run per capita capital stock are mostly positive, in except from industrial and agriculture electricity demand and industrial fossil fuel demand. This result may be driven by increasing efficiency of equipment and by inter-sectoral differences in the mix of industrial and agricultural activities in more developed countries with higher capital stock.

Table 1: energy demand regression results by model

		Weather	model			Climate	model	
	β_1	β_2	δ_1	δ_2	β_1	β_2	δ_1	δ_2
Sector:	(CDD)	(HDD)	(CDD*k)	(HDD*k)	(CCDD)	(CHDD)	(CCDD*K)	(CHDD*k)
				Electricity				
Resid.	-0.0019***	-	0.0003***	-	-0.0010**	-0.0003*	0.0003***	$4.2 \cdot 10^{-5***}$
Comm.	-0.0029***	-0.0006***	0.0004***	$7.0 \cdot 10^{-5***}$	(-0.0015**	-0.0009***	0.0004***	0.0001***
Indus.	-0.0027***	0.0002*	0.0004***	$-2.1 \cdot 10^{-5*}$	-0.0025***	-	0.0004***	-
Agric.	-0.0039***	0.0006***	0.0006***	$-7.3 \cdot 10^{-5***}$	-0.0034***	0.0004*	0.0006***	$-6.8 \cdot 10^{-5***}$
Transp.	-0.0083***	-0.0005**	0.0009***	$5.8 \cdot 10^{-5***}$	-0.0059***	-0.0009***	0.0010***	$8.8 \cdot 10^{-5***}$
				Fossil fuels				
Resid.	-	-0.0013***	-	0.0002***	-	-0.0014***	-	0.0002***
Comm.	-0.0055***	-0.0017***	0.0006***	0.0002***	-0.0068***	-0.0018***	0.0007***	0.0002***
Indus.	-0.0003	0.0013***	0.0001***	-0.0001***	0.0005	0.0013***	0.0001**	$-9.4 \cdot 10^{-5***}$
Agric.	-0.0088***	-0.0011***	0.0010***	$9.7 \cdot 10^{-5***}$	-0.0133***	-0.0009***	0.0012***	$6.0 \cdot 10^{-5***}$
Transp.	-0.0003***	-0.0009***	0.0001***	$3.6 \cdot 10^{-5***}$	-0.0013***	-0.0003**	0.0002***	$3.6 \cdot 10^{-5***}$

Figure 23 shows the estimated impact on per capita energy demand across sectors determined by an increase in *climatic* HDDs and CDDs from the mean value, ranging from 0 to 1000 degree days.

I also test the effect of different weather and climate variables in the econometric specifications based on the stacked sectoral observations, so that the estimated coefficients average out inter-sectoral differences. Also in this case, the results show a statistically significant difference between the coefficients estimated based on weather and climate exposure, both when the modulation effect of capital accumulation is excluded or included (see the Supplementary Materials).

Economic growth

I find that economic growth is affected by annual temperature levels even after accounting for the auto-regressive process of economic growth and by controlling for unobservable effects though flexible fixed-effects and time trends. The impact of annual temperature estimated based on contemporaneous weather variations with no interaction effects is comparable to the results in [69]. Differently from [69], I do not rely on a arbitrary classification of "poor" and "rich" countries for modulating the impact of temperatures on growth, but rather I identify the a statistically significant modulating effect of per capita energy demand levels. This evidence suggests that the energy-intensive adaptation actions that have been identified in the previous section have a role in reducing the vulnerability of economic output from exposure to both hot and cold temperatures. Furthermore, I find that the models based on weather exposure (columns 1-3 in Table 2) differ substantially from the models based on climatic exposure (columns 4-6 in Table 2). The difference between weather and climatic exposure is maintained in the specifications including the modulating effect of per capita energy demand levels (see Figure 24): for instance, a 1°C degree increase in average annual temperatures when starting annual temperatures are around 25°C results in a reduction in economic growth ranging from 1% to 2% based to the weather model and from 2% to 4% according to the climate-based model, depending on the per capita energy demand level.

Projections

Energy demand is significantly amplified around mid-century due to energy-intensive adaptation actions. With constant country-level GDP and capital stock, the climate- (weather-) based response function yields a median increase across 8 GCMs of: 21% (11%) in global energy demand, 50% (20%) in electricity demand and 8% (6%) in fossil fuels demand under SSP

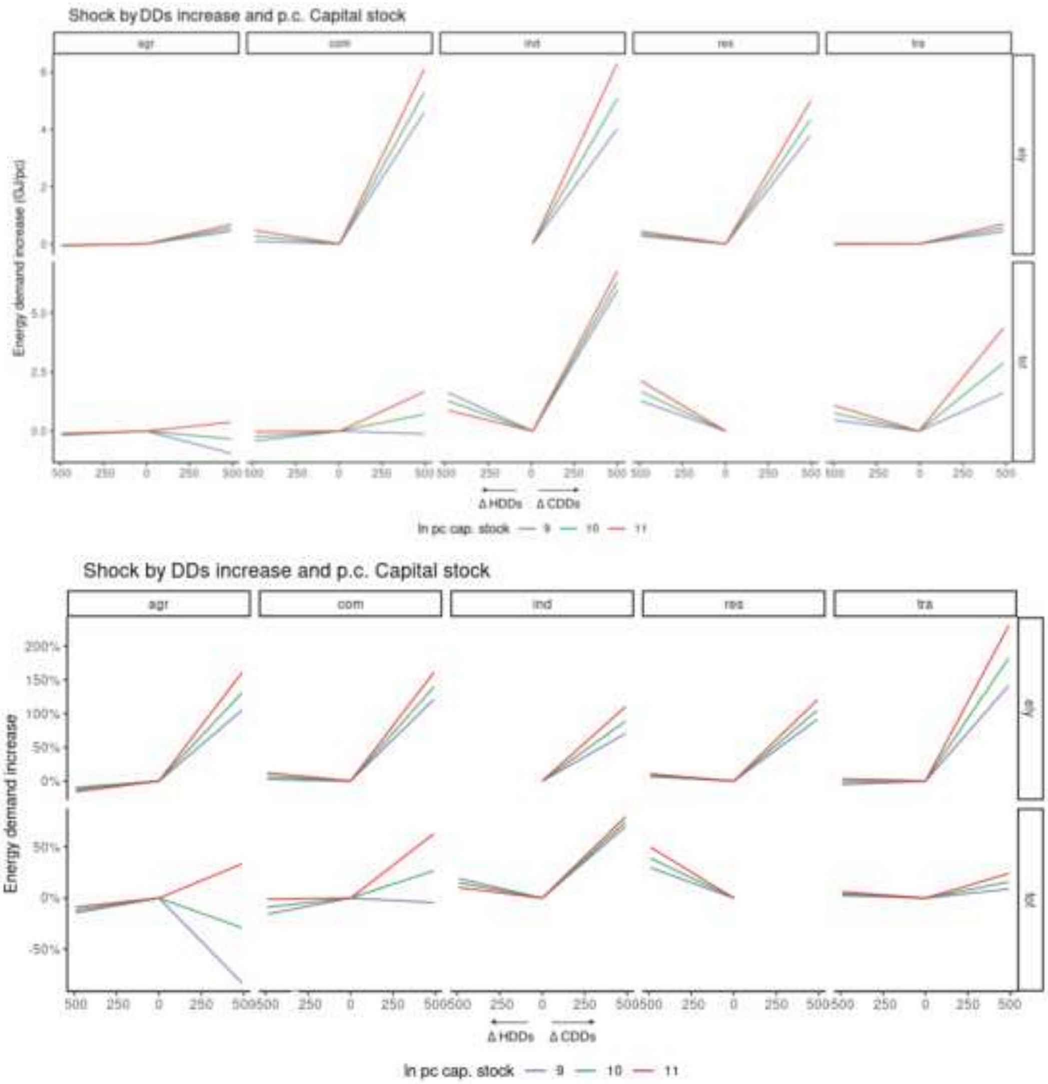

Figure 23. Energy demand responses to climatic variations in CDDs and HDDs by per capita capital stock levels (around 8.000, 22.000 and 60.000 USD/pc, corresponding roughly to the 25%, 50% and 75% quantiles of the sample). Coefficients are estimated though Eq. 35. The upper panel shows the level changes, while the bottom panel the relative changes, with respect to the mean CDD-HDD level..

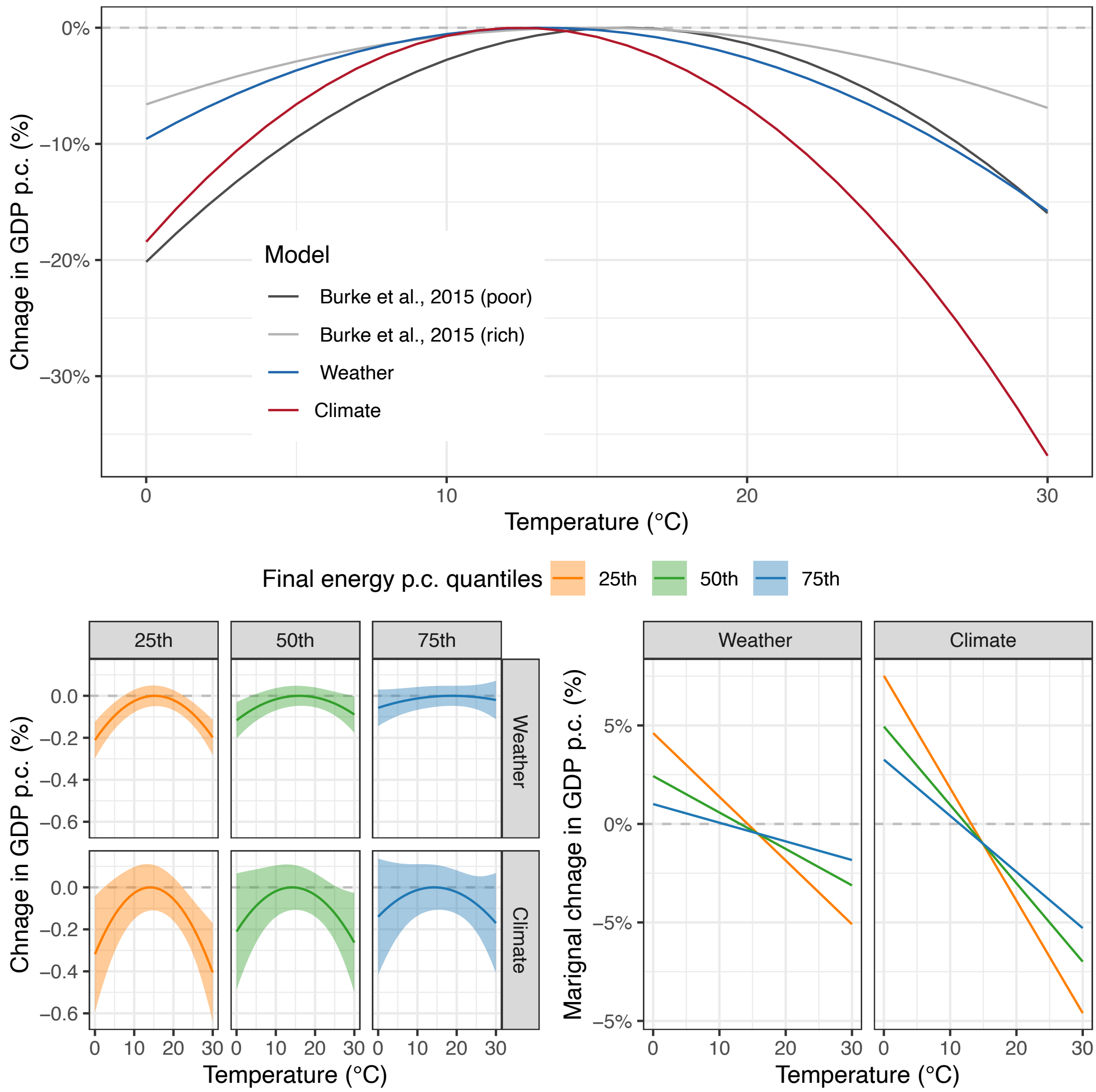

Figure 24. Economic growth responses to weather and climatic variations. Upper panel: comparison between the shocks estimated by [69] and our estimations. Lower panel: modulation of the shock by per capita energy demand levels (25%, 50% and 75% quantiles of the sample). Coefficients are estimated though Eq. 39..

Table 2

Dependent Variable:	fd_ln_gdp_pc			
Model:	(Eq. 14)	(Eq. 16)	(Eq. 15)	(Eq. 17)
Variables				
lag.fd_ln_gdp_pc	0.2048***	0.1865**	0.1970***	0.1833**
	(0.0536)	(0.0742)	(0.0586)	(0.0745)
mean_temp	0.0117***	0.0601***		
	(0.0039)	(0.0080)		
mean_temp_sq	-0.0004***	-0.0020***		
	(0.0001)	(0.0003)		
precip	2.95×10^{-5}***	2.5×10^{-5}*	3.65×10^{-5}***	3.36×10^{-5}**
	(1.02×10^{-5})	(1.49×10^{-5})	(1.11×10^{-5})	(1.47×10^{-5})
precip_sq	-3.39×10^{-9}	-2.53×10^{-9}	-5.89×10^{-9}**	-4.22×10^{-9}
	(2.24×10^{-9})	(3.44×10^{-9})	(2.32×10^{-9})	(3.43×10^{-9})
mean_temp × lag.ln_en_pc		-0.0126***		
		(0.0019)		
mean_temp_sq × lag.ln_en_pc		0.0004***		
		(8.28×10^{-5})		
mean_temp_10ma			0.0120	0.0835***
			(0.0125)	(0.0152)
mean_temp_10ma_sq			-0.0003	-0.0030***
			(0.0004)	(0.0006)
mean_temp_an_pos			-0.0179***	-0.0233***
			(0.0066)	(0.0079)
mean_temp_an_neg			-0.0130**	-0.0103*
			(0.0061)	(0.0057)
mean_temp_10ma × lag.ln_en_pc				-0.0149***
				(0.0022)
mean_temp_10ma_sq × lag.ln_en_pc				0.0005***
				(9.29×10^{-5})
country-time trend	Quadratic	Quadratic	Quadratic	Quadratic
Fixed-effects				
iso3	Yes	Yes	Yes	Yes
Fit statistics				
Observations	7,701	5,246	6,733	5,246
R^2	0.14022	0.19610	0.14458	0.19759
Within R^2	0.09981	0.15636	0.10264	0.15792

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5-8.5 and of 12% (7%) in global energy demand, 31% (13%) in electricity demand and 4% (3%) in fossil fuels demand under SSP 2-4.5. The climate model leads to two-times greater impacts than the weather model, as the former captures long-term extensive margin adjustments, while the latter only short-term intensive margin adjustments. Large regional differences can be found both in the amplification of electricity and fossil fuel final energy demand (Figure 25 and Figure 26): the country with the largest absolute increase in electricity and fossil demand is the United States (over 10 EJ/year of all energy carriers combined in SSP 5-8.5 in the preferred, climate-based, specification), while the county with the largest relative increase in final energy demand is Saudi Arabia (+400%), followed by Brazil (+140%) and Indonesia (+100%). The residential and commercial sector are the largest contributors to the increase in electricity demand, a direct consequence of the higher sensitivity of annual energy demand in these sectors due to buildings' cooling needs. The industrial sector is the largest contributor to the fossil fuel demand amplification. This evidence points to the importance in future energy demand scenarios of heating, ventilation, and air-conditioning (HVAC) systems used by industries, that include both comfort-related energy use and continuous or process-related HVAC, the latter ensuring that the operation of manufacturing systems and production processes (e.g., food processing and storage industry).

It is important to underscore that projections do not account for the future expansion in economic variables, most importantly of variations in the level of capital stock around 2050 across SSPs. Allowing future adjustments in the capital stock both due to economic growth and climate change would influence the projections of energy demand for adaptation, due to the modulating impact of capital accumulation on the energy demand function. The identification of the impact of future capital stock levels is left for future research.

In order to identify mid-century impacts of climate change on aggregated economic output, I use the concave damage function that associates per capita income growth to climatic annual temperatures and energy demand levels. The amplification of annual average temperatures around 2050 results in a non-negligible reduction in global income already by 2050, ranging from 3% to 4% in SSP 2-4.5 and 5-8.5, respectively. Differences across countries are large, both due to the different degrees in annual temperature changes and due to the country-specific modulation effect of per capita energy demand levels. I project the energy-dependent impacts of climate change on per capita income in two cases: i) per capita energy demand levels fixed at the 2015-2019 country-level mean; ii) per capita energy demand levels amplified by the

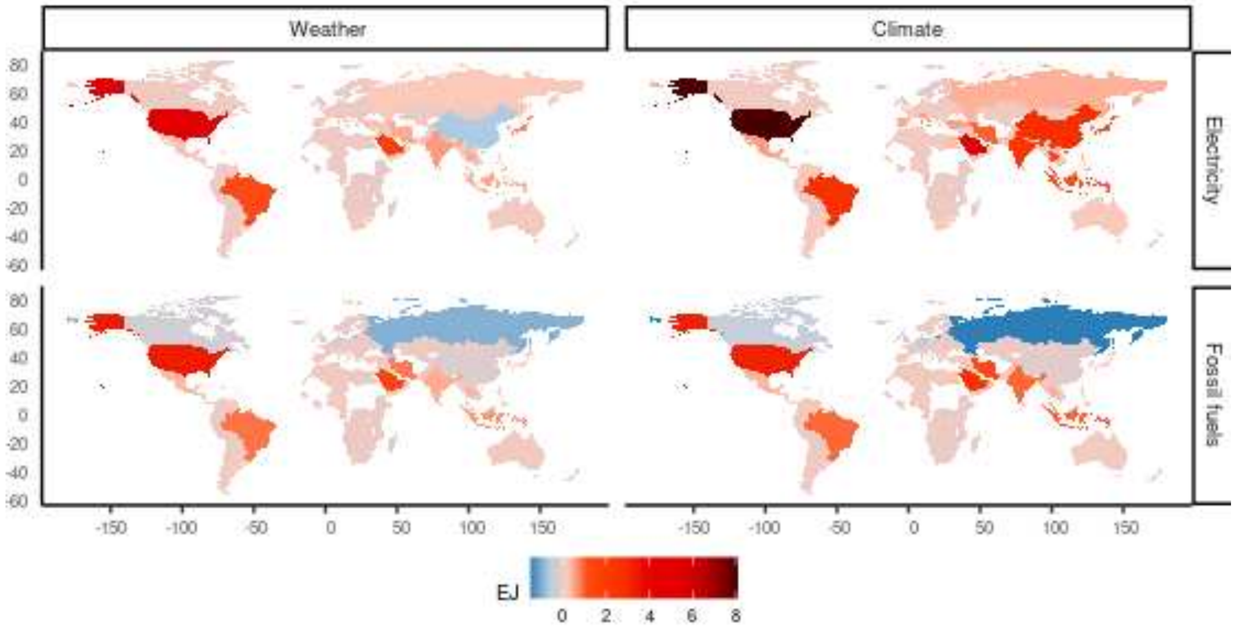

Figure 25. Map of energy demand amplification in SSP 5-85.

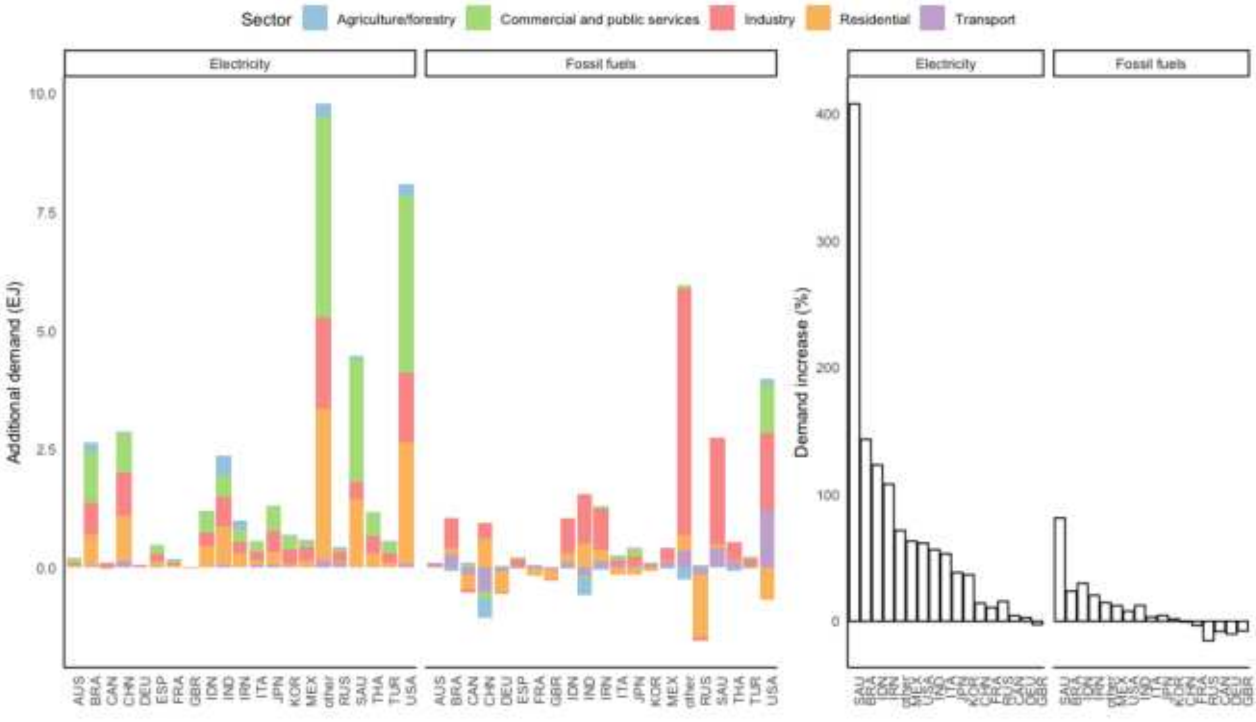

Figure 26. Sectoral energy demand amplification in SSP 5-85 by country and sector.

climate change adaptation effect estimated in the previous section. Note that in both cases projections do not account for the future expansion in energy demand from factors unrelated to climate change adaptation, most importantly from economic growth around 2050 across SSPs, a quantification that is left for future research.

Globally, the role of energy demand to reduce the impacts of climate change on economic growth is non-negligible, although it only marginally attenuates the negative global economic impacts of climate change: under SSP 5-8.5 (2-4.5) the estimated reduction in annual global income goes from -3.6% to -3.2% (from -2.6% to -2.4%) when the modulation of the estimated additional energy demand required for adaptation is accounted for. I conduct a simple back-of-the-envelope quantification of the costs of the additional energy for adaptation by computing the additional expenses for energy demand (assuming hysterical prices in 2019)[15] and of the benefits of energy for adaptation in terms of reduce income losses (assuming historical GDP levels in 2019). This quantification shows that an increase in expenses for energy demand in the order of 2 trillion USD (1 trillion) under SSP 5-8.5 (SSP 2-4.5) would lead to a reduction in the income losses of 0.35 trillion (0.17 trillion) USD (Table 8).

Regional differences in the trade off between the (partial) adaptation costs and benefits I estimate are relevant: in "hot" countries with historical average temperatures above 25°C the reduction in economic loss from higher energy consumption is larger than in countries with temperate or cold climates (left panel of Figure 27). Furthermore, across "hot" countries, higher impacts on per capita income arise when the level of per capita energy demand is lower then average: despite being exposed to similar temperatures, Gulf countries (such as Saudi Arabia, Kuwait, Oman, UAE) and, in Asia, Singapore, achieve much lower economic impacts than African and Asian countries (such as Niger, Togo, Senegal and Bangladesh), thanks to the higher current energy per capita consumption levels and the proportionally higher additional energy increase for adaptation (right panel of Figure 27).

5.4.5 Discussion

The appealing features of the method proposed is that trough the variation that evolves slowly over time in each location one can identify the average impact of long-term climatic changes, the analogue for the extensive margin adjustments, without an explicit measurement of adaptation actions and controlling for time-invariant and time-specific unobservables. I leave for

[15] Assumed global average energy costs: 143 USD/MWh of electricity, 10 USD/MBTU of natural gas and 64 USD/barrel of oil.

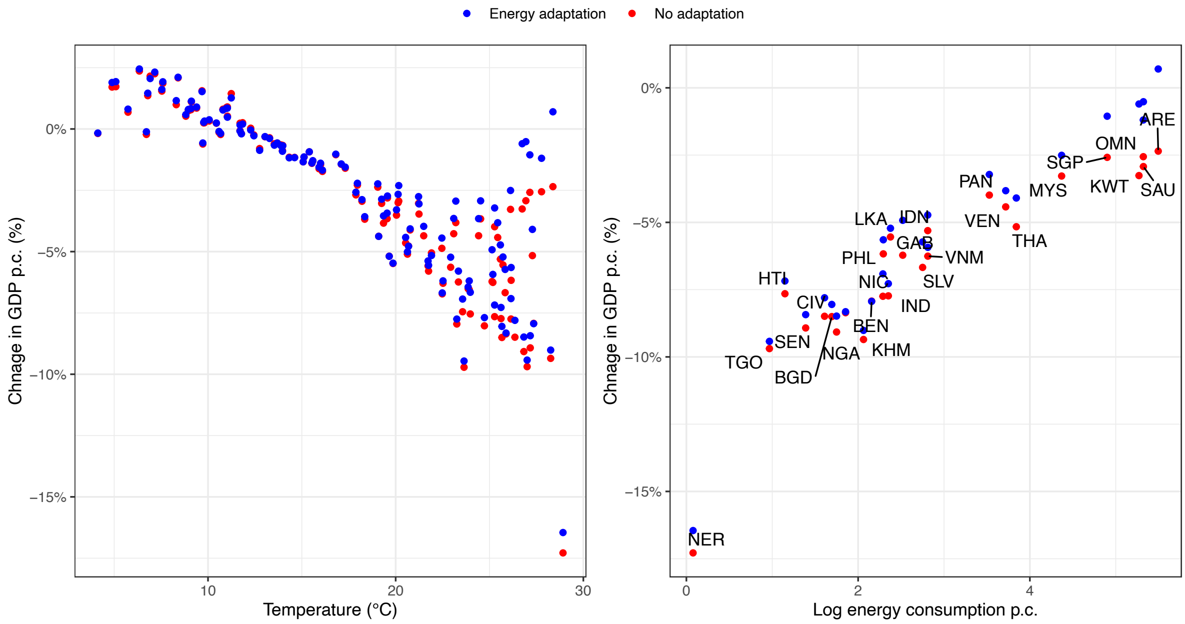

Figure 27. Country-level reduction in per capita growth around 2050 (SSP 5-8.5). Coloured scatters represent the impact without (red) and with (blue) the modulation of additional energy consumption for adaptation.

	SSP 2-4.5	SSP 5-8.5
% GDP loss w/o energy-adaptation	-2.7%	-3.7%
% GDP loss w energy-adaptation	-2.4%	-3.2%
Benefit of energy-adaptation from reduced GDP losses	175 bn USD 2019	347 bn USD 2019
Energy costs for adaptation (electricity)	947 bn USD 2019	1533 bn USD 2019
Energy costs for adaptation (fossil fuels)	64 bn USD 2019	521 bn USD 2019

Table 8: Climate impacts on growth and costs-benefits of adaptation with energy

future work the adoption of weather variables accounting for humidity (i.e. wet-bulb temperatures), and the inclusion of a wider set of controls for seasonal economic activities. A further improvement would be accounting for differences in the long-run response function of income growth across sectors.

The simulated net increase in the global energy demand of residential and commercial buildings for adaptation confirms the literature's finding that energy demand of buildings is underestimated when estimations are beased only on the intensive margin [3]. Here, I show that estimating sector-specific demand functions can provide relevant insights with respect to the assessments that focused on aggregated electrcity and fossil fuel demand [71]. When the cooling needs of the industrial sector is accounted for, the net additional fossil fuel demand for climate chnage adaptation in 2050 turns positive, rather than negative, more than compensating the reduction in demand from lower heating needs in the residential sector.

This analysis is not without caveats. It is important to remark that I only quantify the costs and benefits of the subset of adaptation actions that require energy and that can be inferred from the aggregated macroeconomic energy-climate relationship in the past five decades. Furthermore, I only quantify the benefits in terms of reduced economic losses of such subset of adaptation actions, while I disregard all benefits related to thermal comfort that do not affect economic growth. While I address the risks of endogeneity posed by including the lagged (by one, or alternatively, two years) of the variables that modulate climate impacts in the estimated damage functions, namely capital stock as for energy demand and energy demand as for income growth, I leave to future work the adoption of econometric specifications that explicitly assume that endogeneity and cointegration between the two macro-economic variables of interest (energy and income), such as Error Correction Models [72].

This work's key impact metrics quantify the relative effects of future climatic shifts on energy demand and income growth by assuming that today's structure of the energy markets is maintained in 2050 and that climate-independent energy demand and per capita capital stock are fixed to the current levels. Future projections furthermore depend on the assumption that the historical evolution of energy demand and income growth can be an appropriate measure of the evolution of the extensive margin in the future. The adoption of more efficient adaptation measures (e.g. energy efficient cooling appliances, zero energy buildings, green-based solutions) at a rate higher than the historical one, as well as breakthrough technological changes, can lower the energy demand required to satisfy heating and cooling needs as well as economic impacts of climate change. I also do not account for the implications on the energy supply-side, most importantly on the power generation options that could meet the projected increase in the electric demand. The dynamic implications of adaptation costs and benefits on the energy sector and other economic activities, as well as on carbon emissions, can be evaluated only by coupling the shocks estimated in this work with integrated assessment models.

5.5 Closing remarks

This Chapter has characterized the magnitude of the mitigation challenge arising from climate change adaptation via adoption of AC. It highlights the potential trade-off between mitigation and adaptation, showing that its extent varies significantly across regions with different power systems and across levels of development.

First, the implications of the methodological advancements proposed in this Chapter are broad because energy and income growth are archetypes of a broader class of economic impacts of climate change, all of which have similar structure and might suffer from misattribution if one adopts the assumption that we cannot extract an extensive margin signal from the historical record.

The impacts on developing tropical economies - India and Brazil - are considerably higher than in Europe, both in terms of the magnitude of the additional electricity demand required to provide thermal comfort (188 TWh/year in India, 117 TWh in Brazil and 33TWh/year in Europe, circa 2050 under the RCP 8.5 and high growth SSPs 1-5) and as for the number of population affected by extreme heat. In fact, results show that the current gap between developed and developing countries in the vulnerability to climate change is not eliminated in the future: despite the rapid increase in ownership spurred by economic growth in India 900 million persons will lack AC circa 2050 and will be exposed to substantially higher temperatures than their European counterparts. The global macro-level analysis provides further evidence of regional differences in the trade off between the (partial) adaptation costs and benefits: across "hot" countries, higher impacts on per capita income arise when the level of per capita energy demand is lower then average, and only Gulf countries (such as Saudi Arabia, Kuwait, Oman, UAE) and, in Asia, Singapore, seem endowed with sufficient energy using capital for adaptation.

Fortunately, there are several options for avoiding such a mitigation-adaptation tradeoffs: increasing electricity supply while reducing the emission intensity of generation or reducing the electricity intensity of economic activity more broadly, increasing the energy efficiency of cooling appliances generally and AC specifically, inducing behavioral changes in cooling or adopt zero-energy adaptation measures, such as building insulation or green infrastructures.

Looking ahead, the fundamental need to adapt to more frequent and intense heat while reducing emissions might provide the right mix of incentives for new technologies and behaviours to become widespread. Policies promoting the sales of energy efficient appliances should be prioritized in those areas where the extensive margin adjustments are the main driver on the amplification of demand, while policies promoting behavioural-based efficiencies would contribute to reduce the pressures on the power systems in the areas where intensive margin adjustments are more relevant. A more detailed analysis of the policies implications is presented in the following, concluding Chapter.

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6 Conclusions

Being a key enabling element of development, energy can facilitate adaptation to climate change by ensuring the provision of minimum standards for decent living, including the provision of adequate water supply or safe and comfortable space [1]. air-conditioning diffusion reduces heat-related fatalities [2], and novel empirical findings have related indoor cooling and labor productivity in commercial and industrial sectors [3]. Yet, as recently pointed out by the IPCC, the literature considering energy requirements as a channel of interaction between the impacts of adaptation and sustainable development is scarce [4]. In particular, little or no indication can be found around the extent by which a tradeoffs exists between adapting though the use air-conditioning, sustainable development and mitigation to climate change [5]. There are multiple channels though which adapting by means of energy-intensive technologies such as air-conditioning may result in forms of maladaptation [6]. First, since low-energy-demand development pathways increase the flexibility needed to achieve low temperature mitigation scenarios and reduce the need for negative emissions [7], energy-intensive adaptation actions may jeopardize achieving low-carbon targets. Second, the contemporaneous use of energy-intensive appliances during extreme weather events such as heatwaves may amplify peak power consumption up to levels that exceed system capacity, adversely affecting the grids' reliability and causing power outages at times of high need [8] and eventually resulting in an exacerbation of heat-related heath impacts [9]. This issue is particularly pressing in already vulnerable developing countries, where long-standing infrastructural and new climate change-induced risks may compound.

The objective of this thesis has been to enhance the understanding of the mechanisms though which energy demand for adaptation will evolve in the future, and to propose a suite of methods that elucidate and quantify the tradeoffs between adaptation and mitigation to climate change, with the overarching goal of adding a set of value-added tools for policy and decision making. The remainder of the chapter summarizes the key results of the analyses conducted in the thesis and how they address the overall objectives articulated in Chapter 1, with a focus on the policy implications of results. Then, I examine some caveats associated with the scope of the analyses and methods adopted, underscoring the reasons why results should be interpreted with caution. Finally, I lay down suggestions for future research.

6.1 Key results and policy implications

6.1.1 State of the art and future perspectives for IAMs

Chapter 2 presents a systematic review that compares IAMs' quantitative projections of energy demand for heating and cooling needs at a global level, grouping modeling approaches into a novel classification based on the implementation of the adaptation-energy interplay. Results provide a clear indication to the modeling community, as I find that currently only a few IAMs characterize the energy needed for adaptation, and almost no model characterizes the interaction between mitigation and adaptation though energy endogenously. As a result, the interplay between changes in energy needs for adaptation to climate change and increasingly ambitious mitigation targets remains an understudied topic. These findings clarify one aspect that has been recently stressed by the WGIII of the IPCC, reporting that while several global IAM models have advance considerably in the characterization of buildings, the extremely limited availability of key sectoral variables such as floor space and energy use for individual services in the AR6 scenarios database has prohibited to conduct a detailed analysis of sectoral dynamics [4].

The review has also highlighted that models differ in their representation of the intensive and the extensive margin, the heterogeneity assumed across sectors and regions, the choice of the climate variables driving energy demand. Given such diversity, one key recommendation to the modeling community would be to perform multi-model comparison exercises, focusing on climate impacts on cooling and heating demand, in order to better characterize the range of uncertainty adaptation needs could pose to the decarbonization challenge. Notwithstanding the diversity of implementation strategies across models, the development of a model comparison protocol enabling to harmonize climate and socio-economic could enable to perform such comparison exercises, while leaving full flexibility regarding the actual implementation.

Updating the representation of the energy-adaptation feedback into IAMs constitutes an important step forward in the quantification of sector-specific partial estimates of the Social Cost of Carbon (SCC). The SCC measures the monetized value of all future net damages associated with a 1 metric ton increase in CO2 emissions. Energy sector-specific quantifications of the partial SCC have typically made a relatively small contribution to the overall SCC due to the offset of cooling energy demand by the decrease in heating demand and future technological progress. Recent estimates range from positive values around 10 USD per tonnes of CO_2 from IAM-based projections ([10]) to negligible negative values in empirically founded estimations (i.e. pointing to small net gains at the global level despite large regional differences) [11]. The literature review conducted in chapter 2 and the IAM-based analysis conducted in Chapter 3 suggest that the quantification of the partial SCC may be underestimated by both IAM and empirical frameworks that: i) focus exclusively on the building sector; ii) calibrate shocks based on on short-term energy demand elasticities rather than on long-term extensive margin adjustments; iii) evaluate impacts based on annual mean temperature of CDD-HDD variations rather than from the sub-annual occurrence of extreme temperature events.

Stemming from the evidence gathered though the systematic review, Chapter 4 presents a framework that identifies the most relevant opportunities to update the modeling of the energy-related adaptation-mitigation feedback in IAMs. I show that there is large scope for updating the energy demand elasticities and AC adoption functions as a way to make the energy needed for adaptation endogenous, and to include climate extremes and supply-side impacts as well as demand-side impacts.

6.1.2 Energy for adaptation impacts mitigation pathways

The analysis conducted with the WITCH model, presented in Chapter 3, shows that not including adaptation in mitigation scenarios significantly bias the understanding of the energy transition. Through several model advancements, including notably the adoption of sectoral energy demand elasticities accounting for long-run adjustments, and the identification of impacts due to the occurrence of extreme hot and cold temperatures, the new model simulations provided in Chapter 3 indicate that adapting to climate change will require more energy than previously estimated, leading to higher energy investments and costs. Adapting to climate change by means of adjustments in energy habits, as we did in the past, increases the global demand for electricity by 7% by 2050 and by 18% in 2100. As a result, overall electricity generation costs, including investments in capacity, grids, fuel, operation maintenance costs, will rise by 21% throughout the century. The additional supply-side costs will be passed on to consumers through increases in the price of electricity around 2%-6% due to the adaptation-energy feedback in different regions.

The implications for developed and developing regions in the global north or south change considerably, pointing to a further channel though which climate change may exacerbate current inequalities: Central Africa, the Middle East and South-East Asia will face the largest relative increase in final energy demand for adaptation. The model's results indicate that the largest relative increase in electricity demand occurs in places with power systems poorly prepared to face peaks in power demand for cooling [12]. If these energy requirements cannot be met, extreme temperatures can create health emergencies in developing countries, and this could be one additional channel through which ineffective adaptation may further reinforce global inequalities.

Under the current mitigation policies, production of electricity from coal, gas, and oil is not curbed fast enough to prevent additional investments in polluting generation capacity: the increase in electricity demand for cooling will lead to more physical capital being locked into fossil fuels, corresponding to around 30-35 new large gas-fired plants and 10-15 new large coal- and oil-fired plants each year between now and 2050. This thesis therefore reinforces the urgency to decarbonize the sources used to provide decent living conditions [13, 14].

By making energy shock endogenous, model simulations show that mitigation pathways accounting for the adaptation-energy feedback would require a higher global carbon price, between 5% and 30% higher. This result is relevant to a broad audience ranging from policy makers to the modeling community because it sheds light on a blind spot of the energy transition and of the implementation of climate policies, namely how adaptation needs might reduce the effectiveness of climate policy, making it necessary to revise those policies.

Ambitious mitigation policies can cut by more than half the increase in the costs of the energy system induced by adaptation, depending on the stringency of the climate target. Because of the benefits in terms of reduced adaptation needs, the costs to decarbonize the power system in ambitious mitigation scenarios would be lower than previous estimates, and they would turn negative in well-below-2-degree scenarios, pointing at net gains in terms of power system costs. Overall, two key conclusions can be drawn from this evidence: i) the vicious cycle of global warming, climate extremes and higher energy demand, leading to further emissions and warming, makes early-on mitigation even more important; ii) ignoring the energy system costs required to adaptation from climate change results in an overestimation of the additional costs of mitigation policies, providing a clear indication to modeling community on the relevance of including such feedback and to policy makers on the economic consequences of weak mitigation policies.

6.1.3 AC adoption highlights power system risks

The empirical analyses conducted in Chapter 5 provide a regional assessment of the implications from future AC adoption on the power system, giving at the same time relevant indications on the role of AC to reduce population exposure to heat. At present, the effects of climate change on the electric power systems are poorly understood, leaving the actors liable to ensure the system stability with limited evidence based on historical climate conditions (Yalew et al., 2020). This thesis contributes to shed light on one important component of power system planning, namely the long-term forecast of peak demand. While air-conditioning's benefits in terms of reduced exposure are clear, electricity peak and total demand increase more than previously thought [15, 16], posing a non-negligible additional pressure on power systems. The empirical projections based on the growth of AC ownership and the AC-dependent weather sensitivity of aggregated state-level peak load allow to identify that substantial additional peak generation capacity will be required circa 2050 in order to accommodate the additional cooling demand in Southern European states, Italy (+13 GW) and Spain (+10 GW), and in the Indian states of Punjab, Uttar Pradesh and Maharashtra (+ 4 GW). Fundamental uncertainties are whether future investments in power system capacity and utilization can keep pace with electricity consumers' attempts to adapt to more frequent and severe weather shocks, and to what extent the emissions of greenhouse gases associated with generating that electricity - particularly in developing economies - increase. Furthermore, India is characterized by power system supply-side vulnerabilities that can further amplify the projected demand-side vulnerabilities to climate change. Despite the Indian Government claimed the achievement of its ambitious electrification goal in 2019, the region is still characterized by large differences in the quality of power supply across different communities [17]. The consequences associated with the lack of understanding of power system risks ultimately fall on consumers, who may face more frequent power interruptions and load shedding at times of high need. While households may get accustomed to the recurring lack of power supply, they may place a particularly high value on the provision of electricity when they are facing extreme weather conditions (Casey et al., 2020). The benefits of having a reliable supply of electricity during a heat-wave lasting several hours or days can be very large, since electricity allows to power not only fans and air-conditioning, but also water pumps, reducing the effort to collect clean water, and refrigeration, allowing for the preservation of food and medicines.

While chapter 3 provides a global assessment of the implications on the energy supply-side and emissions when annual changes in energy demand are modeled, the model-based assessments of such impacts with the adoption of sub-annual shocks, in particular of daily and hourly demand though power system models, is outlined as a key area of future research (see section 4.4).

6.1.4 Policies that can limit the adaptation-mitigation tradeoffs

Several policy measures can address the adaptation-mitigation tradeoffs identified though the integrated assessment (Chapter 3) and empirically (Chapter 5). Taking as a reference the additional electricity demand and emissions for cooling estimated in the high-frequency analysis of impacts in India and Europe (see section 5.2), here I conduct a set of back-of-the-envelope calculations on the potential reduction of impacts from different policy measures (for a detail on the method see the Supplementary Material).

Additional renewable or low-carbon dispatchable generation allows the electricity demand increases from expanded cooling to be accommodated without increasing emissions. To compensate for the projected increase in emissions, the CO_2 intensity of electricity would need to decline from 270 gCO2e/kWh to 265 gCO2e/kWh in Europe and from 775 gCO2e/kWh to 700 gCO2e/kWh in India by 2050. In the latter case this would entail displacement of 147 TWh of coal generation annually, corresponding to around 17 GW of capacity—around 7% of India's current coal fleet [18]. Where CO_2 emissions are regulated, reductions in the carbon intensity of generation can be achieved though more stringent abatement targets or higher carbon prices. Using the relationship between carbon prices and regional power generation CO_2 intensities developed in Chapter 3, the latter effect may be on the order of 5-30%.

Electricity consumption offsets could also be achieved on the demand side, through reductions in overall electricity intensity that might shift some of the burden of abatement to other sectors of the economy. Extrapolating historical electricity-GDP trends, by 2050 India's electricity intensity is comparable to that of Europe today, while Europe's electricity intensity declines by 30%—within the range simulated in Chapter 3. Additional declines necessitated by cooling are small in Europe (from 102 GWh/Bn \$ to 100 GWh/Bn \$) but substantial in India (149 GWh/Bn \$ to 135 GWh/Bn \$). Focusing on AC specifically, end-use efficiency improvements could facilitate reductions in heat exposure with smaller increases in electricity consumption. Improving AC units' seasonal energy efficiency ratios (SEERs) from their current region-specific average levels to their best available levels [19] could moderate annual electricity consumption increases by 50% (17 TWh) in Europe and 40% (109 TWh) in India (See the

Supplementary Material).

Changes in households' cooling behavior can also moderate electricity consumption increases. One such response is cooling technology substitution. Compared to AC, ventilation is a less efficacious but much lower-energy alternative for reducing thermal discomfort. A recent simulation study showed that coupling AC with fans allows comfortable indoor temperatures to be maintained with up to 76% less additional electricity [20]. We identify the relationship between air speed and air temperature offsets from the ASHRAE Thermal Environmental Conditions for Human Occupancy [21] for household occupants undertaking primarily sedentary activity, selecting a 3.0°C offset achieved with air-speed at 0.8 m/s. Despite the additional electricity consumption from the use of fans, running an AC unit at a higher temperature threshold would save annual electricity consumption by 40%-60% in Europe and 50%-60% in India, depending on the temporal pattern of fans' operation (See the Supplementary Material).

Although we project a two- to four-fold increase in the macro-regional AC prevalence rates in households in Europe and India respectively, AC remains not affordable for many under the socio-economic assumptions of SSP5 and SSP2. Adaptation options alternative to AC should account for the needs of the most exposed and poorest parts of society, as we find that circa 2050 almost 640 million people across India and 60 million across Europe remain exposed to extreme temperatures while having no AC in their homes.

Additional responses, whose attractiveness and efficacy are difficult to quantify, involve household members shifting activities in time and space to avoid heat exposure [22]. Outdoor activities may be shifted to cooler hours of the day, while hot hours may be spent in public or private air conditioned environments outside the home (e.g., in malls, offices, or even vehicles). Theresidential AC-based electricity demand amplification estimates do not specifically account for adjustments in commercial cooling capacity, utilization or energy consumption. If the latter are subject to economies of scale, their use as substitutes for residential AC could make mitigation-adaptation tradeoffs less severe.

The decomposition between intensive and extensive margin adjustments and of their underlying drivers (see section 5.2) indicates how and why that mix might differ regionally. The analysis of macro-level implication of long-run climate 5.4 provides further evidence that extensive margin adjustments can be captured though climatic indicators constructed as local moving averages in panel data. The analysis of high-frequency energy demand shows that in northern Europe, where increased heat exposures and overall electricity demand amplification are both small, adaptation could prioritize shifting activities, or ventilation. Southern Europe's larger overall amplification effects, with similarly sized temperature-driven intensive margin and income-driven extensive-margin components, suggest behavior-based policies incentivizing ventilation during the shoulder seasons, augmented by appliance efficiency standards and subsidization of energy efficient AC. In India, where the income-driven extensive-margin adjustments are the main driver behind the amplification of electricity demand and current market average SEER is particularly low, Minimum Energy Performance Standards (MEPS) and subsidization of energy efficient AC should be prioritized over behavior-based policies.

The macro level analysis shows that energy demand adjustments to climate change will depend on the available capital stock per capita, and that in turn energy demand per capita grants a non-negligible reduction in the economic impacts of climate change in hotter areas of the world. While here I provide an indication on different approaches though which policy-making can address the adaptation-mitigation tradeoffs, I leave for future work the identification of a cost-optimal mix of policies, as well as the assessment of several other measures that can contribute to reduce the impacts of energy for adaptation on electricity consumption and emissions. In the long-term, one can expect planned adaptation strategies, including, for example, passive cooling, reflective roofs and urban greening to become more common [23, 24]. More energy efficient buildings in the global North, and better performing new residential buildings in the global South, could significantly reduce the energy requirements needed to adapt to extreme temperatures [25, 26]. Smart grids and Demand Side Management strategies can achieve peak shifting and shaving at times of cooling-induced peak demand [27].

6.2 Caveats

The model-based and empirical analyses conducted in this thesis are not without caveats. A first set of caveats relates to methodological aspects. As for the analysis of global impacts conducted with the WITCH model, the main methodological limits are associated: i) to the inability to model sectoral-specific and end-use specific endogenous energy demand shocks, due to aggregated nature of the energy demand functions represented in the model; ii) to the limited representation of the impacts of climate change on the annual peak electricity demand, affecting investments in new power capacity. As for i), although in the current implementation of the energy-adaptation feedback one cannot explicitly associate the estimated changes in energy consumption to specific end-use services, it is reasonable to assume that, for example, the increase in electricity demand in response to greater exposure to heat can be associated with higher demand for cooling [28]. As for ii), due to the lack of global-level empirical evidence of peak demand sensitivity to weather shocks, the analysis assumes that peak demand grows at the same rate of the annual demand increase. Therefore, the projected power system investment needs and costs can be an underestimation of future impacts if peak electricity demand is more sensitive to extreme temperatures than total electricity demand [15]. Future work could explore the costs of an increase in the peak load due to more cooling needs at fine temporal scales by soft-linking global Integrated Assessment Models to bottom-up power capacity expansion and optimal dispatch models (see the discussion in Chapter 4 and in the next section).

As for the empirical analyses conducted in Chapter 5, the choice of focusing on the high-frequency component of electricity demand comes at the cost of giving up the possibility to identify sector-specific impacts, since hourly and daily load data is stored by Transmission System Operators almost exclusively aggregated by sector. Similarly, lack of data on commercial-sector air-conditioning availability prevented to conduct a separate analysis of the extensive margin potentials in this sector. By assuming that total load shocks are modulated uniquely by the residential sector prevalence rates, I assume implicitly that commercial sector extensive margin follows the same growth rates of the residential sector. This may result in an underestimation of the load shocks if, as found by [28], electricity consumption in commercial buildings is more sensitive to extreme temperatures than in residential buildings [28]. Another caveat of the methodological approach of chapter 5 is the measurement of population exposures to heat based exclusively on the presence of AC. Lacking to account for the technological options alternative to AC, such as fans or efficient building insulation, results in an overestimation of exposed population. Yet, on the other hand, this method tends to underestimate exposures as I do not account for the exposure of population owing an AC occurring during the time spent outdoors for commuting, work or leisure activities.

Furthermore, the empirical analysis conducted in this thesis do not account for the possible role of energy prices in shaping the response of energy demand for adaptation. Price elasticises of energy vary considerably depending on the scope of the study as well as on the estimation technique, but meta-analyses tend to confirm that the price elasticity of electricity consumption is limited with respect to other fuels, and that it is higher in the long run than in the short run [29]. For this reason, the impact of electricity prices on the temperature-load response function estimated based on the daily co-variation between variables do not pose a limit to the estimation strategy. In the Error-Correction Model adopted to study monthly electricity consumption on the other hand I explicitly consider electricity prices as a confounder, controlling for variations in their level though in econometric specification. On top of direct impacts on aggregate consumption behaviours, energy prices may affect the energy-adaptation feedback by affecting technological adoption in multiple ways and in opposite directions: by reinforcing the benefits of purchasing energy efficient appliances versus inefficient ones, by promoting fuel substitution (e.g. from gas boilers to heat pumps), by reducing the purchasing power of families, in turn affecting the basket of consumer goods. An important open question concerns investigating how energy price shocks – such as the ones that are being experienced in Europe in the aftermath of the global pandemic and of the war between Russia and Ukraine [30] – may exacerbate energy poverty, hence reducing the ability of households to respond to thermal discomfort though the adoption and operation of heating and cooling appliances.

A second set of caveats relates to the scope of the analysis conducted. While I show that ignoring the energy system costs and the environmental implications of rising adaptation needs in IAMs results in an overestimation of the relative costs of ambitious mitigation policies, the potential tension between mitigation and adaptation would be much more significant if the integrated approach proposed were expanded to include other mechanisms through which responses to climate change affect energy demand [31], such as water supply and treatment, transportation, and cooling chains, and if the welfare and well-being implications of both adaptation and residual damages were considered. Mitigation can reduce the health costs associated with carbon-intensive adaptation, since additional fossil-fuel-fired generation contributes to air pollution. Although empirical estimates on adaptation benefits are growing [32, 33], they remain difficult to be included in IAMs. Developing scenarios that gather more evidence on the positive side-effects of mitigation policies can help accelerate the tightening of the emission reduction targets within the framework of the Paris Agreement.

The next section expands the discussion on these aspects, and underscores how they constitute key areas for future work.

6.3 Future work

6.3.1 Broader assessment of energy impacts

The impacts on power market operations of the compound influence of cooling-induced peaks in the electricity demand and supply-side vulnerabilities to extreme weather events are mostly disregarded by the literature, despite the growing empirical evidence on the vulnerability of both power system grid and generation infrastructure [34, 35, 36, 37]. For instance, if load exceeds the forecasted peaks and if power generation or transmission are partially impaired, power system operators can incur additional costs in the form of balancing services, load shedding, or, at worst, unplanned outages. Coupling high-frequency supply and demand forecasts under extreme weather conditions withing a common modeling framework can allow to evaluate the most suitable operational responses. Detailed power dispatch models could investigate options to strengthen the resilience of power systems though changes in the dispatch mix, balancing services and cross-border trade. Furthermore, given that conventional generation technologies play a dominant role in setting wholesale prices as they meet the net-load, i.e. residual demand not satisfied by renewable sources, extreme weather events may result in wholesale price fluctuations. Understanding the characteristics of power markets' operations during extreme weather may bring to the surface possible limitations of the current power systems, leading not only to volatility in power prices but possibly also to higher costs for managing the grid. Capacity expansion models quantify the investments in generation and transmission capacity required to meet the future power load, typically under alternative decarbonization policy scenarios. The additional slack generation capacity required due to climate change can be quantified by feeding into a capacity expansion model the simulations of the hourly and peak load response to future extreme weather events. Furthermore, the ability of different power system mixes (e.g. with varying shares of renewables and storage) to provide a reliable flow of peak power generation during extreme events can be investigated by coupling a capacity expansion model to a dispatch model. This framework would allow to understand if highly decarbonized power mix could be more resilient to climate change by being more synchronized (if peak load due to air-cooling is met by photovoltaic generation) or more challenging to manage (if the continuation of the peak load during the evenings, coupled with falling photovoltaic generation, amplifies the thermal generation ramp up requirements). These analyses would therefore provide a holistic view of how electricity supply in the future can remain reliable during extreme weather events. Models with a detailed representation of the use of electric appliances and of the behavioral aspects of consumption can be adopted to investigate the demand-side potentials for reducing the peak-load during extreme events.

6.3.2 Adaptation and the Energy-Water-Land nexus

This thesis focuses on the direct energy requirements occurring to maintain thermal comfort in buildings and ensuring the stability in industrial operations under extremely high or low temperatures. An important channel thorough which adaptation can result in higher energy demand requirements is though the decrease in water availability, resulting in energy-intensive adaptation actions such as desalination and wastewater-treatment as well as in higher irrigation needs. The expansion of irrigation under a changing climate is expected to have significant impacts on energy consumption, since pumping of groundwater is 25% more energy-intensive than surface-water irrigation [38]. Furthermore, water availability impacts energy generation technologies, most importantly hydro-power and nuclear power plants. Yet, water and electricity system climate vulnerabilities and adaptations are often studied in isolation, without considering how multiple interactive risks may compound. At the same time, the growing literature addressing the inter-linkages of the Energy-Water-Land (EWL) provides examples of holistic assessments of climate change adaptation.

Understanding of how adaptation strategies relate to the EWL nexus is important because it facilitates the evaluation of the net impact of individual adaptation measures and it enables to consider the compound effects of concurrent implementation of different adaptation measures, as an outcome of either coordinated or uncoordinated parties' actions [39]. In order to perform such type of evaluations, insights from the physical and social sciences should be coupled together and put in relation with local characteristics. At the same time, the compound effects of global-level deployment of different type of adaptation measures should be studied in order to assess, over a range of likely future climate and socio-economic scenarios, what options minimize the potential negative impacts of climate change. Works assessing the role of adaptation with respect to the energy-water side of the nexus is growing [40, 41, 42]. As all major IAMs account for the interactions among energy, land-use, economic and climate systems and generate long-term scenarios at the global and regional level, they are considered particularly relevant tools for the assessment of adaptation options and their long-term impacts on the EWL nexus both at regional case-study level [43] as well as at the global level (for instance building on the work by [44] on multi-sectoral global climate risks). Key research areas are assessing the inter-linkages of water required for irrigation-based adaptation with water supply technologies and accounting for short-term water availability in combination with high-frequency energy demand fluctuations, as adaptation to co-occurring extreme weather events such as heat waves and droughts may pose multiple pressure on different sides of the nexus.

6.3.3 Welfare and well-being implications

Although air-conditioning is a key option for protecting people to thermal stress, direct empirical evidence on the contribution of such technology to reduce heat-related mortality, reduced morbidity and increased productivity - as well as of the associated welfare gains is still limited.

The seminal work by [2] finds that the growth in residential AC ownership in the United States in the 1960–2004 period played a critical role in reducing the incidence of heat-related fatalities (reducing premature fatalities by about 18,000 annually). Other empirical analysis focusing on the US find mixed results on the benefits of AC on health, depending on the type of the AC units (central AC appear to be more robustly associated to reduced deaths from heat stress than room AC [45, 46]). More recent assessments exploiting daily co-variation between mortality and hot temperatures in different world locations show that increased air-conditioning prevalence reduces the relative risks and fractions of heat-attributable excess deaths, although other attenuating factors may play an equal or more important role in increasing the resilience of populations [47].

Impacts on morbidity and increased productivity have been rarely captured empirically so far. Recent model-based simulations show that air-conditioning can prevent production losses in the manufacturing and service sectors [3]. New adoptions of AC could avoid macroeconomic cost of up to 3-4% of global total GDP (in 2100 under RCP8.5) that would otherwise be associated to interruptions of indoor working activities to ensure heat-related illness prevention.

Direct estimates of the welfare gains from AC from both reduced mortality and morbidity and increased productivity are constrained by lack of data and problems of endogeneity in the household choice of owning an AC and energy consumption. Only [2] provide an indirect quantification of the full consumer surplus, based on the construction of AC-dependent long-run electricity supply curves, finding that owning ACs is associated with substantial gains (from 5 to 10 billion 2012 dollars annually, or 112–225 2012 dollars per household at the 1980 AC penetration rate, depending on the methodological assumptions). Expanding the empirical evidence on the benefits of air-conditioning on mortality, morbidity, increase productivity and on the associated welfare gains of AC, especially in the regions that will face the largest adaptation-mitigation tradeoffs (such as India and Brazil, as shown in Chapter 5), constitutes a key area of future research.

6.3.4 Innovation in energy intensive adaptation technologies

Technological adaptation options are still the most common adaptive responses to climate change, although there is growing experience of the value for ecosystem-based, institutional, and social measures [48]. At the same time, adaptation strategies will vary over time depending on climate forcing plus other factors such as technology availability and maturity [49]. Technological change will hence play a critical role for coping with a changing climate. Technological innovation and diffusion can enhance adaptive capacity, but the resulting impact on the energy system is unclear, as it depends on the degree of energy efficiency of future adaptation technologies as well as on the diffusion and adoption of the most efficient technologies when multiple options are available on the market [50]. Despite the great importance of understanding the development and transfer of technology options for climate change adaptation, the literature focusing on inventive activity and diffusion of clean technologies has so far been mostly limited to the analysis of mitigation technologies [51, 52]. One of the few studies assessing both mitigation and adaptation technologies finds that inventive activity has been growing rapidly in both areas in the last decades [53]. New research could investigate: i) the emerging dynamics of the innovation activity of adaptation technologies; the demand and supply determinants of adaptation technology innovation, diffusion and adoption. Recent evidence focusing on the United States shows that climate change may contribute to push new innovation in adaptation technologies, as extreme heat exposure results in an increase of 7.5% greater innovation in the form of patent filings by up to 2 years after a county has experienced extreme heat [54].

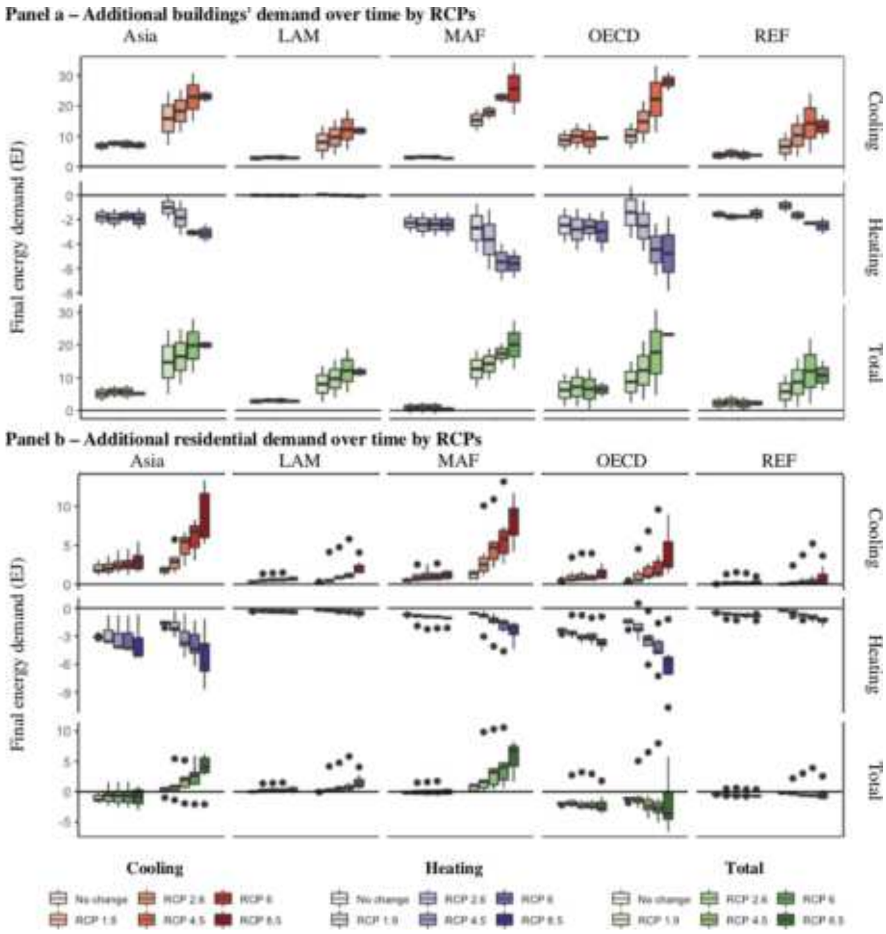
7 Supplementary Material

7.1 Supplementary Material of Chapter 2

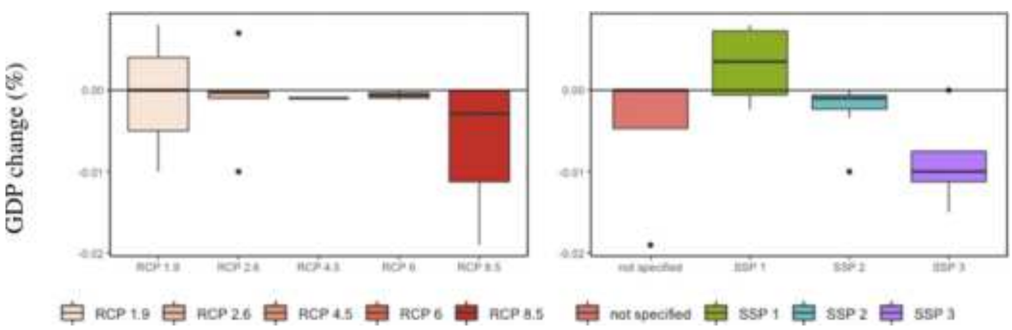
The search terms used for the meta-analysis included ‘energy demand’ OR ‘energy use’ OR ‘energy consumption’ AND ‘climate change’ AND ‘conditioning’ OR ‘cooling’ AND ‘heating’. Other terms were progressively added to refine the search, such as AND (‘GDP’ OR ‘wealth’ OR ‘economic loss’ OR ‘economic gain’); AND (‘scenario’ OR ‘projection’ OR ‘impacts’); AND (‘integrated assessment model’ OR ‘energy model)’.

All macro regions are characterized by a net increase of a building’s energy demand for thermal adaptation, ranging from 0.5 to 7 EJ in 2050 and from 6 EJ to 23 EJ in 2100, depending on the region and the degree of warming. Sharp increases in median additional energy due to cooling requirements from 2050 to 2100 are projected for all regions, with a median addition in Asia, the Middle East and Africa (MAF) and OECD countries between 23 EJ and 28 EJ under the highest warming scenarios. As for the residential sector, the median additional energy due to cooling requirements in 2100 ranges from 1.9 EJ to 8.7 EJ in Asia, from 1.4 EJ to 9.1 EJ in MAF, from 0.3 EJ to 2.4 EJ in OECD countries, from 0.3 EJ to 1.7 EJ in Latin America (LAM) and from 0.02 to 0.3 in Russia (REF), depending on the RCP. In temperate regions, OECD and REF, sharp decreases in heating energy needs result in a median value of total additional energy requirements in 2100 which ranges from 1.1 to 3.6 in the former and 0.3 and 0.9 in the latter region, depending on the RCP. On the other hand, in Asia and MAF the total energy requirements range in 2100 from 0.5 to 4 EJ (an almost tenfold increase from RCP 1.9 to RCP 8.5) in the former region and from 1 EJ to 6 EJ in the latter. In LAM total additional demand goes from almost zero to 1 EJ. The additional energy demand projected in higher warming scenarios, with respect to the low warming scenarios, is greatly amplified from the second half of the century in both the residential and the commercial sector.

The figure presents the results of the climate-related impact on GDP due to variations in energy demand for cooling and heating as a response to global warming. Substantial impacts are identified under the RCP 8.5 scenarios, with a median relative variation in GDP equal to 0.29%, with the lowest value reaching 1.9%. The projections based on the SSP 1 are characterized by a positive median GDP percentage change of relatively small magnitude,9 while a negative median GDP percentage change is found in the projections based on SSP 2 and SSP 3.



Supplementary Figure Ch.2-1



Supplementary Figure Ch.2-2

7.2 Supplementary Material of Chapter 3

The IAM approach

WITCH is a dynamic global model that fully integrates a simplified representation of the economy, the energy system, and the climate system. The economy is modeled through an inter-temporal optimal growth model. A representative agent chooses consumption to maximize regional welfare, and consumption decisions are related to investment choices. The energy sector is hard-linked with the rest of the economy. Energy investments and resources are chosen optimally together with the other macroeconomic variables. Energy demand and, in particular, fuel and technology choices are optimized intertemporally, under a set of constraints, including carbon and other energy prices. A climate model (MAGICC) computes the future changes in global average temperature on the basis of the GHG emissions generated by economic activities and the energy system. A fully-integrated module translates regional GHG emissions into global temperature through atmospheric concentrations. Another module links the global average temperature increase to changes in regional average temperature based on linear statistical downscaling model of country-level mean temperature estimated by using future warming scenarios (Representative Concentration Pathways, RCPs, see Section 1 in the Supplementary Methods). WITCH integrates an air pollution module, FASST(R). It is a source-receptor model based on the TM5-FASST model developed by JRC-Ispra, that computes the annual concentrations of several pollutants, namely Sulfur Dioxide (SO2), Nitrogen Oxides (NOx), fine Particulate Matter (PM2.5) and ground-level Ozone (O3). The fine PM 2.5 concentrations include Particulate Organic Matter (POM), secondary inorganic PM, dust and sea-salt. The FASST(R) model produces concentrations on a world spatial grid of resolution of one degree by one degree, and has previously been used to assess premature death from air pollution exposure [1, 2].

Modeling advancements

Regarding the adaptation - energy feedback loop, a set of equations links the occurrence of extreme temperatures to energy demand. The energy demand shocks in WITCH are matched to the available empirical evidence from [3] and therefore use Extreme Temperature Indicators (ETIs) defined as the yearly count of days in which average temperatures fall above the threshold of 27.5°C and below the threshold of 12.5°C, respectively. The moderate temperature intervals are excluded, and adjacent extreme bins are aggregated in order to focus on the two temperature intervals of exposure to extreme heat and cold (T < 12.5°C and T > 27.5°C).

The heterogeneous relationship between the vector of ETIs ($\boldsymbol{\eta_{i,t}}$) and temperature across climate conditions is captured by grouping countries in clusters (Supplementary Methods). I use a polynomial function (f) of yearly mean temperatures ($T_{i,t}$). I estimate a panel, fixed-effect model with ordinary least square (OLS) on yearly, country-level observations for 180 countries from 1970 to 2010 (Supplementary Methods). The regional future realizations of the ETIs are then determined endogenously within the model and defined for climatic clusters as follows, c, as:

$$\boldsymbol{\eta}_{i,t} = f(T_{c\in i,t}, T^2_{c\in i,t}) \tag{40}$$

where

i regions (17 regions)

c clusters (4 clusters)

t 5-year time step in the model from 2005 to 2100

Sector-specific, semi-elasticities are used to link energy demand and $\boldsymbol{\eta_{i,t}}$. They are calibrated after the estimates published by [3], which model the long-term relationship between energy demand, weather, income, and prices as a dynamic adjustment process. Semi-elasticities indicate the percentage by which demand shifts relative to its conditional mean level, in consequence to an additional day occurring in a given interval (j) with respect to the reference temperature interval. The semi-elasticities are specific to two macro-regional groups: temperate and tropical countries. In both macro-groups the number of days falling within the extreme temperature intervals lies in the tails of the daily temperature distribution. The semi-elasticities provided by [3] capture how energy responds to long-term weather shocks, allowing us to project future energy demand shocks that account for extensive margin adjustments (e.g., purchase of air conditioners, improvements in energy efficiency). Other appealing features of the analysis developed in [3] are that it captures the potential non-linearity in the demand responses to weather and climate, provides asymmetric responses in temperate and tropical countries, and separates the influence of humidity and temperature on demand. The lack of empirical evidence providing alternative demand response functions for multiple fuels, sectors of the economy and climate areas limits the scope for assessing the robustness of the results based on [3]. The transmission of the climate shock in the commercial and industrial sectors in tropical economies reflects the extensive use of distributed petroleum-fired generators to satisfy final electricity demand.

Sectorial semi-elasticities ($\beta_{i,f,s,j}$) are aggregated with the share of the final energy demand of each sector over total final energy demand as weights ($\lambda_{i,f,s,t}$), for each fuel and for each time step of the model. The share is computed from the baseline model projections in each 5-year time step. The aggregation yields a set of semi-elasticities $\overline{\beta}_{i,f,t,j}$ specific to each region (i), energy vector (f) and year (t).

$$\overline{\beta}_{i,f,t,j} = \sum_{s} \lambda_{i,f,s,t}\beta_{i,f,s,j} \tag{41}$$

where

i regions (17 regions)

t time step in the model, 2005-2100

f energy vector (electricity EL, non-electric energy GAS and OIL)

s sectors (residential, commercial, industrial)

j average daily temperature interval

Climate-induced shocks on energy demand, ($\Phi_{f,i,t}$), combine historical and future realizations of the ETIs with average sectorial semi-elasticities aggregated over the two temperature intervals (j):

$$\Phi_{i,f,t} = \frac{\exp(\sum_j \overline{\beta}_{i,f,t,j} \boldsymbol{\eta_{i,t}})}{\exp(\sum_j \overline{\beta}_{i,f,j} \boldsymbol{\eta_{i,t}})} - 1 \tag{42}$$

where

i regions (17 regions)

t time step in the model, 2005-2100

f energy vector (electricity EL, non-electric energy GAS and OIL)

j average daily temperature interval

The climate-induced energy demand shocks affect the productivity of the energy inputs entering into the aggregate production function, as proposed by [4]. If climate-induced shocks increase energy demand, it is as if the economic systems needed more energy to produce output.

Climate-related positive shocks (i.e. increase in energy demand) are therefore modeled as technological retrogression, requiring more inputs to generate a given output. In the WITCH model, energy (EN) is a combination of electricity (EL) and non-electric energy (NEL), which includes coal, gas and oil. Electricity and non-electric energy can be substituted with an elasticity of substitution, ρ_{EN}:

$$\mathrm{EN}_{i,t} = [\tilde{\alpha}_{\mathrm{EL},i}\mathrm{EL}_{i,t}^{\rho_{\mathrm{EN}}} + \tilde{\alpha}_{\mathrm{NEL},i}\mathrm{NEL}i,t^{\rho_{\mathrm{EN}}}]^{\frac{1}{\rho_{\mathrm{EN}}}} \tag{43}$$

In this formulation, the productivities of electricity and non-electricity are endogenous functions of climate shocks:

$$\tilde{\alpha}_{EL,i,t} = \alpha_{EL,i}\frac{\Phi_{EL,i,t}Q_{EL,i,t}}{\sum_f Q_{f,i,t}} \tag{44}$$

$$\tilde{\alpha}_{NEL,i,t} = \alpha_{NEL,i}\left[\frac{\Phi_{GAS,i,t}Q_{GAS,i,t}}{\sum_f Q_{f,i,t}} + \frac{\Phi_{OIL,i,t}Q_{OIL,i,t}}{\sum_f Q_{f,i,t}}\right] \tag{45}$$

Quantification of additional new capacity

In the WITCH model, investments in new power generation plants to fulfill electricity demand depends on: i) the cost of electricity generation of the different technologies, which combines capital costs, Operation and Maintenance (O&M) expenditure, and the costs for fuels in an endogenous way; ii) the lifetime power plants; iii) a constraint on the flexibility of the power generation fleet to accommodate the integration of renewables; iv) an installed capacity constraint on the power generation fleet to guarantee that sufficient capacity is built to meet the instantaneous peak electricity demand (for further details see [5]).

The cumulative additional new capacity added in response to the variation in electricity demand required for adaptation that we report ($\Gamma_{h,i,t}$) for each technology h in region i at time t is computed as follows:

$$\Gamma_{h,i,t} = \sum_{t=2005}^{t}(K_{h,i,t}^{Ada} - K_{h,i,t}^{NoAda}) \tag{46}$$

$$K_{h,i,t+1} = K_{h,i,t}((1-\delta_{h,i,t+1}))^{\Delta_t} + \Delta_t\frac{I_{h,i,t}}{SC_{h,i,t}} \tag{47}$$

Where $\delta_{h,i,t+1}$ is a depreciation rate based on a finite lifetime of the power plant, $I_{h,i,t}$ are the annual investments and $SC_{h,i,t}$ the investment cost.

Quantification of energy costs

Power generation costs (C_GEN), include the investments in generation capacity (I), R&D investments in power generation technologies (I_RD), O&M costs (OM) and fuel expenditures for power generation (E_FUEL):

$$\mathrm{CGEN_{i,t}} = \sum_{h} (\mathrm{I_{h,i,t}} + \mathrm{I\_RD_{h,i,t}} + \mathrm{OM_{h,i,t}} + \mathrm{E\_FUEL_{h,i,t}}) \tag{48}$$

where

i regions (17 regions)

t time step in the model, 2005-2100

j power generation technology

Fuel costs (C_FUEL) include the investments and O&M costs in fossil fuel extraction (OM_ex) and the expenses associated with liquids and gas consumption (EXP_ff), excluding the expenses related to fuel consumption in the power sector:

$$\mathrm{C\_FUEL_{i,t}} = \sum_{f} (\mathrm{OM\_ex_{i,t,f}} + \mathrm{EXP\_ff_{i,t,f}}) \tag{49}$$

where

i regions (17 regions)

t time step in the model, 2005-2100

f fuel

Investments in the electrical grid (I_GRID) are computed based on grid capital. The grid capital stock is adjusted by taking into account a linear relationship between grid capacity and the capacity of traditional power generation technologies and the investments for integrating the generation of variable renewables. A detailed description is available in [5].

Scenarios

In the current policy scenario, GHG emission targets extrapolate beyond 2020 the implied ambition levels of current climate policies until 2020. Overall, the current policy scenario with no energy-adaptation feedback leads to cumulative carbon emissions of about 5,000 $GtCO_2eq$, from 2018 until 2100 9. More stringent mitigation scenarios keep the increase in global mean temperature in 2100 at 2.5°C and well-below 2°C, resulting in cumulative GHG emissions from 2018 until 2100 of 3,600, and 1,500 $GtCO_2eq$, respectively. Non-CO_2 greenhouse gases in these scenarios are priced equivalently to the implied CO_2 prices, by using 100-year global warming potentials for conversion. We use explicit GHG pricing, and climate stabilization targets are achieved in a global cost-optimal way, with no international compensation scheme or carbon emission trading.

Table 9: Climate scenarios assessed in this study

Scenario	Fixed carbon budget	Carbon emissions (2018-2100)	Global mean temperature increase (2100)
Current policy	No	5,000 $GtCO_2eq$	3.23°C
2.5°C	Yes	3600 $GtCO_2eq$	2.56°C
Well below 2°C	Yes	1500 $GtCO_2eq$	1.65°C

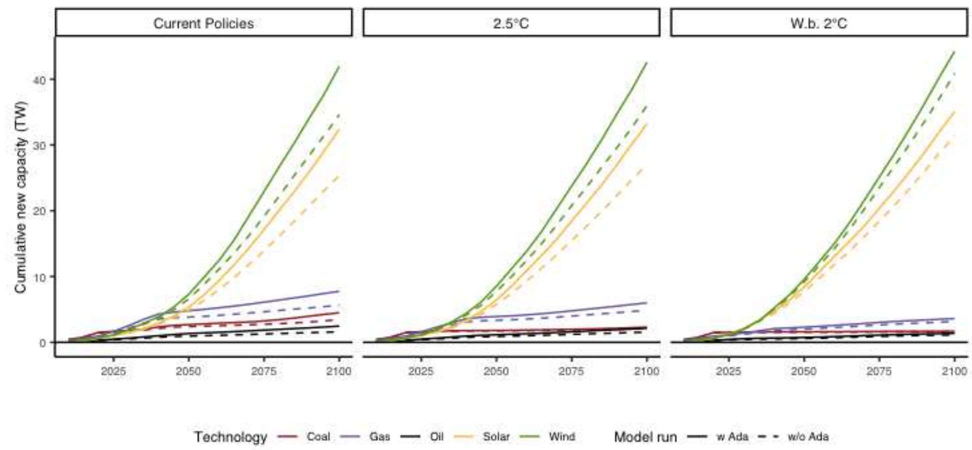
Population [6] and country-level GDP projections implemented by using Purchasing Power Parities (PPP) [7] are based on the basic and extended SSPs [8]. The main results use the Shared Socio-Economic Pathway Middle-of-the Road (SSP2), which is a continuation of the historical trends, while the Summpelentary Materialpresents some results across SSPs. For more information on the implementation of key aspects such as energy productivity, land-use and power technologies and fossil fuel resources, see [5].

Supplementary Figures

New power capacity requirements

The additional pressure posed on power generation by the increase in electricity demand results in a scale-up of both fossil-based and renewables capacity, as well as of storage capacity. The additional new generation capacity required in the next few decades for adaptation comprises both fossil-based and renewable generation. Renewables and storage constitute most of the additional new capacity in the second half of the century across all scenarios (Supplementary Figure Ch.3-1). The share of the additional coal, oil and gas capacity on the total additional capacity required to fulfill adaptation needs ranges from 85% (current policies) to 80%-65% (ambitious mitigation scenarios) in 2030, from 40% to 20%-10% in 2050 and up to

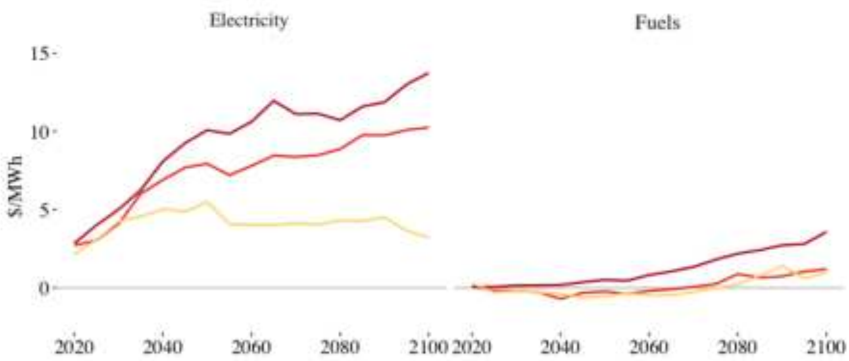
10% in 2100 in the current policies. Supplementary Figure Ch.3-1 shows the cumulative generation capacity required to meet the electricity demand with (w Ada) and without (w/o Ada) the adaptation feedback, including fossil fuels, renewable energy and storage.



Supplementary Figure Ch.3-1

Variation in the energy system costs

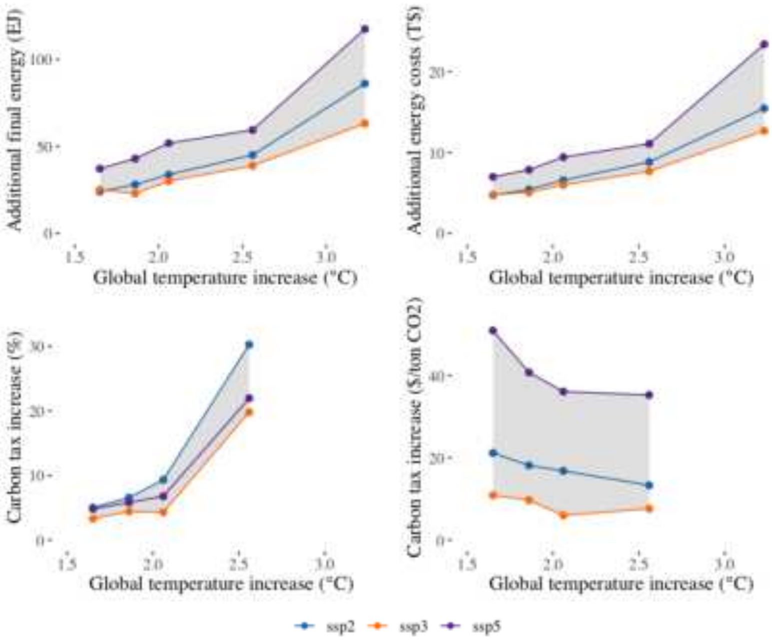
Supplementary Figure Ch.3-2 shows the decomposition of the additional energy supply costs by a unit of total final energy demand. The additional electricity supply costs over total electricity consumption increase sharply from 2-5 USD/MWh in 2030 to up to 10-15 USD/MWh in 2050-2100 under the current policies scenario, while remain stably below 5 USD/MWh over the whole period in the well below 2°C scenario. The unitary additional energy supply costs for fuels remain below 3-4 USD/MWh even in the current policies scenario.



Supplementary Figure Ch.3-2

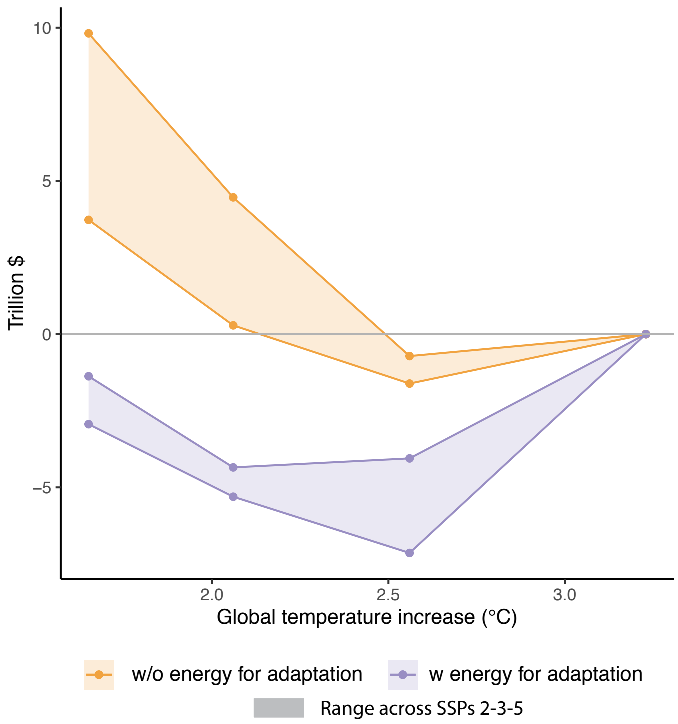
Results by SSPs

Supplementary Figure Ch.3-3 presents the incremental energy demand and costs (panel a) and the increase in the carbon tax (panel b) due to climate change in 2100 across SSPs and climate policy outcomes. The impacts on the energy system across socio-economic pathways are scaled uniformly from the lower end of the range in SSP 3 to the higher end in SSP 5. The level of the additional demand and costs in the SSP 5 are roughly two times the levels in the SSP 3, while the moddle-of-the-road SSP 2 lies in between (being closer to the SSP 3 as for the energy costs and the absolute carbon tax increase). The increase in the global average temperature in 2100 of an additional +0.5°C, from +2°C to +2.5°C, strongly affects mitigation policies. While the energy demand, the supply-side costs and the level of the carbon tax increase only marginally, the relative change in the carbon tax goes from a 5%-10% variation to a 20%-30% variation.



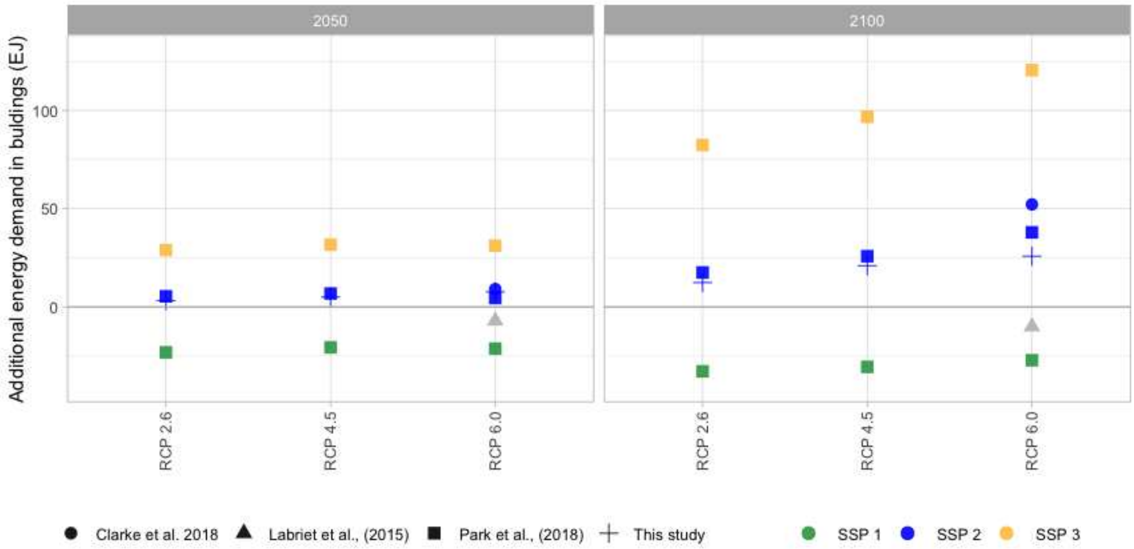
Supplementary Figure Ch.3-3

Supplementary Figure Ch.3-4 shows the variation in the cumulative ESC for power system costs associated to the more ambitious mitigation policy scenarios with respect to the current policies scenario, across SSPs and in the case without and with the adaptation-energy feedback. The Net Present Value (NPV) is computed based on a i.r. of 3%.



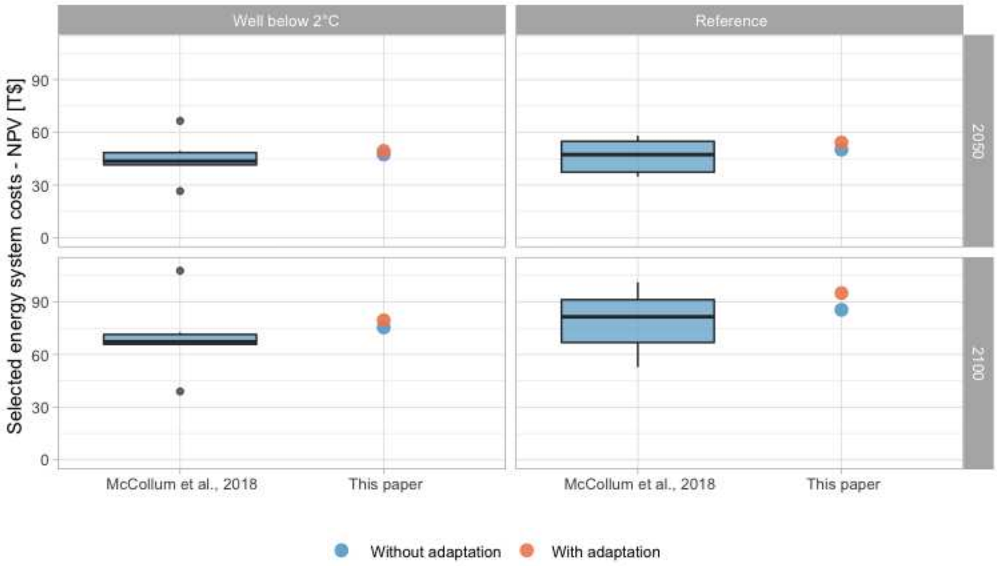
Supplementary Figure Ch.3-4

Supplementary Figure Ch.3-5 compares our results with the few IAM-based projections providing the variation in global buildings' final energy demand induced by climate change adaptation in 2050 and 2100 [9, 10]. Our projections, ranging from 3 to 5 EJ (12 to 26 EJ) in 2050 (2100) depending on the extent of global warming, are in line with the literature's projected increase under the same socio-economic scenario (SSP2).



Supplementary Figure Ch.3-5

Supplementary Figure Ch.3-6 compares the future energy system costs presented in this study with six leading IAMs' projections reported in [11]. Differently from Figure 4, fuel consumption costs are excluded from the selected energy system costs reported in ??, because [11] only focuses on energy systems' investments. Only comparable energy system costs have been considered, namely: investments in extraction and conversion of fossil fuels, investments in electricity generation and investments in the electricity's transport, distribution and storage. The multi-model median NPV of energy system costs in 2050 (2100), excluding the energy-adaptation feedback, in the current policies scenario is 47 (81) Trillion USD, while we project an NPV of 50 (85) Trillion USD without adaptation and of 54 (95) Trillion USD with adaptation.



Supplementary Figure Ch.3-6

7.3 Supplementary Material of Chapter 5

Conceptual framework

The final electricity use that matches the total load transmitted through grid results from the demand of consumption and production processes, including usages unrelated to outdoor meteorological conditions and activities that directly respond to meteorological conditions, such as the utilization of electrical heating, ventilation and cooling assets (henceforth "utilization" for thermal regulating services component, or q) [16]. We assume that, at each point in time, peak electricity demand responding to meteorological conditions (q) can be decomposed into a “long-run” extensive margin component (q_E) and “short-run” intensive margin component (q_I):

$$q = f(q_E, q_I) \tag{50}$$

Changes in expected climate conditions, C, modify the decisions of final users regarding the adoption of cooling and heating appliances or assets, a, and therefore, at the extensive margin, in the latent actual electricity use. Over the long-run, we can identify a latent average utilization value, $q_E(\overline{a}, C)$. Income conditions, Y, modulate discretionary expenditure on durable assets, affecting both assets and the latent average utilization, $\overline{a}(C, Y)$.

The level of per capita income and the climate together jointly determine the size of the

[16] Although there are other activities that respond to meteorological conditions, with impacts on total and peak load (change in time allocation, consumption of other appliances, water heating), we assume that the electricity associated with those activities is of secondary importance.

durable stock and the average level of its utilization, and therefore the average level of q. We aim to identify their combined effect of the low-frequency extensive margin component (q_E):

$$q_E = h(\overline{a}, \overline{q}_E) = h(C, Y) \tag{51}$$

When actors are faced with a weather realization (T) that corresponds to the expected climate ($\mathbb{E}(T|C = C)$, no adjustment occurs at the intensive margin, and therefore:

$$q = f(q_E) = h(C, Y) \tag{52}$$

If an unanticipated daily weather anomaly (ω) arises, shifting the exposed temperature from the expected climate C to $T = C + \omega$, the optimal response to the expected C, $h(C, Y)$, will be modified by an additional intensive margin component (I), capturing the extent to which actors adjust their utilization following a deviation from the expected climate. At the intensive margin (I), temperature anomalies leading to higher or lower exposure to high and low temperature levels can be accommodated by making electricity consumption more or less sensitive to weather. Higher income levels facilitate adaptation through increased discretionary expenditure on more intensive utilization of the existing durable stock, with correspondingly larger demand demand responses to positive and negative anomalies. Importantly, the short-run response is constrained by the durable stocks and their average use patterns, as described in Equation (2):

$$q_I = g(C + \omega, Y | h(C, Y)) \tag{53}$$

Assuming the two components add up linearly, total final demand reads as follow:

$$q = f(q_E, q_I) = h(C, Y) + g(C + \omega, Y | h(C, Y)) \tag{54}$$

Climate and per capita income are the low-frequency variables that should capture extensive margin adjustments, while daily weather anomalies are the high-frequency variables that can interact with per capita income as well and capture intensive margin adjustments (i.e., adjusting utilization over the short run, conditional on durable stocks and their average use patterns).

Identification strategy

The identification strategy relies on the assumption that for a given observed maximum temperature, $T = C_k + \omega_{p(k)}$, the estimated response to long-term, temperature exposure D_k^C is:

$$U = h(C, Y) + g(C + \omega, Y, h(C, Y)) = \gamma_k^C + \beta_k^C y + \omega(\gamma_{p(k)}^{\omega} + \beta_{p(k)}^{\omega} y) \tag{55}$$

On the other hand, given $T = C_{k'}$ and $\omega_{p(k')} = 0$, the estimated response to long-term, temperature exposure D_k^C is:

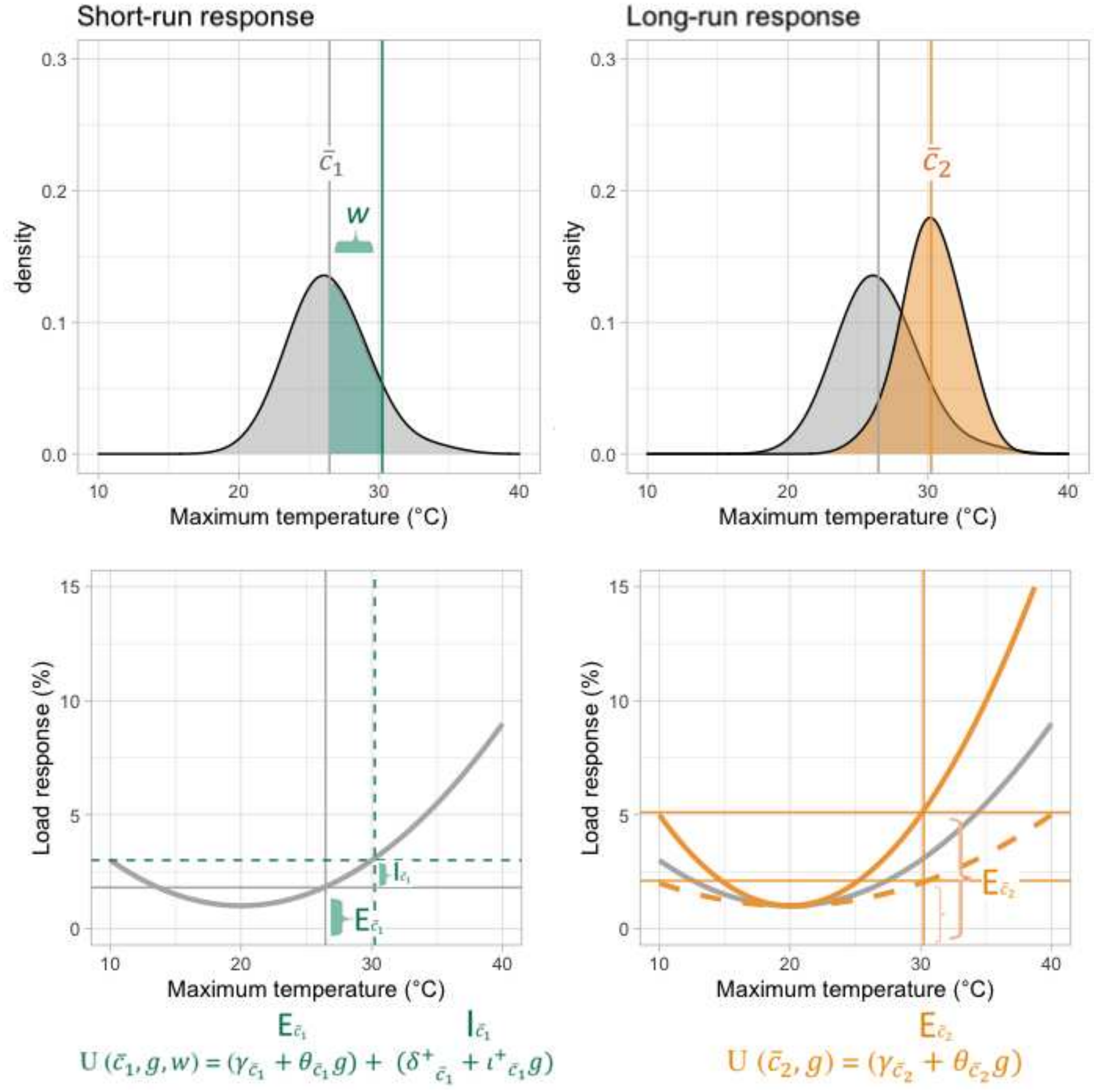
$$U = h(C, Y) = \gamma_{k'}^C + \beta_{k'}^C y \tag{56}$$

Therefore, the empirical approach allows to test if:

$$\gamma_{k'}^C + \beta_{k'}^C y \neq \gamma_k^C + \beta_k^C y + w(\gamma_{p(k)}^{w} + \beta_{p(k)}^{w} y) \tag{57}$$

In particular, if under the *same* observed maximum temperature T, $U(C_k, Y) > U(C_k + \omega_{p(k)}, Y)$, then the peak load response under a hotter climate C_k is higher than its response under the combination of the colder climate $C_{k'}$ and the positive anomaly $\omega_{k'}$, meaning that adapting to the hotter climate increases the sensitivity of energy demand to temperature (for instance due to a variation in the stock of cooling appliances). If, on the other hand, $U(C_k, Y)$ $< U(C_{k'} + \omega_{p(k)}, Y)$, then the peak load response under the hotter climate C_k is lower than the its response under the colder climate $C_{k'}$ and the positive anomaly $\omega_{p(k)}$, meaning that adapting to the hotter climate decreases the sensitivity of energy demand to the same observed maximum temperature T (for instance due to acclimatization or energy efficiency effects). A graphical representation of this comparison is provided in figure **??**, where I show the case in which $T = 30$°C, $C_{k'} = 27$°C, $\omega_{p(k')}$ +3°C and $C_k = 30$°C and y is fixed. Since the term $U(C_k, y)$ is only affected by the extensive margin adjustments, I consider it as the analog for a *long-run* response to T. On the other hand, since the term $U(C_{k'} + \omega_{p(k')}, y)$ is affected by the extensive margin adjustment to $C_{k'}$ and the intensive margin adjustment to $\omega_{p(k')}$, I consider it as the analog for a *short-run* response to T. Note that a *short-run* response includes both an extensive margin component and an intensive margin component.

Supplementary Figure Ch.5-1 shows the stylized short-term and long-term responses. Panel a shows a stylized distribution of daily maximum temperatures in a given calendar day, characterized by a mean value equal to c_1 and a weather shock equal to w_1, leading to an observed daily maximum temperature equal to t_2. Panel b shows how a shift in the stylized distribution of daily maximum temperatures translates into a variation in the local climate from c_1 to c_2. Panel c shows the value U(c_1,w_1, y), computed as the sum of the extensive margin response to c_1 and of the intensive margin response to w_1. Panel d shows the value U(c_2, y), equal to the extensive margin response to c_2 and alternatively higher (solid line) or lower (dashed line) than U(c_1,w_1, y).



Supplementary Figure Ch.5-1

Data

Daily peak and total electric load are defined as the sum of power generated by plants on transmission networks, from which the balance (export–import) of exchanges on interconnections between neighboring bidding zones and the power absorbed by energy storage resources is deduced. The total load represents the power demand on the transmission and distribution networks, while any power demand served by distributed networks is not included in the statistics.

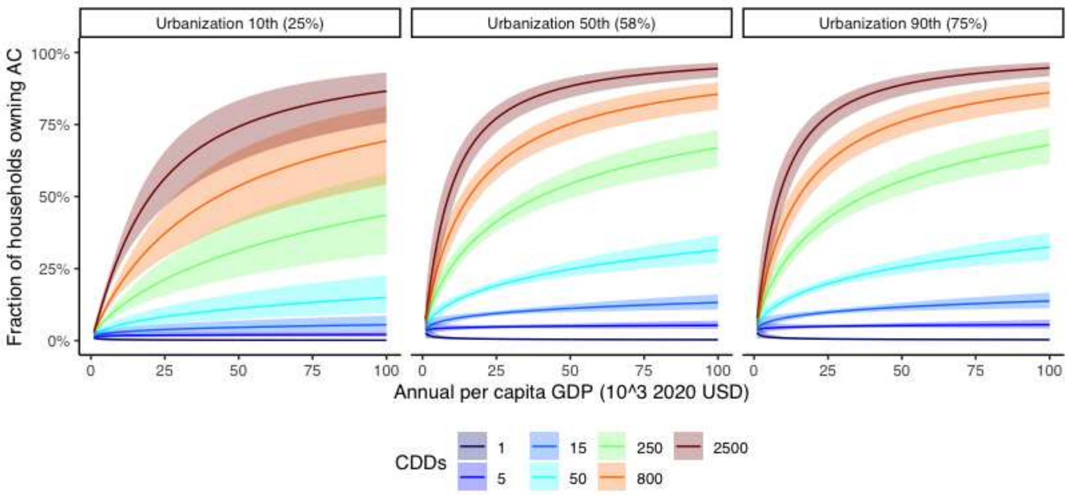
Table 10: Data sources

Variable	Region	Source
AC ownership	Europe	ENERDATA-ODYSSEE MURE [12]
AC ownership	India	CMIE [13]
Electricity demand	Europe	ENTSO-E[14]
Electricity demand	India	CEA [15]
GDP and Population	Europe	Eurostat [16]
GDP and Population	India	Reserve Bank of India [17]
Downscaled population by SSP	-	Olen et al., 2022 [18]
Downscaled GDP by SSP	-	Murakami et al., 2021 [19]
Historical daily temperatures	-	ERA-5 Land [20]
Projected daily temperatures	-	NASA NEX-GDDP-CMIP [21, 22, 23]

This aspect influences our measure of the total load, reducing it at times of high generation of renewables in distributed networks. Despite such difference, throughout the paper we refer to load and electricity demand interchangeably.

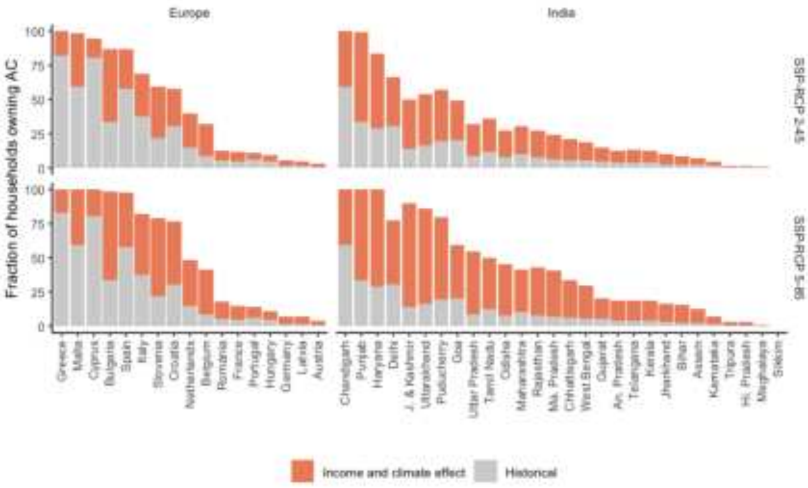
Supplementary Figures

Supplementary Figure Ch.5-2 shows the AC ownership adoption function by urbanization level. Coloured lines represent the income-AC curves at different levels of exposure to CDDs under the 10th, median and 90th quantile of urbanization level. Coloured shades present the 5th-95th confidence interval of the estimated adoption function.



Supplementary Figure Ch.5-2

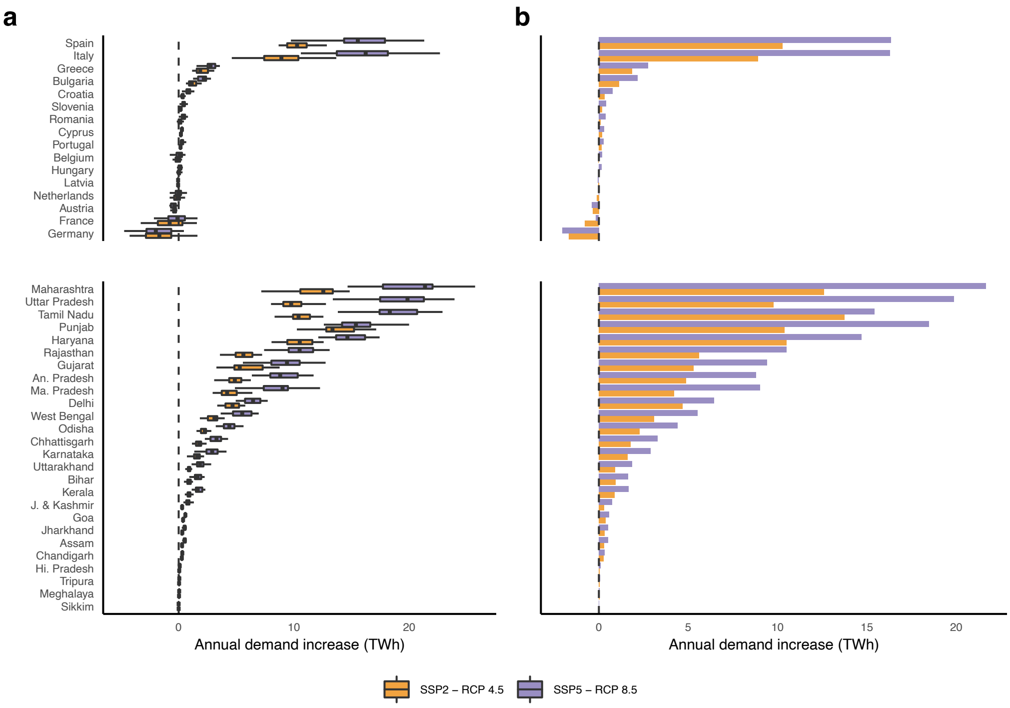
Supplementary Figure Ch.5-3 shows the AC prevalence projection by state and climate scenario. The grey bars present the historical (2015) observed level of AC prevalence, while



Supplementary Figure Ch.5-3

the coloured bars present the projected increment in AC prevalence due to both income and climate drivers as estimated from 8.

Supplementary Figure Ch.5-4 shows the Electricity demand increase due to climate change circa 2050 from intensive and extensive margins combined by SSP-RCP. Panel a shows the relative increase in the annual total load across 29 GCMs. Panel b shows the absolute median increase in the annual total load.



Supplementary Figure Ch.5-4

Income-dependent climate shocks in a dynamic error correction model

In order to adopt the ECM, I first investigate the presence of non-stationarity in the sectoral per capita electricity demand, per capita GDP, and thermal discomfort (measured by the alternative set of weather variables), finding that all variables contain unit roots; secondly, we investigate the presence of cointegration in the regressions of the log of per capita electricity demand, per capita GDP, and thermal discomfort with the statistic proposed by [7], which always rejects the null of no cointegration against the alternative hypothesis of some or all panels being cointegrated; finally, we test the direction of the causality in the cointegration relation by adopting a Granger-causality test for panel data [8], finding evidence of a bi-directional causality in the case of per capita electricity and per capita GDP, of unidirectional Granger causality between electricity demand and thermal discomfort and of no Granger causality between GDP per capita and thermal discomfort.

I test for the presence of cross-sectional heterogeneity, serial correlation and multicollinearity among the variables (see Tables S4-S5). The results of the tests point to the presence of cross-sectional dependence and serial correlation, while do not confirm the presence of multicollinearity. The use of time fixed effects can be seen as a first way to deal with cross sectional dependencies, and it is justified as in our case the cross-sectional dependency in the data may derive from sources that commonly impact all members of the panel, being the units regions of a large country [9]. We account for the cross-sectional dependence and serial correlation by employing a covariance matrix estimation robust to heteroskedasticity and both cross-sectional and serial correlation in the panels [10,11].

I compare different specifications based on the Adjusted R-squared, the Residual Mean Square Error (RMSE), the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), [12]. Smaller values of the RMSE, AIC and BIC information criteria are associated with the best model performance. Bold numbers are associated with the best score across all model specifications (equation and thermal discomfort variable), while underlined numbers are associated with the best score between the Eq. 14 and 17 for each thermal discomfort variable. The models based on the wet-bulb temperature bins are associated with the lowest RMSE, AIC and BIC in almost all combinations of sectors and equations specifications (Table S6). Furthermore, the econometric specification based on Eq. 17 generally results in a lower RMSE, AIC and BIC compared to 14, underscoring the relevance of taking into account the evolution of income in the estimation of the long-run effects of thermal discomfort on

Table S1: Unit root tests for panel data

Test	Levin-Lin-Chu	Maddala-Wu	Hadri	Im-Pesaran-Shin
$\mathbf{H_0}$	Non stationarity	Non stationarity	No series has a unit root	Non stationarity
Exogenous variables	Individual intercepts and trends			
Results (p-value)				
Residential electricity consumption per capita	Accept H_0 (1)	Accept H_0 (0.881- 0.945)	H_0 rejected (< 2.2e-16)	Accept H_0 (0.930 - 0.974)
Commercial electricity consumption per capita	Accept H_0 (1)	Accept H_0 (1)	H_0 rejected (< 2.2e-16)	Accept H_0 (1)
Industrial electricity consumption per capita	Accept H_0 (0.999)	H_0 rejected (3.941e-06- 1.925e-06)	H_0 rejected (< 2.2e-16)	H_0 rejected (5.279e-05- 0.0126)
Public and Rural electricity consumption per capita	Accept H_0 (1)	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
GDP per capita	Accept H_0 (1)	Accept H_0 (1)	H_0 rejected (< 2.2e-16)	Accept H_0 (1)
$CDDs^{wet}$	Accept H_0 (1)	H_0 rejected (< 2.2e-16)	Accept H_0 0.924)	H_0 rejected (< 2.2e-16)
$CDDs^{dry}$	Accept H_0 (1)	H_0 rejected (< 2.2e-16)	Accept H_0 (0.924)	H_0 rejected (< 2.2e-16)
Monthly Temperature	Accept H_0 (1)	Accept H_0 (1)	Accept H_0 0.9998)	H_0 rejected (< 2.2e-16)

Note: p-values range based on lags selection method

Table S2: cointegration tests for panel data				
H_0	No cointegration			
Specifications tested:	1; 'none', 2: 'intercept', 3:'intercept and time trend'			
x / y	**GDP per capita**	**$CDDs^{wet}$**	**$CDDs^{dry}$**	**Monthly Temperature**
Residential electricity consumption per capita	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)
Commercial electricity consumption per capita	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)
Industrial electricity consumption per capita	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)
Public and Rural electricity consumption per capita	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)	H_0 rejected (1,2,3)

Table S3: Granger causality panel test (Residential sector)					
H_0: No granger causality in all individuals					
x / y	**Electricity consumption per capita**	**GDP per capita**	**$CDDs^{wet}$**	**$CDDs^{dry}$**	**Monthly Temperature**
Electricity consumption per capita	-	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
GDP per capita	H_0 rejected (< 2.2e-16)	-	H_0 not rejected (0.38)	H_0 not rejected (0.19)	H_0 not rejected (0.87)

Table S4: Test for cross-sectional dependence in panels		
	H_0= No cross-sectional dependence	
	Eq.3a (temperature bins)	Eq.4a (temperature bins)
Residential	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
Commercial	H_0 rejected (4.334e-15)	H_0 rejected (1.875e-15)
Public & Rural	H_0 rejected (3.933e-16)	H_0 rejected (3.769e-16)
Industrial	H_0 not rejected 0.2547	H_0 not rejected 0.2834

Table S5: Durbin-Watson test for serial correlation in panel models		
	H_0= No serial correlation in idiosyncratic errors	
	Eq.3a (temperature bins)	Eq.4a (temperature bins)
Residential	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
Commercial	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
Public & Rural	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)
Industrial	H_0 rejected (< 2.2e-16)	H_0 rejected (< 2.2e-16)

electricity demand. The higher performance of the models based on the wet-bulb temperature bins variable motivates us to adopt such specification for the projection of future electricity demand shocks.

Table S8 reports the projected national electricity demand in 2050 across SSPs and RCPs. The additional demand required from adaptation is computed based on both the model excluding the interaction between weather and income Eq. 14 and including the interaction Eq. 17. Total demand includes the baseline demand and the additional demand.

Table S6: ECM Models' comparison

	Bins^{dry}		Bins^{wet}		CDDs^{dry} 24°C		CDDs^{wet} 18°C		CDDs^{wet} 24°C	
	Eq. 14	Eq. 17	Eq. 14	Eq. 17	Eq. 14	Eq. 17	Eq. 14	Eq. 17	Eq. 14	Eq. 17
Residential										
Adj. R^2	0.408	**0.460**	0.327	0.369	0.386	0.434	0.324	0.366	0.287	0.294
RMSE	0.047	**0.045**	0.050	0.049	0.048	0.047	0.052	0.052	0.050	0.049
AIC	-14234	**-14550**	-13653	-13935	-14074	-14324	-13646	-13885	-13401	-13411
BIC	-12868	**-13180**	-12313	-12530	-12772	-13016	-12344	-12577	-12099	-12103
Commercial										
Adj. R^2	0.445	**0.462**	0.361	0.382	0.377	0.397	0.333	0.362	0.326	0.331
RMSE	0.0449	**0.044**	0.048	0.047	0.046	0.046	0.048	0.049	0.049	0.049
AIC	-14762	**-14890**	-14127	-14267	-14431	-14550	-13891	-13889	-14091	-13990
BIC	-13396	**-13479**	-12786	-12863	-13129	-13242	-12789	-12695	-12589	-12581
Public and Rural										
Adj. R^2	0.270	**0.276**	0.211	0.211	0.235	0.236	0.182	0.192	0.179	0.181
RMSE	0.0644	0.0642	**0.067**	0.066	0.065	0.065	**0.067**	**0.067**	**0.067**	**0.067**
AIC	-11499	**-11522**	-11154	-11237	-11443	-11446	-11123	-11122	-11162	-11120
BIC	**-10133**	-10111	-9814	-9833	-10141	-10138	-9860	-9825	-9821	-9813

Supplementary Tables of Chapter 5.4

Supplementary methods on the time-demeaning of interactions terms

The standard way of specifying interaction terms in an FE regression is to treat the product term as any other variable and, accordingly, to demean it. For any measurement i,t, the demeaned interaction term $z_{i,t}x_{i,t} - \overline{(zx)}_i$ can be written as:

$$z_{i,t}x_{i,t} - \frac{\sum_{t=1}^{T} z_{i,t}x_{i,t}}{T_i} \tag{58}$$

where every $z_{i,t}$ and $x_{i,t}$ consisting of a unit-specific component $\overline{z_i}$, $\overline{x_i}$ and a measurement-specific idiosyncratic anomaly $\mathcal{A}(z_{i,t})$ and $\mathcal{A}(x_{i,t})$.

We follow Giesselmann et al, 2022 and consider two different cases of among the factors z and x: (1) only one factor shows intra-unit variation, or (2) both factors show intra-unit variation.

In the case (1) Let z be constant within units and, therefore, $z_{i,t} = \overline{z_i}$ for all i,t. In this case, equation 61 can be written as:

Table S7: Error Correction Model results - Equation 14				
	Residential	***Commercial***	***Public&Rural***	***Industrial***
	Δlog elercons percap	*Δlog elercons percap*	*Δlog elercons percap*	*Δlog elercons percap*
Δlog price	0.126** (0.059)	0.077* (0.044)	0.035 (0.062)	-0.184 (0.213)
Δlog gdp percap usd	0.561*** (0.133)	0.421*** (0.112)	0.405*** (0.116)	0.430 (0.380)
Δbin_low_12	0.001* (0.001)	-0.003*** (0.001)	-0.004** (0.002)	-0.001 (0.001)
Δbin_12_15	-0.001 (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	0.002 (0.001)
Δbin_15_18	-0.003*** (0.001)	-0.005*** (0.001)	-0.003* (0.002)	-0.001 (0.001)
Δbin_18_21	-0.0003 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)
Δbin_24_27	0.002***(0.0004)	0.003*** (0.0005)	0.003*** (0.001)	0.002** (0.001)
Δbin_27_30	0.006***(0.0005)	0.005*** (0.0005)	0.006*** (0.001)	0.003*** (0.001)
Δbin_gt_30	0.011*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.001 (0.003)
lag log res elercons percap	-0.357*** (0.021)	-0.465*** (0.030)	-0.441*** (0.033)	-0.501*** (0.091)
lag log gdp percap usd	0.706*** (0.213)	0.525*** (0.130)	0.486*** (0.131)	0.063 (0.487)
lag log price	0.343** (0.149)	0.168* (0.096)	0.039 (0.133)	-0.124 (0.379)
lag bin_low_12	0.001 (0.002)	-0.004*** (0.001)	-0.014*** (0.005)	0.001 (0.002)
lag bin_12_15	-0.004 (0.003)	-0.007*** (0.002)	-0.011*** (0.004)	0.006 (0.004)
lag bin_15_18	-0.001 (0.002)	-0.006*** (0.002)	-0.008 (0.006)	-0.004 (0.002)
lag bin_18_21	-0.002 (0.002)	-0.002** (0.001)	-0.006** (0.003)	0.003* (0.002)
lag bin_24_27	0.003*** (0.001)	0.003*** (0.0005)	0.001 (0.002)	0.001 (0.001)
lag bin_27_30	0.008*** (0.001)	0.007*** (0.001)	0.006*** (0.002)	0.002** (0.001)
lag bin_gt_30	0.015*** (0.001)	0.011*** (0.001)	0.009*** (0.003)	0.004 (0.003)
Time fixed effects	Yes	Yes	Yes	Yes
Unit fixed effects	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Economic crisis dummies	Yes	Yes	Yes	Yes
Observations	4,482	4,482	4,482	4,482
R^2	0.437	0.472	0.305	0.324
Adjusted R^2	0.409	0.446	0.271	0.286
F Statistic	122.268*** (df = 19; 4271)	131.096*** (df = 19; 4271)	96.253*** (df = 19; 4271)	45.200*** (df = 19; 4271)
Note:	*p**p***p<0.01		*p**p***p<0.01	

Standard errors are robust to cross-sectional dependence and serial correlation and are based on the delta method function

		Table S8			
		Additional demand (GWh)		**Total Demand (GWh)**	
SSP	RCP	No income effect	Income effect	No income effect	Income effect
SSP1	RCP 4.5	27.537	93.905	666.905	733.273
SSP1	RCP 8.5	38.569	117.156	677.937	756.524
SSP2	RCP 4.5	22.236	62.843	537.049	577.657
SSP2	RCP 8.5	31.097	79.329	545.911	594.143
SSP3	RCP 4.5	18.060	39.834	429.687	451.462
SSP3	RCP 8.5	25.204	51.342	436.831	462.969

$$\overline{z_i}x_{i,t} - \frac{\sum_{t=1}^{T} \overline{z_i}x_{i,t}}{T_i} \tag{59}$$

factoring out, equation 59 can be written as:

$$= \overline{z_i} \cdot \mathcal{A}(x_{i,t}) \tag{60}$$

If both variables are time-dependent, equation 58 can be written as:

$$\overline{z_i}\mathcal{A}(x_{i,t}) + \overline{x_i}\mathcal{A}(z_{i,t}) + \mathcal{A}(z_{i,t})\mathcal{A}(x_{i,t}) - \frac{\sum_{t=1}^{T} \mathcal{A}(z_{i,t})\mathcal{A}(x_{i,t})}{T_i} \tag{61}$$

The final transformation in equation 61 reveals that, for each measurement i,t, the size of a demeaned interaction term with two variables z and x showing intra-unit variation depends on the unit-specific levels of both z and x.

Step-by-step time demeaning in FE models

Initial equation:

$$q_{i,t} = \alpha + T_{i,t}(\beta_1 + \beta_2\overline{C_i} + \beta_3 x_{i,t}) + \beta_4 x_{i,t} + \mu_i + \varepsilon_{i,t} \tag{62}$$

Applying time-demeaning to equation 62 and rearranging terms (see supplementary methods), it can be shown that the time-demeaned FE estimation leads to:

$$(q_{i,t} - \overline{q_{i,t}}) = \\ \beta_1 \mathcal{A}(T_{i,t}) + \beta_2 \mathcal{A}(T_{i,t}) \cdot \overline{C_i} + \\ \beta_3 \left(\overline{T_i}\mathcal{A}(x_{i,t}) + \overline{x_i}\mathcal{A}(T_{i,t}) + \mathcal{A}(x_{i,t})\mathcal{A}(T_{i,t}) - \frac{\sum_{t=1}^{T} \mathcal{A}(x_{i,t})\mathcal{A}(T_{i,t})}{T_i} \right) \tag{63}$$

Re-arranging terms by each weather component $\mathcal{A}(T_{i,t})$ and $\overline{T_i}$:

$$(q_{i,t} - \overline{q_{i,t}}) = \\ \mathcal{A}(T_{i,t}) \cdot \left(\beta_1 + \beta_2 \overline{C_i} + \beta_3 \overline{x_i} + \mathcal{A}(x_{i,t}) - \frac{\sum_{t=1}^{T} \mathcal{A}(x_{i,t})}{T_i} \right) + \\ \overline{T_i} \cdot (\beta_3 \mathcal{A}(x_{i,t})) \tag{64}$$

The part of the equation dependent upon $\mathcal{A}(T_{i,t})$ identifies the intensive margin, as it zero when $\mathcal{A}(T_{i,t}) = 0$. The extensive margin is captured not from CDDs ($\overline{C_i}$) but only by the term $\beta_3 \overline{T_i} \mathcal{A}(x_{i,t})$ and is obtained from the interaction with income anomalies, rather than on income levels."

Pooled sectors energy demand shocks

Here we simulate the impact of a stylized change in climate and income, comparing the estimators of the three alternative models presented. In model 1 we rely on co-variation between annual electricity demand and annual temperature bins, as in Eq. 59. In model 2 temperature bins are interacted with $\overline{CDDs}$ (2a) and with time-varying per capita capital stock (2b), as in Eq. 23. Our preferred specification decomposes annual temperature bins into the 10-year moving average temperature bins and its anomalies in isolation (3a) or modulated by per capita capital stock (3b-3c), as in Eq. 29.

Table 11: Estimated variation in energy demand by specification

Fuel	Shock	pc K level	Model				
			(1)	(2)	(3a)	(3b)	(3c)
		median	1%	1.2%	1.9 %	2%	2.2%
Elec.	+10 CDDs	25th	-	0.8%	-	1.6%	1.8%
		75th	-	1.6%	-	2.4%	2.6%
			(1)	(2)	(3a)	(3b)	(3c)
		median	2%	1.1%	2%	2.5%	2.1%
Fossils	+10 HDDs	25th	-	0.5%	-	1.8%	1.5%
		75th	-	1.8%	-	3.1%	2.7%
		median	1%	1.4%-	2.4%	2.6%	-
Elec.	+1 day >30C	25th	-	1.3%	-	2.5%	-
		75th	-	1.6%	-	2.7%	-

Dependent Variable:	ln_electricity_pc				
Model:	(1)	(2)	(3a)	(3b)	(3c)
Variables					
hdd15	0.0001***	0.0002**			
	(2.95×10^{-5})	(0.0001)			
cdd24	0.0010***	-0.0026***			
	(9.32×10^{-5})	(0.0003)			
ln_gdp_pc_10ma	0.4005***	0.3898***	0.3958***	0.3870***	0.3864***
	(0.0163)	(0.0167)	(0.0163)	(0.0168)	(0.0168)
ln_gdp_pc_10ma_sq	0.0163***	0.0086***	0.0170***	0.0092***	0.0091***
	(0.0017)	(0.0020)	(0.0017)	(0.0021)	(0.0021)
hdd15 × ln_ks_pc_10ma		-1.58×10^{-5}			
		(1.11×10^{-5})			
cdd24 × ln_ks_pc_10ma		0.0004***			
		(3.07×10^{-5})			
hdd15_clim			0.0002***	0.0001	0.0001
			(4.37×10^{-5})	(0.0001)	(0.0001)
cdd24_clim			0.0019***	-0.0020***	-0.0018***
			(0.0001)	(0.0004)	(0.0004)
cdd24_neg_anom			-0.0007**	-0.0007*	-0.0076***
			(0.0003)	(0.0004)	(0.0025)
cdd24_pos_anom			0.0001	1.22×10^{-5}	-0.0037***
			(0.0002)	(0.0002)	(0.0012)
hdd15_neg_anom			7.73×10^{-6}	2.23×10^{-5}	0.0011
			(6.96×10^{-5})	(7.01×10^{-5})	(0.0008)
hdd15_pos_anom			2.25×10^{-5}	4.03×10^{-5}	0.0007
			(9.16×10^{-5})	(9.22×10^{-5})	(0.0011)
hdd15_clim × ln_ks_pc_10ma				-3.44×10^{-6}	-1.96×10^{-6}
				(1.16×10^{-5})	(1.21×10^{-5})
cdd24_clim × ln_ks_pc_10ma				0.0004***	0.0004***
				(3.43×10^{-5})	(3.5×10^{-5})
cdd24_neg_anom × ln_ks_pc_10ma					0.0008***
					(0.0003)
cdd24_pos_anom × ln_ks_pc_10ma					0.0004***
					(0.0001)
hdd15_neg_anom × ln_ks_pc_10ma					-0.0001
					(7.85×10^{-5})
hdd15_pos_anom × ln_ks_pc_10ma					-6.34×10^{-5}
					(9.86×10^{-5})
Fixed-effects					
sector_region	Yes	Yes	Yes	Yes	Yes
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	22,137	21,248	22,137	21,248	21,248
R^2	0.87310	0.87619	0.87362	0.87653	0.87663
Within R^2	0.09165	0.10321	0.09535	0.10567	0.10645

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:			ln_fossil_fuel_pc		
Model:	(1)	(2)	(3a)	(3b)	(3c)
Variables					
hdd15	0.0002^{***}	-0.0005^{***}			
	(3.91×10^{-5})	(0.0001)			
cdd24	0.0003^{***}	-0.0016^{***}			
	(0.0001)	(0.0004)			
ln_gdp_pc_10ma	0.3007^{***}	0.3282^{***}	0.3001^{***}	0.3266^{***}	0.3264^{***}
	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.0154)
ln_gdp_pc_10ma_sq	0.0159^{***}	0.0096^{***}	0.0160^{***}	0.0091^{***}	0.0090^{***}
	(0.0017)	(0.0020)	(0.0017)	(0.0021)	(0.0021)
hdd15 × ln_ks_pc_10ma		$6.11 \times 10^{-5***}$			
		(1.07×10^{-5})			
cdd24 × ln_ks_pc_10ma		0.0002^{***}			
		(3.37×10^{-5})			
hdd15_clim			0.0002^{***}	-0.0004^{***}	-0.0004^{***}
			(6.38×10^{-5})	(0.0001)	(0.0001)
cdd24_clim			0.0003^{*}	-0.0019^{***}	-0.0017^{***}
			(0.0002)	(0.0005)	(0.0005)
cdd24_neg_anom			-8.54×10^{-5}	-0.0001	-0.0071^{**}
			(0.0004)	(0.0004)	(0.0029)
cdd24_pos_anom			0.0003	0.0002	-0.0014
			(0.0002)	(0.0002)	(0.0015)
hdd15_neg_anom			-5.96×10^{-5}	-7.77×10^{-5}	-0.0003
			(8.97×10^{-5})	(8.94×10^{-5})	(0.0009)
hdd15_pos_anom			0.0002^{*}	0.0002	-0.0009
			(0.0001)	(0.0001)	(0.0011)
hdd15_clim × ln_ks_pc_10ma				$6.54 \times 10^{-5***}$	$6.12 \times 10^{-5***}$
				(1.07×10^{-5})	(1.12×10^{-5})
cdd24_clim × ln_ks_pc_10ma				0.0002^{***}	0.0002^{***}
				(3.87×10^{-5})	(3.89×10^{-5})
cdd24_neg_anom × ln_ks_pc_10ma					0.0008^{**}
					(0.0003)
cdd24_pos_anom × ln_ks_pc_10ma					0.0002
					(0.0002)
hdd15_neg_anom × ln_ks_pc_10ma					1.87×10^{-5}
					(8.44×10^{-5})
hdd15_pos_anom × ln_ks_pc_10ma					9.73×10^{-5}
					(0.0001)
Fixed-effects					
sector_region	Yes	Yes	Yes	Yes	Yes
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	23,965	23,001	23,965	23,001	23,001
R^2	0.81207	0.81760	0.81210	0.81773	0.81782
Within R^2	0.04304	0.05345	0.04315	0.05414	0.05460

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:			ln_electricity_pc			
Model:	(1)	(2a)	(2b)	(3a)	(3b)	(3c)
Selected variables (full in SI)						
temp_g30	0.0097***	0.0064**	-0.0146**			
	(0.0015)	(0.0032)	(0.0054)			
temp_g30 × mean_cdd24		6.26×10^{-6}**	$1.12e-5$***			
		(2.76×10^{-6})	(3.03×10^{-6})			
temp_g30 × ln_ks_pc_10ma			0.0017***			
			(0.0005)			
temp_g30_10ma				0.0242***	0.0136**	0.0140**
				(0.0025)	(0.0066)	(0.0066)
temp_g30_an				0.0037**	0.0024	-0.0098
				(0.0018)	(0.0018)	(0.0100)
temp_g30_10ma × ln_ks_pc_10ma					0.0013**	0.0012**
					(0.0006)	(0.0006)
ln_ks_pc_10ma × temp_g30_an						0.0014
						(0.0012)
Fixed-effects						
iso3	Yes	Yes	Yes	Yes	Yes	Yes
sector_region	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	21,463	21,463	20,556	21,463	20,556	20,556
R^2	0.86734	0.86825	0.87375	0.86856	0.87360	0.87365
Within R^2	0.10192	0.10805	0.13030	0.11020	0.12932	0.12960

Heteroskedasticity-robust standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Electricity demand regressions

Dependent Variable:	ln_electricity_pc				
Sector:	(Res)	(Com)	(Ind)	(Agr)	(Tra)
Variables					
hdd15_clim	-0.0003*	-0.0009***	8.69×10^{-5}	0.0004*	-0.0009***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
cdd24_clim	-0.0010**	-0.0015**	-0.0025***	-0.0034***	-0.0059***
	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0015)
ln_gdp_pc_10ma	0.5273***	0.4666***	0.5100***	0.1882***	0.3509***
	(0.0348)	(0.0449)	(0.0317)	(0.0493)	(0.0641)
gdp_pc_anomaly	0.0012**	-0.0009	0.0009*	-0.0001	-0.0003
	(0.0005)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
cdd24_neg_anom	-0.0005	-0.0005	-0.0003	-0.0013*	0.0017*
	(0.0003)	(0.0006)	(0.0004)	(0.0006)	(0.0010)
cdd24_pos_anom	0.0002	-5.49×10^{-5}	0.0003	0.0002	0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0006)
hdd15_neg_anom	2.69×10^{-5}	7.84×10^{-5}	-2.06×10^{-5}	9.69×10^{-6}	-0.0002
	(5.75×10^{-5})	(8.53×10^{-5})	(6.69×10^{-5})	(0.0001)	(0.0001)
hdd15_pos_anom	5.43×10^{-5}	9.65×10^{-5}	-3.02×10^{-5}	-0.0001	0.0002
	(8.21×10^{-5})	(0.0001)	(8.31×10^{-5})	(0.0002)	(0.0001)
hdd15_clim × ln_ks_pc_10ma	4.25×10^{-5}***	0.0001***	-1.07×10^{-5}	-6.85×10^{-5}***	8.84×10^{-5}***
	(1.32×10^{-5})	(1.71×10^{-5})	(1.17×10^{-5})	(2.28×10^{-5})	(2.22×10^{-5})
cdd24_clim × ln_ks_pc_10ma	0.0003***	0.0004***	0.0004***	0.0006***	0.0010***
	(4.17×10^{-5})	(5.05×10^{-5})	(4.24×10^{-5})	(4.36×10^{-5})	(0.0001)
Fixed-effects					
sector_region	Yes	Yes	Yes	Yes	Yes
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,158	4,770	5,185	3,514	2,621
R^2	0.96798	0.94165	0.95299	0.88904	0.95036
Within R^2	0.28222	0.15930	0.27188	0.08965	0.15591

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Fossil fuel demand regressions

Dependent Variable:	ln_fossil_fuel_pc				
Sector:	(Res)	(Com)	(Ind)	(Agr)	(Tra)
Variables					
hdd15_clim	-0.0014***	-0.0018***	0.0013***	-0.0009***	-0.0003**
	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0001)
cdd24_clim	0.0005	-0.0068***	0.0005	-0.0133***	-0.0013***
	(0.0005)	(0.0017)	(0.0005)	(0.0012)	(0.0003)
ln_gdp_pc_10ma	0.4297***	0.3474***	0.7098***	0.0895	0.3804***
	(0.0411)	(0.0654)	(0.0317)	(0.0678)	(0.0208)
gdp_pc_anomaly	0.0009	0.0018**	0.0019***	0.0010	0.0015***
	(0.0006)	(0.0007)	(0.0005)	(0.0009)	(0.0003)
cdd24_neg_anom	-0.0011***	0.0012	-0.0004	-0.0002	-0.0003
	(0.0004)	(0.0010)	(0.0005)	(0.0011)	(0.0003)
cdd24_pos_anom	-0.0006**	0.0004	0.0001	0.0006	0.0002
	(0.0003)	(0.0005)	(0.0003)	(0.0006)	(0.0002)
hdd15_neg_anom	5.78×10^{-5}	-0.0004**	1.59×10^{-6}	-0.0002	1.83×10^{-5}
	(0.0001)	(0.0002)	(7.87×10^{-5})	(0.0002)	(6.32×10^{-5})
hdd15_pos_anom	0.0006***	7.02×10^{-5}	1.33×10^{-5}	0.0002	-3.81×10^{-6}
	(0.0002)	(0.0002)	(9.65×10^{-5})	(0.0002)	(7.16×10^{-5})
hdd15_clim × ln_ks_pc_10ma	0.0002***	0.0002***	-9.44×10^{-5}***	6.02×10^{-5}***	3.67×10^{-5}***
	(2.37×10^{-5})	(2.33×10^{-5})	(1.34×10^{-5})	(2.04×10^{-5})	(1.21×10^{-5})
cdd24_clim × ln_ks_pc_10ma	4.38×10^{-5}	0.0007***	0.0001**	0.0012***	0.0002***
	(4.53×10^{-5})	(0.0001)	(4.14×10^{-5})	(8.85×10^{-5})	(2.91×10^{-5})
Fixed-effects					
sector_region	Yes	Yes	Yes	Yes	Yes
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,205	3,652	5,150	3,680	5,314
R^2	0.91396	0.87065	0.93635	0.83233	0.95321
Within R^2	0.09227	0.06553	0.25679	0.07799	0.17864

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Income regressions

Dependent Variable:	fd_ln_gdp_pc				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
mean_temp_10ma	0.0318***	0.0192***	0.0835***	0.0664***	0.0300
	(0.0074)	(0.0070)	(0.0152)	(0.0176)	(0.0209)
mean_temp_10ma_sq	-0.0001	6.3×10^{-5}	-0.0030***	-0.0019**	-0.0012
	(0.0003)	(0.0003)	(0.0006)	(0.0007)	(0.0008)
mean_temp_an_pos_above24	-0.0155*	-0.0161**	-0.0233***	-0.0176**	-0.0229***
	(0.0083)	(0.0076)	(0.0079)	(0.0083)	(0.0088)
mean_temp_an_neg_below15	-0.0215***	-0.0147**	-0.0103*	-0.0078	-0.0088*
	(0.0075)	(0.0071)	(0.0057)	(0.0049)	(0.0049)
precip	3.82×10^{-5}**	2.98×10^{-5}**	3.36×10^{-5}**	2.09×10^{-5}	1.61×10^{-5}
	(1.51×10^{-5})	(1.49×10^{-5})	(1.47×10^{-5})	(1.52×10^{-5})	(1.5×10^{-5})
precip_sq	-5.7×10^{-9}	-4.11×10^{-9}	-4.22×10^{-9}	-1.62×10^{-9}	-3.1×10^{-9}
	(3.52×10^{-9})	(3.45×10^{-9})	(3.43×10^{-9})	(3.54×10^{-9})	(3.48×10^{-9})
mean_temp_10ma × lag.ln_en_pc	-0.0055***	-0.0043***	-0.0149***	-0.0192***	-0.0189***
	(0.0009)	(0.0008)	(0.0022)	(0.0025)	(0.0024)
mean_temp_10ma_sq × lag.ln_en_pc	0.0002***	0.0001***	0.0005***	0.0007***	0.0007***
	(3.66×10^{-5})	(3.6×10^{-5})	(9.29×10^{-5})	(0.0001)	(0.0001)
lag.fd_ln_gdp_pc		0.2421***	0.1833**	0.1102	0.0763
		(0.0726)	(0.0745)	(0.0771)	(0.0800)
country-time trend	No	No	Linear	Quadratic	Quadratic
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
year					Yes
Fit statistics					
Observations	5,269	5,246	5,246	5,246	5,246
R^2	0.08596	0.13760	0.19759	0.26085	0.30756
Within R^2	0.04112	0.09497	0.15792	0.22431	0.20809

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

7.4 Supplementary Material of Chapter 6

Energy efficiency and behavioral policies

I compute end-use efficiency improvements based on the regin-specific seasonal energy efficiency ratios (SEERs) available from [24], comparing the current market average SEER to the best available SEER: the latter is 50% and 40% lower than the former in Europe and India, respectively. I assume that a proportional reduction in the additional electricity demand associated to air-conditioning could be achieved though a shift from current market average to the best available SEER in the two regions.

Table 12: Demand reductions from energy efficiency of appliances

	Average SEER	Best available SEER	Fractional AC demand reduction	Residual demand
Europe	5.5	11	50%	17 TWh
India	3.5	6	41%	109 TWh

I compute the decrease in energy consumption from coupling AC with fans in three steps. First, I identify the potential reduction in air temperature from the operation of fans at different speeds based on the ASHRAE Thermal Environmental Conditions for Human Occupancy (ASHRAE, 2004). I focus on the case of household occupants undertaking primarily sedentary activity, and select the suggested maximum offset of 3.0°C achieved with air-speed at 0.8 m/s. We compute the new demand amplification circa 2050 (ψ_v^*) by assuming a uniform 3.0°C reduction in air temperatures yielding the exposure to bins ${\mathcal{T}^*}_k^F$, when maximum daily temperatures surpass 24°C.

$$\psi_v^* = \frac{\exp\left[\sum_k \widehat{\beta}_{k,v}^T \widetilde{\mathcal{T}^*}_k^F + \sum_k \widehat{\beta}_{k,v}^{TAC}\left(\widetilde{\mathcal{T}}_k^F \cdot \widetilde{s}^F\right) + \widehat{\beta}_v^Y \widetilde{y}^F\right]}{\exp\left[\sum_k \widehat{\beta}_{k,v}^T \widetilde{\mathcal{T}}_k^C + \sum_k \widehat{\beta}_{k,v}^{TAC}\left(\widetilde{\mathcal{T}}_k^C \cdot \widetilde{s}^C\right) + \widehat{\beta}_v^Y \widetilde{y}^C\right]} \tag{65}$$

Comparing ψ_v^* to ψ_v obtained from Eq.

Second, I quantify the additional electricity consumption from the use of fans (τ_{i,d^*}) in each state (i) in the days when maximum temperatures surpass 24°C (d^*). Following [25], I assume that each household (h) owning an AC circa 2050 operates a typical 48 inch ceiling fan using 75W of power for a time ranging from 3 to 9 hours/day (r), and that average consumption per hour of operation is 0.075 kWh.

$$\tau_i = \sum_{k,d} (0.075 \cdot r \cdot d_i^* \cdot h_i) \qquad (66)$$

Third, I derive the residual demand amplification by taking the sum between ψ_v^* and the additional demand for fans operation (τ_{i,d^*}).

Table 13: Demand reductions from coupling AC and fans

	Fractional AC demand reduction	Additional demand from fans (3-9 hours/day)	Residual demand
Europe	39% - 63%	2 TWh - 7 TWh	16 TWh - 21 TWh
India	50% - 57%	6 TWh - 19 TWh	81 TWh - 94 TWh

Università Ca'Foscari Venezia

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DICHIARAZIONE SOSTITUTIVA DELL'ATTO DI NOTORIETA'

(Art. 47 D.P.R. 445 del 28/12/2000 e relative modifiche)

Io sottoscritto FRANCESCO PIETRO COLELLI

nato a PADOVA (prov. PD) il 06-11-1992

residente a BOLZANO in VIA DEI BOTTAI, 14 n. ……

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The energy requirements for rising adaptation needs: mechanisms and impacts

Dottorato di ricerca in SCIENZA E GESTIONE DEI CAMBIAMENTI CLIMATICI

(in cotutela con ……………………………………)

Ciclo 34

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