Cooling demand in Integrated Assessment Models: a Methodological Review

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Abstract

We systematically review and compare 88 scenarios of energy demand in commercial and residential buildings that include the additional energy use or saving induced by thermal adaptation to heating and cooling needs at global level. We group the resulting studies in a novel classification that makes it possible to systematically understand why IAM-based energy projections vary depending on how changes in climatic conditions and the associated adaptation needs are modelled. We show that projections underestimate the building sector's energy demand when only income, population, and not changing climatic conditions and the associated adaptation needs, drive energy demand. Across the studies reviewed, already in 2050 climate change induces a median percentage variation of buildings' energy demand for cooling of 80% (90%) and of -22% (-24%) for heating, leading to a 10% (13%) increase when cooling and heating are combined, under the RCP 4.5 (8.5). We show that models lacking extensive margin adjustments and models that focus on residential demand highly underestimate the additional cooling needs of the building sector. Improving the characterization of adoption of energy-using goods that provide thermal adaptation services and better articulating the heterogeneous needs across sectors are topics deserving further investigation.

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1. Introduction

Global warming, by causing more frequent high temperature extremes and a long-run increase in global mean temperature, will augment the demand for cooling services and in the energy necessary to deliver them (IEA, 2018). Cooling needs will be an increasingly important driver of future energy demand, while heating requirements are expected to be reduced (Seleshi et al. 2020). The issue is particularly pressing, as the rapid need to adapt might lead to quick responses that are energy-intensive and lock our societies into maladaptive solutions, translating into higher emissions and higher energy prices, burdening particularly the most vulnerable household groups, reducing the incentive and opportunities to revert towards more sustainable forms of adaptation in the future (Barnett and O'Neill, 2010).

The interplay between energy needs for adaptation and increasingly ambitious mitigation targets remains an understudied topic. Energy scenarios are predominantly generated by Integrated Assessment Models (IAMs), which describe the relationship between human (economy, technology, energy) and natural (climate, environment) systems. These models still need to integrate the climate-energy feedback when conducting their assessments. We therefore still lack a thorough understanding of how an increase in the energy needs for adaptation might affect the economy, the energy systems, and the environment in the context of ambitious goals to move towards cleaner energy systems, industries, and commercial activities.

In this paper we systematically review and compare quantitative projections of energy demand in commercial and residential buildings that include the additional energy use or saving induced by thermal adaptation to heating and cooling needs at global level under alternative socioeconomic and warming scenarios. We group the selected studies into a novel classification that considers the detail of the energy system, the relationship between the energy and the economy, the technical representation of the specific demand for heating and cooling. Such classification makes it possible to systematically understand whether IAM-based projections under-estimate the building sector's energy demand when changes in climatic conditions and the associated adaptation needs are not considered and why.

Several articles have already reviewed the modelling or the ex-post empirical literature on the topic of climate change impacts on energy demand. Schaeffer et al., (2012) present a summary of the approaches and results of the studies estimating the impacts of climate change on energy demand at the local level, as they find that these constitute the majority of existing studies. Auffhammer and Mansur (2014) review the empirical papers on how climate affects energy expenditures and consumption, while they do not include a detailed analysis of the estimates and methodologies of the studies adopting engineering and/or energy models in IAMs. Ciscar and Dowling (2014) review how IAMs have estimated the impacts of climate in the energy sector, including the modelling of space heating and cooling demand. The review presents the different modeling approaches of the cooling and heating demands and the macro-economic results across the IAM literature, but it does not include a quantitative comparison of heating and cooling projections nor an evaluation of the possible factors driving models' heterogeneous results. Gambhir et al., (2019) assess over 200 integrated assessment model scenarios achieving 2°C and well-below 2°C targets, drawn from the IPCC's fifth assessment report database combined with a set of 1.5 °C scenarios. When focusing on energy demand projections across the 2020-2100 period, the authors show that buildings sector median final energy is noticeably lower in the below 1.5°C scenarios compared to the below 2 °C scenarios. Gambhir et al., (2019) report total energy projections without identifying the additional contribution of climate change across climate scenarios and do not provide detailed insight on the reasons behind different models' heterogeneous results. Emodi et al., (2019) conduct a systematic scoping review to identify consistent patterns of climate change impacts on the energy system. The authors find evidence of consistent increase in energy demand for Africa, the Americas and Asian continent, as well as of a consistent decrease in Northern and Eastern Europe. The authors conduct an analysis of the literature's data by presenting the overall direction of the demand projections, distinguishing between "increased", "decreased", "inconsistent results" and "no change". The study only conducts a qualitative assessment of the projected sing of the variation in energy demand, while it does not quantify the magnitude of the variations obtained by different IAM models at global and regional level. Seleshi et al., (2020) 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 achieve a general conclusion regarding the expected sign of change in the future, but they do not analyze the mechanisms and the heterogeneities across models being the paper a more general assessment of the vulnerability of the overall energy sector.

A systematic and detailed analysis of IAMs' results quantifying and comparing the magnitude of future cooling and heating demand projections is lacking. In this paper we analyze the IAMs that have explicitly addressed the representation of heating and cooling needs with the objective of 1) reviewing the methodological approaches used, 2) highlighting the relevance for the economy and the environment, 3) clarifying what are the main sources of variation and heterogeneity that should be addressed by future studies.

We 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. Across the studies reviewed, climate change in 2050 induces a median percentage variation of buildings' energy demand for cooling of 80% (90%) and of -22% (-24%) for heating, leading to a 10% (13%) increase when cooling and heating are combined, under the RCP 4.5 (8.5).

Across model types we have identified two main archetypes of modelling the extensive margin and we show that models lacking extensive margin adjustments highly underestimate the additional cooling needs of the building sector. Our review also highlights the much larger uncertainty that characterizes the commercial sector, which often, due to the lack of specific data or evidence, is modelled similarly to the residential sector.

The remainder of the paper is organized as follows. Section 2 describes the methodology used for the identification, selection, and classification of the literature. Section 3 presents in detail the major methodological approaches used to model heating and cooling demand. Section 4 presents the results and critically discusses the implications and the sources of variations. Section 5 concludes and gives suggestions for future research.

2. Methodology

2.1. Identification and selection of the literature

We review the IAM-based studies that have evaluated the long-run potential impacts of thermal adaptation on the energy sector and that simultaneously take into account climate and socioeconomic changes. We adopt a three-stage literature review procedure (Figure 1). First, we analyze previous reviews in order to investigate the major literature gaps, and we develop our review topics accordingly (Phase 1 in Figure 1). At this stage, we chose to exclude the studies which model cooling and heating demand without considering climate change impacts (such as Urge-Vorsatz et al., 2015 and Grubler et al., 2019) or that are based on regional assessments (Zhou et al., 2014, McFarland et al., 2015, Hsiang et al., 2017 for the US, Paardekooper et al., 2018 for Europe, Li et al., (2018) for China, Daioglou et al., 2012 for developing countries). These initial screening criteria are adopted in order to restrict the analysis to a comparable set of IAM-based projections, in order to facilitate the investigation of the main drivers affecting models' results. We identify two review topics: projection of future buildings' energy demand deriving from changes in heating and cooling thermal-comfort adaptation at global level, projections of the ex-post macroeconomic impacts of buildings' energy demand changes in heating and cooling at global level.

Three-Stage Literature Review Procedure

Phase 1: Gaps and topics	**Phase 2: Study selection**	**Phase 3: Dataset creation**
- Identification of gaps in the literature from the analysis of past reviews - Choice of key review topics	**Search sources:** - Structured keyword queries run in Scopus - Google Scholar and Institutional Websites - Forward tracing and backward tracing of seminal papers and reviews **Filtering:** - Analysis of titles and abstracts - Detailed assessment by reading full papers	**Inclusion of results in the projections' dataset:** - Clear definition of the methodology (functional form and calibration sources) - Detailed reporting of results (tables, figures and supplementary data availability). When not available, we requested additional inputs from the authors

Information for refined search terms and exclusion criteria

Full set of IAM-based studies and of empirical studies used for IAMs calibration

Figure 1: Overview of the literature review procedure utilized for selecting the evidence featured in this review.

The collection of publication data was obtained by adopting different methods (Phase 2 in Figure 1). First, we search for the topics and keywords in the Elsevier Scopus database[1]. Second, we extend the search to Google Scholar to identify peer-review articles from journals that were not indexed in Elsevier Scopus database. Third, we adopt also citation tracing to supplement the databases' search. We use both forward tracing and backward tracing of seminal papers (such as Isaac and van Vuuren, 2009) key literature review papers on the theme (Schaeffer et al., 2012; Auffhammer and Mansur, 2014; Emodi et al., 2019). This approach is used not only in order to identify the main group of IAM-based studies to be reviewed but also to identify the empirical studies adopted by such works in their models' calibrations. Finally, in order to obtain grey literature results, we search the Institutional Websites of the key organizations such as the International Energy Agency and the Energy Information Administration. 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 our analysis, and add each study's projections to our dataset, we adopt a further filtering procedure (Phase 3 in Figure 1). We select only those articles presenting a clear definition of the methodology adopted and a detailed enough description of the results obtained. For some papers, we also request additional inputs from the authors.

[1]Table 1 in Supplementary Materials presents the number of documents resulting from the different searches. 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)"

As a result of such combined search and filtering procedure, we identify 14 publications which constitute the main group of IAM-based articles analyzed. The energy demand and macroeconomic impacts' projections retrieved from the selected studies are classified based on the socio-economic and climate assumptions adopted. Based on such data analysis, we build 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 energy demand variations), each 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 (available as Supplementary Data).

3. Classification

In order to investigate how different modeling approaches can affect the projections' results, we classify the methodologies adopted by the studies identified according to different modeling aspects: the representation of the economy; the representation of the energy sector; the climate transmission to the energy sector.

3.1. Economy

The relationship between the energy system and the economy can be modeled by: i) partial equilibrium models representing the energy or building sector; ii) general equilibrium models of the energy sector, the economy, and their interactions.

Partial equilibrium models provide the ex-ante climate-induced potential impacts prior to any adjustment induced by market interactions with energy supply and the rest of the economy through price changes. There shocks are instead accounted for in general equilibrium modeling framework. Of the fifteen studies considered in this review, five rely exclusively on a partial equilibrium approach, generally an energy sector or an energy demand model. Four studies have coupled a partial equilibrium model with a general equilibrium model (Labriet et al, 2015; Hasegawa, et al., 2016; Park et al., 2018; Clarke et al. 2018), three studies (Eboli et al. 2010; Bosello et al. 2012; Roson and der Mensbrugghe, 2010) have used a general equilibrium model on its own and one study (Tol, 2013) has used an optimization model.

3.2. Energy sector

The detail of the energy sector can be modeled by: i) process-based, bottom-up simulations, in which engineering bottom-up models are applied to simulate 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 derive 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 which couple a general equilibrium model or an integrated assessment framework with a more detailed energy or building sector bottom-up model. Eboli et al. (2010) and Bosello et al. (2012) for instance couple the top-down recursive-dynamic computable general equilibrium model (ICES), used for the assessment of the macro-economic impacts of climate change, with the bottom-up POLES model. Specifically, shocks from the POLES energy system model are used to calibrate the intensive margin in ICES. Labriet et al. (2015) couple the general equilibrium GEMINI-E3 with the bottom-up, energy system model TIAM-WORLD (TIMES Integrated Assessment Model). The adoption of the economy-wide model GEMINI-E3 allows to examine the overall macroeconomic implications of the changes in heating and cooling energy demand due to climate change. Hasegawa et al. (2016) and Park et al. (2018) conduct a general equilibrium framework analysis by combining a dynamic CGE model (Asia- Pacific Integrated Model/Computable General Equilibrium, or AIM/CGE) with the AIM/End-use model, a bottom-up, energy system model (Fujimori et al., 2012).

3.2 Transmission of climate shocks to final energy demand

The literature identifies two separate mechanisms through which climate shocks are transmitted to energy demand (Auffhamer and Mansur, 2014; Sue Wing and Lanzi, 2014): short run demand responses to weather (henceforth "intensive margin") and long-run demand responses driven by an increase in the penetration of air conditioner appliances (henceforth "extensive margin"). The short-run intensive margin transmission of weather conditions to energy demand characterizes both cooling and heating services in a similar way. On the other hand, long-run adjustments due to appliance penetration have usually been considered explicitly only for cooling services, under the assumption that saturation of heating appliances has already occurred across the world. While the extensive margin adjustments amplify the cooling services' demand due to the utilization of newly acquired appliances, capital stock replacement of heating appliances, under the hypothesis of more efficient appliances replacing 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 the inclusion in the energy demand function for the thermal adaptation service ($EDCC$) of a multiplicative term based on the level (equation 1a) in the climate variable ($CLIM_{t,r}$) or in its relative increase with respect to the level in the baseline year ($CLIM_{baseline,r}$), in region *r* and with a time step of *t* equation 1b).

$$EDCC_{t,r}^{service} = CLIM_{t,r}^{service}\ ED_{t,r}^{service} \quad \text{(1a)} \qquad \text{or} \qquad EDCC_{t,r}^{service} = \frac{CLIM_{t,r}^{service}}{CLIM_{baseline,r}^{service}}\ ED_{t,r}^{service} \quad \text{(1b)}$$

Where *ED* is the energy demand for the thermal adaptation *service* (cooling or heating) without climate change and $EDCC$ is the energy demand for the thermal adaptation service under climate change. The climate variables ($CLIM_{t,r}$) that most commonly are used to capture thermal stress are typically 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 day by day (ASHRAE, 2017):

$$CDD = \sum_{i=1}^{n}(T_d - T_b)+ \quad \text{and} \quad HDD = \sum_{i=1}^{n}(T_b - T_d)+ \qquad (2)$$

where '+' signifies only positive values accumulate over n days in the chosen time period, T_d the daily mean outdoor air temperature and T_b the threshold temperature. All the studies reviewed adopting the scaling factor set T_b to 18°C, while few of them evaluate alternative thermal comfort thresholds (Hasegawa et al., 2016; Park et al., 2018).

In some cases, the scaling factor is associated with an empirically estimated parameter, β, that modulates the proportional variation in the climate indicator, either in a linear (equation 2a) or an exponential way (equation 2b):

$$EDCC_{t,r}^{service} = \beta_r \frac{CLIM_{t,r}^{service}}{CLIM_{0,r}^{service}}\ ED_{t,r}^{service} \quad \text{(3a)} \qquad \text{or} \qquad EDCC_{t,r}^{service} = \left(\frac{CLIM_{t,r}^{service}}{CLIM_{0,r}^{service}}\right)^{\beta_r} ED_{t,r}^{service} \quad \text{(3b)}$$

Equation (1a-1b) is the most commonly adopted approach to be found both by the engineering, end-use demand models – they add the scaling factor to the building energy consumption model (Labriet et al., 2015; IEA, 2018; Levesque et al., 2018; Clarke et. al., 2018), and by energy system bottom-up analyses - they add the scaling factor to their stylized income-demand relationship (Isaac and van Vuuren (2009), Mima and Criqui (2009), Hasegawa et al. (2016), Park et al. (2018). Equation 3a is adopted by Tol (2013), while equation (3b) by Clarke et al. (2018).
The scaling factor method relies on the computation of CDDs and HDDs (Equation 2) from the historical and future mean air temperature. The increase in energy demand across different warming scenarios therefore will be dependent upon two transmissions mechanisms: how mean temperature increases affect CDDs and HDDs; how variations in the CDDs and HDDs affect the cooling and heating demand via the scaling factors (Equations 1 and 3). Therefore, if the relation between mean temperature and degree days is non-linear (Mourshed, 2012), the relation between temperature and energy demand will be non-linear, even when models include a simple proportional factor between energy and the degree days (Equation 1a and 1b).

An empirical estimation of the non-linear transmission from temperature to degree days and energy demand is presented in Figure 2. We develop a pooled regression model between temperature , CDDs and HDDs (Panel a), computed with varying thresholds: 18°C and 22°C as for CDDs, 18°C and 16°C as for HDDs (Equation 2). Meteorological data is obtained from the NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-GDDP)[2] dataset, for the years from 1986 to 2005. The left quadrants show the best fit (cubic) obtained from the regression model. We furthermore compute a stylized relation between the country-level, mid-century mean temperature shocks (temperature scale factor) and the shock on the CDDs and HDDs. For all variables, we look at the percentage variation of the mean future realization (mean of 2041-2060) with respect to the variables' historical level (mean of 1986-2005). The indicator corresponds to the energy demand shock that models adopting the scaling factor would transmit on cooling and heating energy demand at the country-level. Results underscore that a given annual mean temperature percentage variation leads to a more-than proportional increase (decrease) in the CDDs (HDDs) percentage variation (as most observations fall above or below the bisector). Furthermore, the magnitude of the degree days' percentage variation associated to a given temperature shock increases sharply when the higher threshold for CDDs is adopted and in RCP 8.5, while the shock is more uniform across thresholds and climate scenarios as for HDDs.

[2]NEX-GDDP is a large ensemble of downscaled and biased-corrected 0.25 gridded daily meteorological fields from 21 Global Climate Models (GCMs) that simulate vigorous (RCP 8.5) and moderate (RCP 4.5) warming under the Coupled Model Intercomparison, Phase V (CMIP5) climate model exercise. https://cds.nccs.nasa.gov/nex-gddp/.

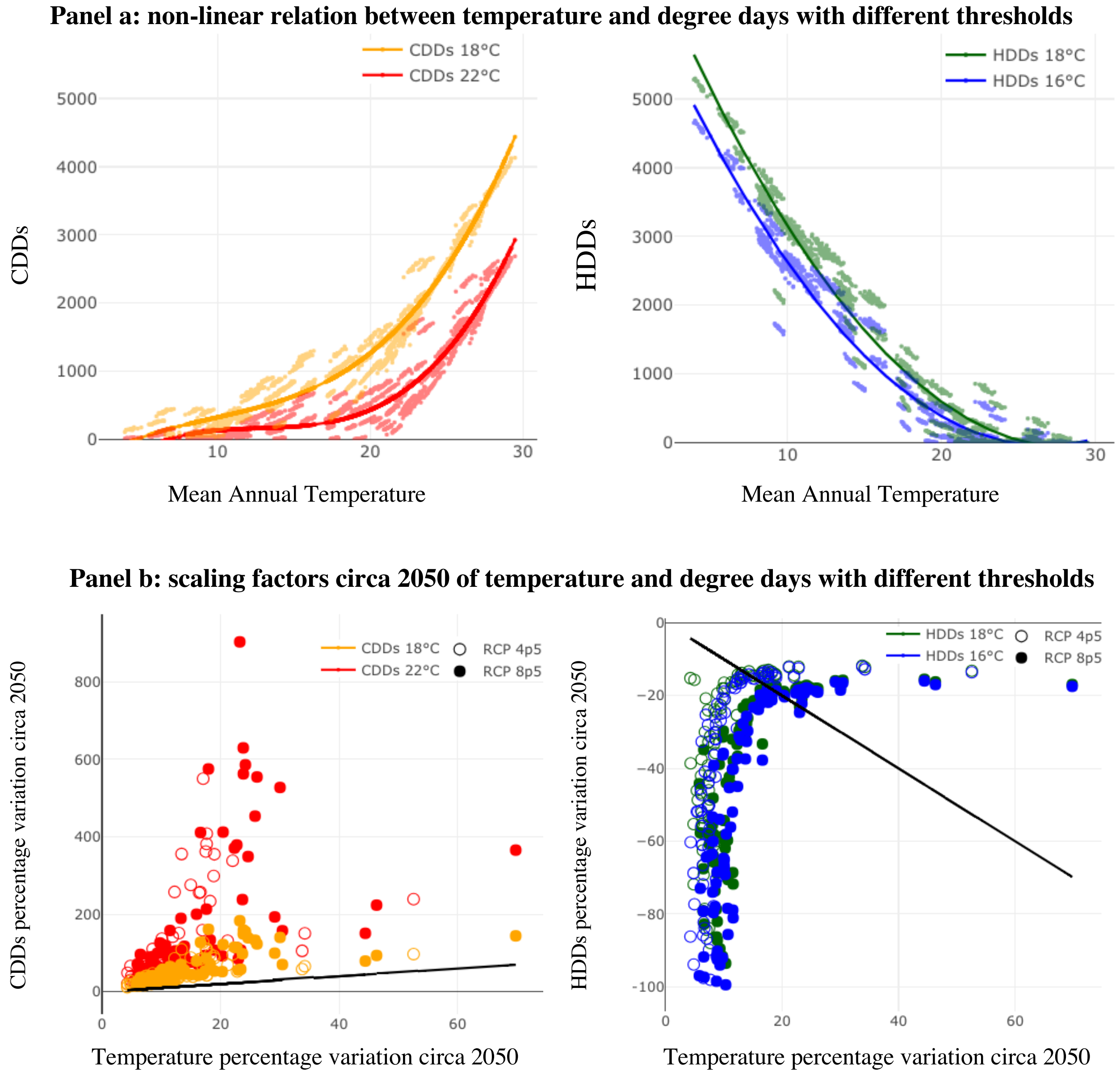

Figure 2.
Panel a: non-linear relation between temperature and degree days with different thresholds. Country level observations are constructed from the population-weighted aggregation of gridded data from NEX-GDDP. The left quadrant shows the best model fit of the yearly mean temperature on the degree days, between different polynomial specifications (linear, quadratic, cubic) selected based on the lowest Residual Mean Square Error (RMSE) and on the statistical significance of the coefficients.
Panel b: percentage variation of temperature and degree days circa 2050. We use NEX-GDDP data of mid-21st century climate (2041 to 2060), under the RCP 4.5 and RCP 8.5, to compute the scaling factor of the country-level mean temperature, CDDs and HDDs circa 2050.

The “exogenous shift parameters” approach varies key model parameters related to the efficiency of energy use and therefore, indirectly to the demand of energy, based on empirically-estimated parameters estimated using historical data. This approach entails a different representation of the responses to weather shocks with respect to the “scaling factor”. First, elasticities are estimated for the demand of different fuels (typically oil, gas and electricity) rather than for specific end-user services. Therefore, the estimation of fuel-specific coefficients provides a measure of the shock that aggregates the contribution of different thermal adaptation services. Second, the climate indicators are generally mean temperature levels (De Cian et al., 2013) or temperature “bins” (De Cian and Wing, 2019), rather than CDDs and HDDs. The distinction between cooling and heating requirements is achieved by the modulation of the empirically-estimated parameters for different levels of the climate variable. For instance, a “V” shaped or a linear-spline response (Figure 3) allows to relate heating requirements based on the coefficient associated to the temperatures lower than the reference level, while cooling requirements are associated to the coefficient related to temperatures higher than the reference level.

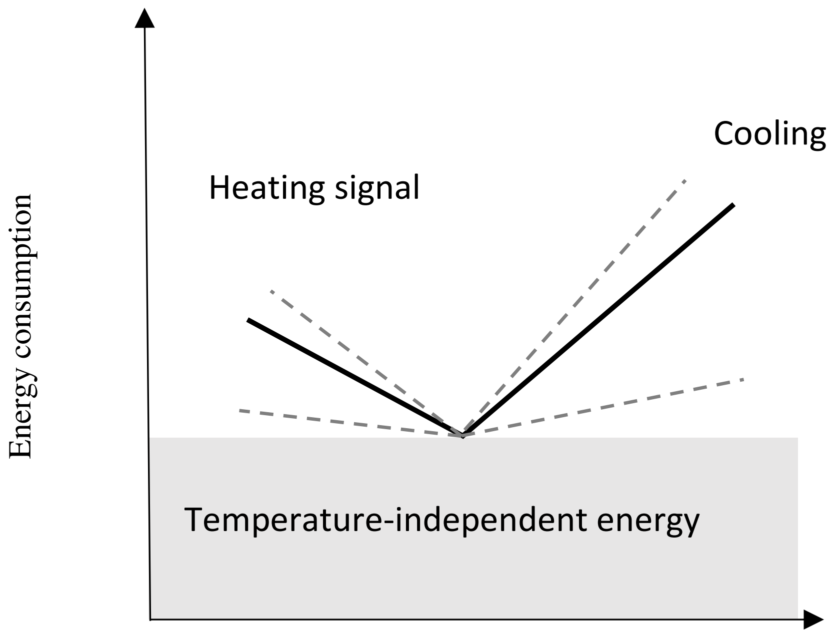

Figure 3. Stylized V relationship between energy demand and temperature

The climate change impact metric is derived from the computation of the differences in exposure between GCM-simulated current and future climates, achieved by adopting a ‘delta’ change method (Equation 4):

$$\Psi_{f,t,c} = \left[\left\{\frac{exp\left(\widehat{\boldsymbol{\beta}}_{f,c}^{CLIM} * \widetilde{\boldsymbol{CLIM}}_{c,t}^{Fut}\right)}{exp\left(\widehat{\boldsymbol{\beta}}_{f,c}^{CLIM} * \widetilde{\boldsymbol{CLIM}}_{c,t}^{Hist}\right)}\right\} - 1\right] * 100 \quad (4a)$$

$$EDCC_{f,t,c} = \Psi_{f,t,c} ED_{f,t,c} \quad (4b)$$

Where Ψ represents the change in energy demand due to future climate, relative to historical computed for each fuel f, country c and at time t; ED and EDCC are defined as above and β is the calibration parameter computed for each climate variable ($CLIM$). Computable General Equilibrium

(CGE) models (Eboli et al. 2010, Bosello et al. 2012, Roson and der Mensbrugghe 2010) have used climate-induced shocks on energy demand, such as those estimated by De Cian et al., (2013[3]), De Cian and Wing, (2019), or by van Ruijven et al., (2019) to calibrate the exogenous shifts in their model parameters. Here it is important to distinguish the empirical studies estimating those shocks, which are top-down partial equilibrium studies that often do not take prices adjustments into account, and the CGE modelling studies, which are top-down assessment that explicitly account for general equilibrium adjustments. The parameters of thermal adaptation's response to temperature ($\widehat{\boldsymbol{\beta}}_{f,c}^{CLIM}$) can be estimated using dynamic models (such as error correction models) that make it possible to identify the long-run elasticities, combining the contributions of the intensive and extensive margins in a unique parameter. The parameters of thermal adaptation's response to temperature ($\widehat{\boldsymbol{\beta}}_{f,c}^{CLIM}$) are generally estimated based on dynamic models (such as Error Correction Models) that enable to identify the long-run shocks, combining the contributions of the intensive and extensive margins in a unique parameter.

The extensive margin has been modelled through a market penetration model that explicitly estimates the market penetration of air-cooling appliances. Most studies (Isaac and van Vuuren, 2009; Mima and Criqui, 2009; Hasegawa et al., 2016; Park et al., 2018; Levesque et al., 2018[4], Arnell et al., 2019) rely on the "two-stage" penetration model by McNeil and Letschert (2008, 2010) and Sailor and Pavlova (2003)[5], in which Penetration (P) of air-cooling appliances is a function of two components: the Climate Maximum, CM (Figure 4, panel a, left quadrant), 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 4, panel a, right quadrant), which identifies the share of the

[3] De Cian et al. (2013) assess the climatic impact on the demand for three different types of fuel, gas, oil products and electricity, using a world panel of 31 countries. Temperature variations are segmented using seasonal (spring, fall, summer and winter) temperatures. Geographic variability is taken into account by introducing climatic clusters among countries. In particular, De Cian et al. (2013) group the countries into three clusters. The authors find for instance that, for electricity, the short-run effect of summer temperature is significant in all groups, but with a different sign. In very cold countries an increase in summer temperature of 1% reduces annual demand by 0.51%. In very hot countries it increases electricity demand by 1.66%. In mild countries the increase in electricity demand is lower and it equals 0.54%. The authors find the same direction of short-run variations but coefficients of a bigger magnitude.

[4] Levesque et al., (2018) do not include the "Availability" function in their penetration model, estimated solely by adopting the "Climate Maximum" component from Sailor and Pavlova (2003).

[5] As for the Climate Maximum, Sailor and Pavlova, (2003) and McNeil and Letschert (2008, 2010) are based on data from 40 US cities (Figure 4, panel a, left quadrant). The estimated equation is applied to all world regions by IAM-based studies under the assumption that penetration levels in the US have been unconstrained by income considerations and can therefore be considered as the upwards threshold of penetration under a give climate condition. As for the "availability" relation, the two empirical evaluations conducted, by Isaac and van Vuuren (2009) and by McNeil and Letschert (2008, 2010), are based on the same cross-section dataset of 24 countries provided by McNeil and Letschert, (2007). Most IAM-based studies (Mima and Criqui, 2009; Hasegawa et al., 2016; Park et al., 2018; Arnell et al., 2019) follow McNeil and Letschert (2008, 2010) as for the Climate Maximum and Isaac and van Vuuren (2009) as for the Availability calibration, resulting in the AC appliance penetration levels varying both due to CDDs and income (Figure 4, Panel b).

Climate Maximum which is actually achievable given the income level of the population (I). Penetration, P is defined as the product of these two components (Figure 4, panel b).

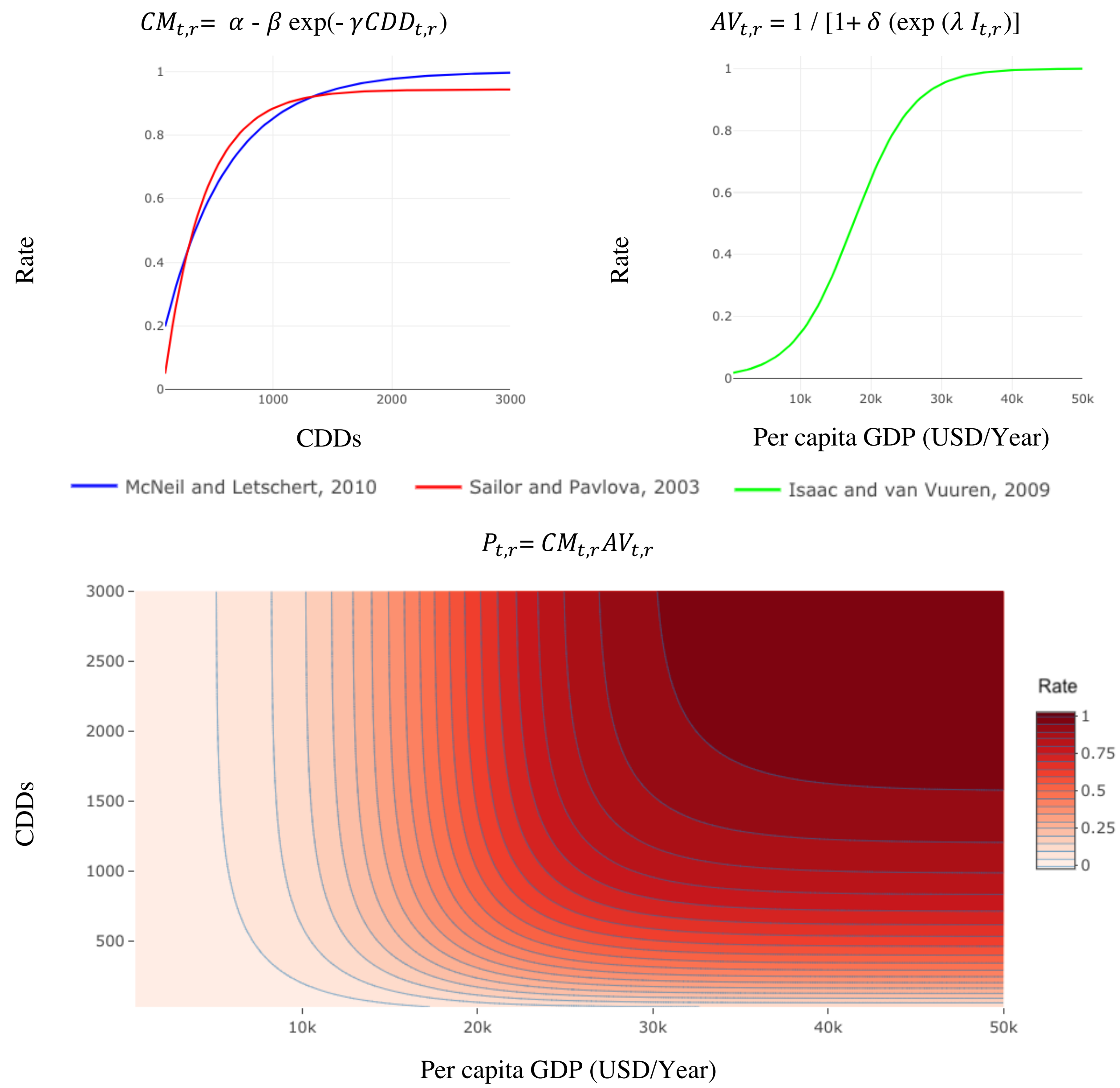

Figure 4. Calibration values of the AC Climate Maximum, Availability and Penetration functions.

A few studies rely on different approaches. IEA (2018) uses a "stock model" approach. In this case the modeling of penetration is derived taking into account the stock of cooling equipment that is necessary to meet the required energy service demand. Assumptions on average equipment lifetimes are applied 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. Clarke et al., (2018) 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 (Tol et al., 2013; Labriet et al., 2015), while AC penetration can be implicitly accounted for through an exogenous shift parameters which, as argued in the previous section, allow to identify both short and long-run energy demand elasticities to temperature variations.

3.2.1. Sectoral heterogeneity

The sectoral detail of the transmission of climate shocks on thermal adaptation services varies across IAMs: as for the intensive margin, the models that rely on the scaling factor assume that a given climate shock affects identically the two sectors' response. In its most general formulation, the scaling factor approach allows to disentangle the difference between residential and commercial short run shocks, as a sector-specific modulation parameter can be included in the function. In all cases analyzed nevertheless this modulation parameter is either set to unity (Labriet et al., 2015; Hasegawa et al., 2016; Park et al., 2018) or assumed to be constant across sectors (Clarke et al., 2018). As for the extensive margin, the device penetration ratio obtained in the residential sector is generally used for the commercial sector (Park et al., 2018, Hasegawa et al., 2016). The studies that model the transmission via the "exogenous shift parameters" adopt on the other hand sectoral-specific parameters, as the panel econometric models used for calibration estimate the equations separately for each sector (De Cian and Wing, 2019).

3.3. Combined classification

We combine the different modeling characteristics pertaining the relationship between the economy and the energy system, its level of detail, the representation of the climate feedback into the final use of energy into five overall model types (Table 1). Type 1 models (bottom-up, partial equilibrium 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 partial equilibrium simulation approaches deploying exogenous shifts) have been adopted only by two studies, while Type 4 (CGE coupled with a process-based representation of the energy sector characterizing only the intensive margin) shows the contribution made by a single study. The comparison of consistent scenarios between Type 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.

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 (2010); Bosello et al., (2012)	ICES-POLES; ENVISAGE	General eq. (CGE)	Top-down simulation	Exogenous shift parameters		Type 5

Table 1. IAMs classification

4. Analysis of IAMs projections

4.1. Projections: Global and regional trends in heating and cooling demand

Models' results underscore that at the global level the increases in energy demand driven by higher cooling needs more than compensate the decreases in energy demand due to lower heating needs. Figure 5 shows the distribution of the results obtained across different climate change scenarios (RCPs) as for cooling services, heating services and combined for all buildings and the residential sector only. Projections are reported for 2050 and 2100, in quantity (left quadrants) and in relative terms with respect to the demand in 2016 (right quadrants). The range in the projections expressed by the boxplots represents differences across models and socioeconomic scenarios (SSPs) in Panel a and Panel b, while differences across models and climate scenarios (RCPs) in Panel c. The projections point to a relevant increase in energy for thermal adaptation, as the combination of cooling demand increase and heating demand decrease. The evidence of the increase (decrease) in cooling (heating) demand is consistent across warming scenarios and over time. There are, depending on the combination of service, sectors, and RCP scenarios, relevant 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 results' range of the projections is much wider as for cooling demand than for heating demand and for the total buildings 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 as for the Residential sector and in the first half of the century. Differences across socio-economic scenarios are instead more evident in the building sector in 2100, both as for cooling and heating demand. Overall, the 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 to the need of further investigating how different mechanisms of propagation between climate and energy demand can affect models' projections.

We quantify the additional contribution of the climate-induced shock on energy demand for thermal adaptation by computing the difference between the projected demand in a given RCP scenario to 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 socio-economic trends (Panel c). The studies included in Panel c correspond to the one included in Panels a and b, with the addition of the projections by Van Rujiven et al., (2019). We single out the projections of Van Rujiven et al., (2019), highlighted as an asterisk and not used to compute the distribution of the boxplots, to ease the comparison between Panel a and c, as this study only provides results in terms of the additional contribution due to climate change.

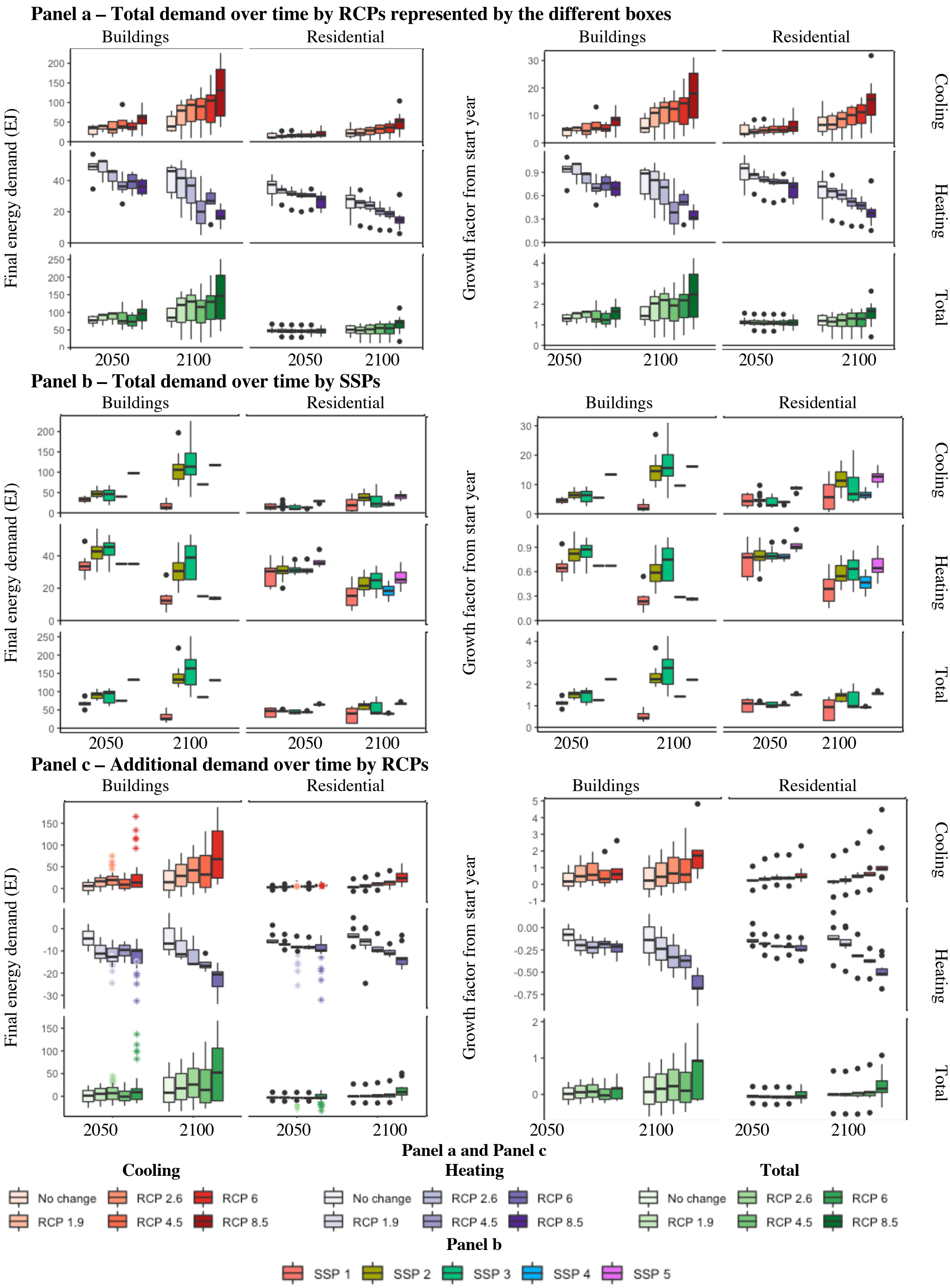

Figure 5 - Energy demand boxplot across RCPs (panel a), energy demand boxplot across SSPs (Panel b), Energy demand, additional contribution due to climate change (panel c). Data reported in the boxplots in taken from:

Labriet et al., (2015); IEA, (2018); Levesque et al., (2018); Clarke et al., (2018); Isaac and van Vuuren, (2009); Mima and Criqui (2009); Park et al., (2018); Arnell et al., (2019). Data points with the star marker refer to the results from van Rujiven et al., (2019). Different temperature change scenarios have been converted to RCP scenarios 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. The "No Change" scenario represent the cases in which current climate conditions (CDDs/HDDs) are assumed through the time period. Historical values for 2016 are computed using data from IEA (2018) and Park et al., (2018).

As for cooling, the climate change-induced median variations in building sector's energy demand range from 4 EJ to 17 EJ (from 20 EJ to 84 EJ) in 2050 (2100), depending on the climate scenario. As for heating, the climate change-induced median variations in building sector's energy demand range from -4 EJ to -11 EJ (from -4 EJ to -23 EJ) in 2050 (2100), depending on the climate scenario. 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 to 8.5 EJ (61 EJ) under the RCP 8.5 in 2050 (2100). Current usages of energy 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 on energy demand, as residential sectors' specific projections show 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 climate change-induced variations in residential and buildings energy demand with respect to the no-climate change scenario are amplified at the regional level (Figure 6). All macro regions are characterized by a net increase of buildings' 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 the median additional energy due to cooling requirements from 2050 to 2100 are projected for all regions, with a median addition in Asia, 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 both in the residential and commercial sector.

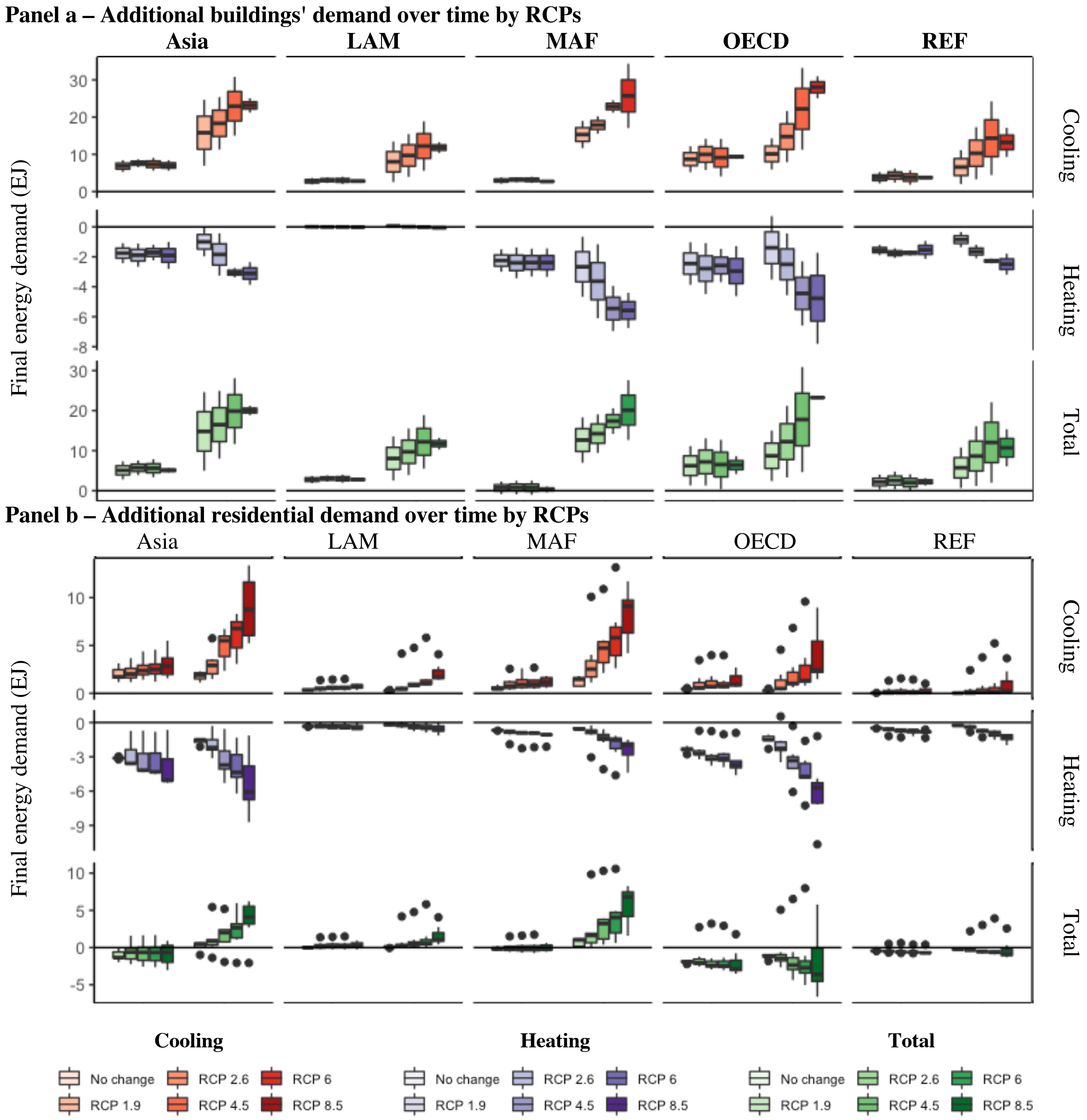

Figure 6. Additional demand over time by world region

Additional contribution due to climate change in value in five world macro-regions in the buildings (Panel a) and residential (Panel b) sectors. Results are grouped by RCPs scenarios. Studies in Panel a: Park et al., (2018); Studies in Panel b: Park et al., (2018); Arnell et al., (2019). Regional results from van Rujiven et al., (2019) are not reported for clarity but a graph with those results is available upon request. van Rujiven's estimates for cooling demand in buildings circa 2050 reach 55, 12, 50 EJ (22, 5, 21 EJ) in Asia, MAF, OECD, respectively, under the RCP 8.5 (RCP 4.5). Heating estimates reach -6 and -12 EJ (-4 and -9 EJ) in Asia and OECD, respectively, under the RCP 8.5 (RCP 4.5).

Some of the studies analyzed (Isaac and Van Vuuren, 2009; IEA, 2018) investigate the extent by which energy efficiency of heating and cooling appliances can affect models' results. Table 2 summarizes the main assumptions and key results: higher appliances' efficiency brings cooling energy demand down by 30% in 2050 (IEA, 2018) and by 45% in 2100 (Isaac and Van Vuuren, 2009), while heating demand would be more than halved in 2100 (Isaac and Van Vuuren, 2009).

Model	**Study**	Sector	**Assumptions of the efficiency scenario**	**Energy demand reduction (% decrease) from baseline at the end of the time horizon**
TIMER IMAGE	Isaac and van Vuuren, (2009)	Residential	Heating: shift from electrical resistance heating to more efficient heat pumps. Cooling: Increase in the energy efficiency ratio (EER) from 2.4 EER to 6.32 (4.39 in the baseline).	Heating: reduction of 17 EJ in 2100 (-56%) Cooling: reduction of 15 EJ in 2100 (-30%)
IEA ETP	IEA, (2018)	Buildings	Cooling: efficiency is 50% higher in 2030 and 80% higher in 2050 than in the baseline scenario.	Cooling: reduction of 10 EJ in 2050 (-45%)

Table 2. IAM-based studies assessing the impact of appliances' efficiency on energy demand projections.

4.2. Relevance: Implications for the economy, and the environment

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 small economic repercussion, which are mainly driven by impacts on the agricultural sector, sea level rise, health and tourism impacts. Figure 7 presents the results of the climate-related impact on GDP due to variations in cooling and heating energy demand 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[6], while a negative median GDP percentage change is found in the projections based on SSP 2 and SSP 3.

[6] The gain appears only in Park et al. (2018) when they run the SSP 1 for 1.5 and 2 °C scenarios. The result could be due: basic economic (GDP) and demographic assumptions differences; HDD/CDD threshold and technological annualized investment cost assumption differences (Park et al. 2018). Under SSP1 the study assumes a threshold for HDDs/CDDs equal to 15°C/26°C. Under these assumptions heating reductions overcompensate cooling increases. In fact, energy demand decreases with respect to the no climate change scenario in Park's SSP1 1.5 / 2 °C scenarios.

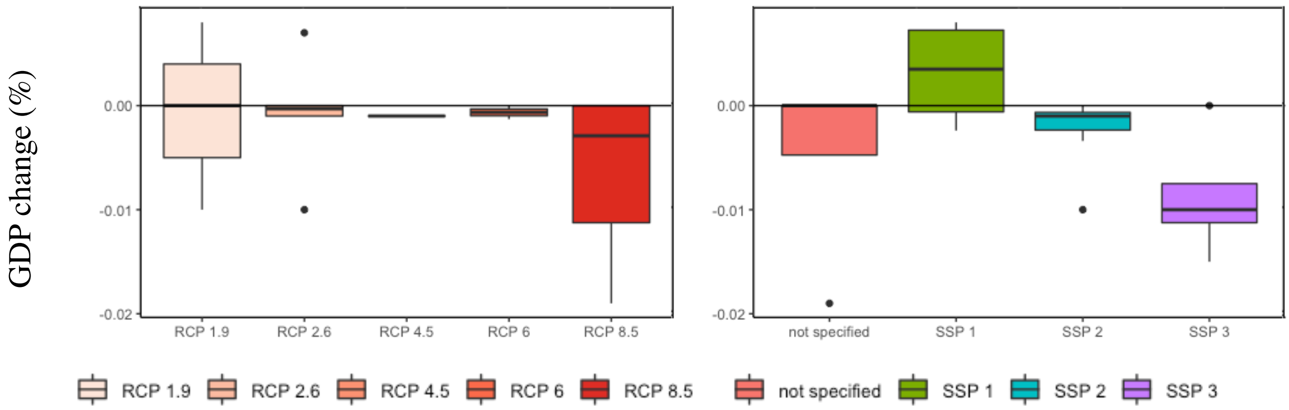

Figure 7. Economic implications of energy demand impacts.
Percentage GDP variation in 2100 across RCPs (left) and SSPs (right) relative to the "no climate change" scenarios. Total number of scenarios: 19. Boxplots represent the heterogeneity across different studies: Park et al., (2018); Hasegawa et al., (2016); Roson and Van der Mensbrugghe, (2012); Tol, (2013); Bosello et al., (2012); Eboli et al., (2010). Different temperature change scenarios have been converted to RCP scenarios using the mean 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.

If early studies find generally a very limited macroeconomic impact in terms of welfare change at global level, more recent analysis identified a higher role of the energy demand with respect to the macroeconomic impacts of climate change. Bosello et al. (2012), Roson and Van der Mensbrugghe (2012) and Dellink et al. (2014), Labriet et al (2015) find negligible impacts of energy demand changes due to HDD and CDD variations. Tol (2013), using the FUND model, finds that the negative impact of the net increase in energy demand is quantified as a variation of –1.9 % of GDP by 2100. Differently from the previous studies, Hasegawa et al. (2016) and Park et al. (2018) include the incremental costs for investments in cooling technology on top of the welfare changes due to the variations in energy demand and find negative median impacts on GDP in 2100, ranging from –0.94% under the RCP 8.5 to –0.05% under the RCP 1.9.

At the regional level, these studies highlight the role of terms-of-trade as driver of GDP changes. The economy will be negatively affected in fossil-fuel-exporting countries, as they experience a reduction in the demand for their exports due to the reduction in heating service, while fossil-fuel-importing countries would benefit from the decrease in the expenses for heating. In some cases, these welfare mechanisms are moderated by the rebound effects generated by the fuels' price changes, as shown by Labriet et al., (2015). The study is the only IAM-based assessment accounting for price-induced rebound effects on consumption. General equilibrium gas consumption for heating is higher than what found in the partial equilibrium. The price-change deriving from the decrease in the gas consumption for heating impact the energy markets through rebound effects that, globally, result in a less-sharp decrease in the heating energy demand (the ex-post percentage decrease is 34.2% - 38.3%

higher than the initial projections, depending on the long term temperature increase going from 1.6°C to 5.7°C)[7].

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. Labriet et al., (2015) quantify the total emissions from the increase in buildings energy demand in 2100 to be 1.2 (2.5) Gt CO2/year under RCP 6 (RCP 8.5), while Isaac and van Vuuren, (2009) 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 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 energy for adaptation needs because the extensive margin is not modelled (Labriet et al. 2015) or because the commercial sector is not included (Isaac and van Vuuren 2009).

4.3. Sources of variation

Notwithstanding the robust general trends with respect to heating and cooling demand, models' results show significant heterogeneity. Figure 8 presents a disaggregation of the incremental energy demand projected by different IAM categories (Type 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, we base the following comparison on the projections which allow us to compare simultaneously the highest number of groups, namely the projections reporting the value of the incremental energy demand in 2050.

The analysis of the projections reported in Figure 8 suggests that models lacking the 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 modelling approaches. This result points to the relevance 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 for the representation of the extensive margin.

[7] The most affected regions are Europe, China, USA, Canada and Former Soviet Union, as in these regions experience higher absolute HDDs long-run variations. As for cooling, the general equilibrium electricity consumption is lower than the partial equilibrium calibration. The rebound effect induced by the electricity prices result in a less-sharp increase in the cooling energy demand (the ex-post percentage increase is 37.5% - 42.4% lower than the initial projections, depending on the long-term temperature increase). The most affected regions are Europe, USA, Canada and the Middle East. In Europe prices would increase by a range between 35% and 66% at the at the end of the time horizon depending on the climate scenario, while in China and India prices would increase up to 30 % and 55% respectively in the warmest months.

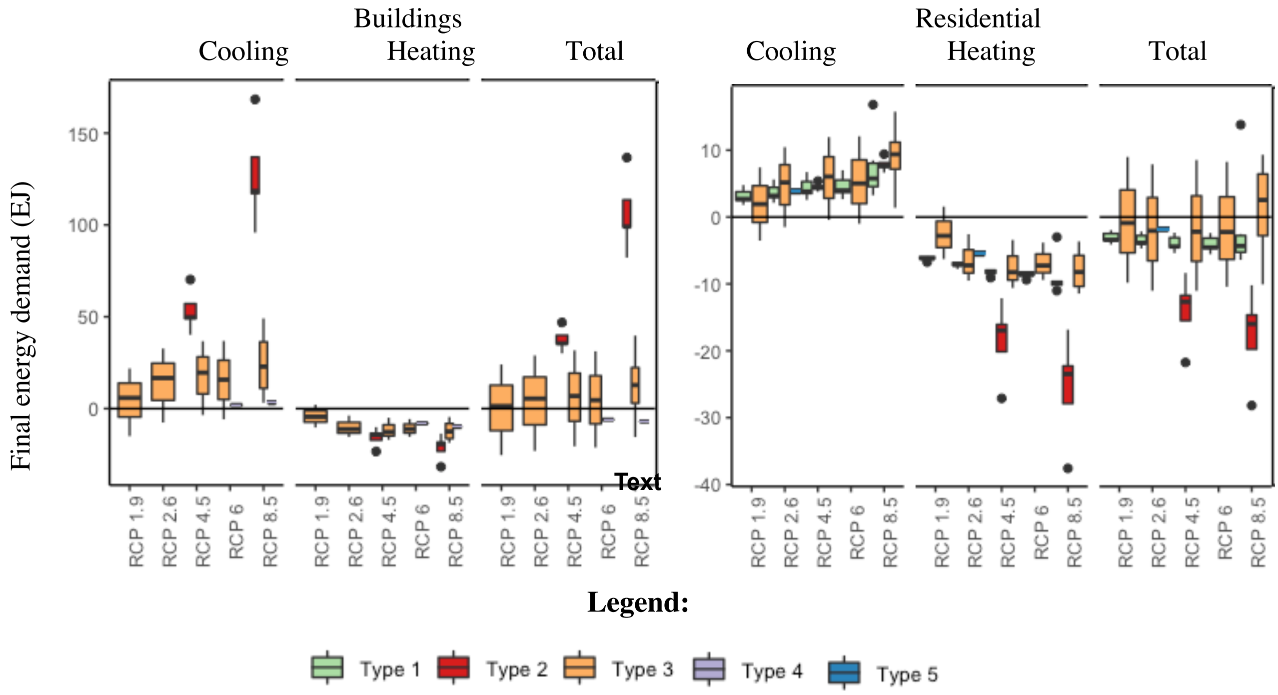

Figure 8. Additional contribution due to climate change in 2050 by model types.
Left quadrant: building (commercial and residential) sector. Right quadrant: residential sector. Type 1 models: TIMER-IMAGE; POLES. Type 2 models: projections from van Ruijven et al., (2019). Type 3 models: AIM/CGE, GCAM. Type 4 models: TIAM WORLD GEM-E3. Type 5 models: ICES.

There is no univocal relation between the projections' results and the modeling of the interactions between the economy and the energy system. Among the processed-based, bottom-up models, Partial Equilibrium IAMs (Type 1) tend to project a median increment of energy in line with the level projected by those General Equilibrium IAMs adopting the same type of modeling of the climate shock (Type 3). Scenarios from Type 1 models show a much smaller dispersion compare to Type 3. Type 1 models – bottom up models – might be more optimistic regarding the role of technological change and efficiency improvements compared to Type 3 models.

Among the top-down simulation models relying on exogenous shifts, Partial Equilibrium IAMs (Type 5) tend to project a higher median increment than General Equilibrium 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. General equilibrium 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 Types' 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 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 climate shock's functional form may affect the projections more sharply than other modeling aspects.

The differences across model Types' projections vary depending on the specific sector and end-use service. The gap between the projections is higher as for the commercial sector's cooling demand (panel a) and for the residential sector's heating demand (panel b). Top-down models based on sectoral-specific exogenous shift parameters project substantially higher increases in the incremental commercial cooling demand. The energy demand for the residential sector projected by Type 2 top-down models (van Ruijven et al., 2019) and by Type 3 models (GCAM by Clarke et al., 2018 and AIM/CGE by Park et al., 2018) under the SSP 2 and RCP 8.5[8] is comparable (8 EJ in the former study and 9-10 EJ in the two latter studies), while it differs remarkably when considering the commercial sector (114 EJ in the former study and 4-22 EJ in the two latter studies). Therefore, the adoption of a transmission mechanisms of climate on energy demand allowing for the sectoral characterization of the shocks can be identified as a key driver of the heterogeneity in the results.

5. Discussion and concluding remarks

The relationship between energy demand and the climate system is bilateral. On the one hand, energy demand, which for centuries has been met through the combustion of fossil fuels, has been a primary source of greenhouse gas emissions. On the other hand, energy is key to coping with the consequences of climate change, as several energy services make it possible to maintain thermal comfort conditions across all sectors of the economy under varying weather and climate conditions. To what extent adapting to climate change might influence the energy and the socio-economic system, and therefore initiate a negative feedback loop has not been inquired. How such interaction actually plays out varies across regions, and depends on the energy system configuration, socioeconomic development, and local climate. Answering this question requires the development of Integrated Assessment Models that integrate climate impacts and policies in a consistent manner, bringing together two research communities that have traditionally worked in parallel.

[8] As Clarke et al. (2018) develop projections only based on SSP 2 and RCP 8.5, we select the projections with the same overall scenario assumptions as for Park et al., (2018) and van Ruijven et al., (2019) to allow a direct comparison across models.

In this paper we systematically review and compare quantitative projections of energy demand in commercial and residential buildings that include the additional energy use or saving induced by thermal adaptation to heating and cooling needs at global and regional level. Despite the huge number of scenarios generated by the IAM community, we are able to identify 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 accounting for the feedback from the climate into energy demand in relation to the SSP-RCP scenario framework. We classify the resulting studies in a novel classification that consider the detail of the energy system, the relationship between the energy and the economy, the technical representation of the specific demand for heating and cooling.

We 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. We find consistent evidence of the increase (decrease) in cooling (heating) demand across warming scenarios and over time, but there are, depending on the combination of service, sectors, and RCP scenarios, relevant differences in the magnitude of the projections. Uncertainty increases over time, especially in relation to cooling demand when commercial activities are also included. Thermal adaptation in buildings due to climate change is projected to require additional energy ranging from a median value of almost 0 EJ (16 EJ) under the RCP 1.9 to 8.5 EJ (61 EJ) under the RCP 8.5 in 2050 (2100). The projected median additional demand in buildings required in 2100 under RCP 8.5 corresponds to a 70% increase of 2100 baseline global cooling and heating demand under no climate change and to a doubling with respect to total buildings' demand in 2016. The median additional increase in energy demand in buildings with respect to current demand would range from roughly 0% to 14% in 2050 and from 26% to 100% in 2100, depending on the extent of the warming.

We show that models lacking extensive margin adjustments highly underestimate the additional cooling needs of the building sector. We have identified two main archetypes of modelling the extensive margin, which are either based on a weak empirical basis (the market penetration approach) or are only implicitly accounting for future dynamics of ownership rates of goods such as air conditioning (the exogenous shift approach). Some recent country-specific studies have highlighted the amplification effect deriving from the growth in appliances ownership in Mexico (Davis and Gertler, 2015) and in California (Auffhamer 2017). Pavanello et al., (2019) bring new evidence on the role socio-economic, demographic, and behavioral factors can have on the diffusion of air-cooling appliances in 8 OECD countries outside the United States. Future research aimed at deepening the integration of climate impact feedback into mitigation and energy scenario need to address two challenges. First, to what extent the empirical basis on the adoption and use of energy-using durables that are particularly sensitive to climate and weather conditions, such as air conditioning, will expand to other countries across the world. Second, how to use the new and emerging evidence across multiple countries, regions, and sectors to build an empirical basis that can be used in IAMs in a consistent way while avoiding double counting. Our review has also highlighted the much larger uncertainty that characterizes the commercial sector, which often, due to the lack of specific data or evidence, is modelled in a similar way to the residential sector, while empirical results suggest that the response to changes in temperature can vary greatly across sectors (De Cian and Wing, 2019).

Almost no attention has been given in IAMs to the nonlinear responses to extreme events such as heat waves. As argued by Ciscar and Dowling, (2014), the greatest challenge derives from the fact that both CGE and bottom-up engineering IAMs typically run with yearly time-step, therefore, stochastic techniques and model-integration should be adopted in order to capture short term events. In order to effectively capture the impacts of future extremes, new empirical studies should adopt datasets rich in term of spatial and temporal resolution and process and aggregation the weather observations and the energy data for estimation purposes in a way that enable to store as much as possible the information from the tails of the weather distribution and from its geographical specificity. Unless the short-run elasticities of demand are calculated at the same temporal and spatial scale as IAM simulations into which they will be incorporated into, the aggregation of short-run elasticities for the adoption in IAM is an important methodological limit (Wing and Lanzi, 2014). Aggregation of regional elasticities implies that several regions are constrained to have similar temperature responses, despite the final demand shock will differ among regions as the scenario's temperature differences vary geographically.

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