Improving projections of residential space cooling electricity demand

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Intellectual Property and Publication Statements

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The work in **Chapter 6** of the thesis has appeared in publication as follows:

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I was responsible for identifying the main research aims and objectives of this paper, collecting data, designing the methodology, performing the formal analysis/investigation, and visualising/validating results. I was also responsible for writing the original draft of this paper and applying subsequent corrections.

The contribution of the rest of authors to the writing of this paper was to facilitate the conceptualisation process, to aid in the development of methods and supervise/coordinate the execution of the research activity. The contribution of other authors was also to review and provide commentary on the content and presentation of this paper.

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Abstract

Air-conditioning (AC) was globally the fastest-growing building end-use over the past three decades, with greater adoption and use in the residential sector set to increase energy demand up to 17-fold by 2050 from current levels. As space cooling is supplied through electricity, the substantial growth in AC demand will raise power generation requirements, while also challenging decarbonisation targets. Despite agreement about the high potential for residential AC demand growth, future projections display significant variability due to uncertainties in the modelling process. This thesis therefore aims to improve projections of future residential AC electricity use.

It first uses econometric modelling to improve understanding of the weather-residential electricity use relationship (2000-18) for south and north United States (U.S.) via alternative climatic metrics. It then integrates climatic and non-climatic impacts into residential electricity use projections in 2050 for the nearly-saturated contiguous U.S. market. Finally, it develops a multi-method approach to model the climatic and non-climatic drivers of residential AC electricity use (2000-15) in the European Union's (EU-28) non-saturated market, and then projects it to 2050.

First, degree days with empirical set-point temperatures and humidity metrics improve regional residential electricity use models, still the evidence is weaker for the national model. Second, U.S.-level projections in 2050 indicate that personal income is the main driver of residential electricity use at an annual level, while degree day effects dominate in summer. Third, AC adoption is the principal driver of EU-28 space cooling electricity use, which in turn depends on growing affluence.

Findings imply that increasing residential electricity demand will affect most baseload and peak generation capacity respectively for the saturated and un-saturated market. They also suggest that personal income/ weather and diffusion effects are better described in integrated assessment models (IAMs). Improving the energy efficiency of technologies and buildings are key policies in mitigating AC demand growth.

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List of abbreviations and acronyms

AC	Air-conditioning
AIC	Akaike Information Criterion
AREA	Useful Household Area
BCCA	Bias-Correction Constructed Analogues
BE	Between Effects
BIC	Bayesian Information Criterion
Cap	Rated Capacity
CDD	Cooling Degree Days
CMIP5	Coupled Model Intercomparison Project-Phase 5
CGE	Computable General Equilibrium
CO_2	Carbon Dioxide
CPI	Consumer Price Index
CRU	Climatic Research Unit
CWD	Cold Wave Day
Diff	Air-conditioning Diffusion
DJF	December-January-February
Eff	Efficiency Indicator of Air-conditioning Systems
EIA	U.S. Energy Information Administration
EL_PC	Residential Electricity Use Per Capita
EP	Electricity Price
ETP	Energy Technology Perspectives
EU	European Union
FE	Fixed Effects
FEU	Final Energy Use
GCM	Global Climate Model
GDP	Gross Domestic Product
GHG	Greenhouse Gas(es)
GW	Gigawatt

HDD	Heating Degree Days
HFC	Hydrofluorocarbons
Hou	Housing Stock
HUM	Mean Air Humidity
HVAC	Heating, Ventilation and Air-conditioning
HWD	Heat Wave Day
IAM	Integrated Assessment Model
IDA	Index Decomposition Analysis
IDEES	Integrated Database of the European Energy Sector
IEA	International Energy Agency
INC	Personal income
JJA	June-July-August
JRC	Joint Research Centre
kWh	Kilowatt-hour
LARS	Leeds Anniversary Research Scholarship
LMDI-I	Log Mean Divisia Index – Method I
MACA	Multivariate Adaptive Constructed Analogs
MAPE	Mean Absolute Percentage Error
MEPS	Minimum Energy Performance Standards
NARR	North American Regional Reanalysis
NCEP	National Centre for Environmental Prediction
NEMS	National Energy Modeling System
NOAA	National Oceanic and Atmospheric Administration
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
Peak	Potential Peak Cooling Electricity Demand
POLES	Prospective Outlook for Long-term Energy Systems
POP	Population

POTEnCIA	Policy-Oriented Tool for Energy and Climate Change Impact Assessment
PPP	Purchasing Power Parity
PICC	Priestley International Centre for Climate
PV	Photovoltaic
PWh	Petawatt-hour
Qspec	Useful Specific Cooling Demand
R^2	Coefficient of Determination
RAC	Room Air-conditioning
RCP	Representative Concentration Pathway
RE	Random Effects
RECS	Residential Energy Consumption Survey
RTS	Reference Technology Scenario
Sat	Air-conditioning Saturation
SRI	Sustainable Research Institute
SEER	Seasonal Energy Efficiency Ratio
SSP	Shared Socio-economic Pathway
StAC	Stock of Air-conditioners
TIMES	The Integrated MARKAL-EFOM System
TMP	Mean Air Temperature
TWh	Terawatt-hour
USA or U.S.	United States
WCRP	World Climate Research Programme

Chapter 1
Introduction

1.1 The climate change challenge

Growing scientific evidence has demonstrated the presence of a persistent global warming trend, due largely to anthropogenic greenhouse gas (GHG) emissions, causing the climate system to go through “unprecedented” changes (IPCC, 2014). Global mean surface temperature in 2018 displayed a 1.19 ℃ increase relative to pre-industrial levels, defined as 1850–1900 period’s average, which makes it the 2nd warmest year in record (Lenssen et al., 2019; GISTEMP Team, 2020). With observed warming rates, average global temperature is projected to reach the critical 1.5 ℃ mark in the 2030-52 period, as shown in Figure 1-1 (IPCC, 2018). This will further increase the plethora of risks borne by human and natural systems that are susceptible to regional climatic characteristics. Furthermore, ambitious goals set out by the Paris agreement for restricting global warming below 2 ℃, and further reduce it down to 1.5 ℃, would require various economic sectors to undergo through a rapid low-carbon transition. The structure of various economic sectors (i.e. in terms of fuel mix, energy service demands, existing and new technologies) is heterogeneous, thus a customised toolkit of energy policies and mitigation measures needs to be developed.

Despite concerted efforts to mitigate emissions of carbon dioxide (CO_2) - the largest GHG contributor to radiative forcing, global CO_2 emissions continued to

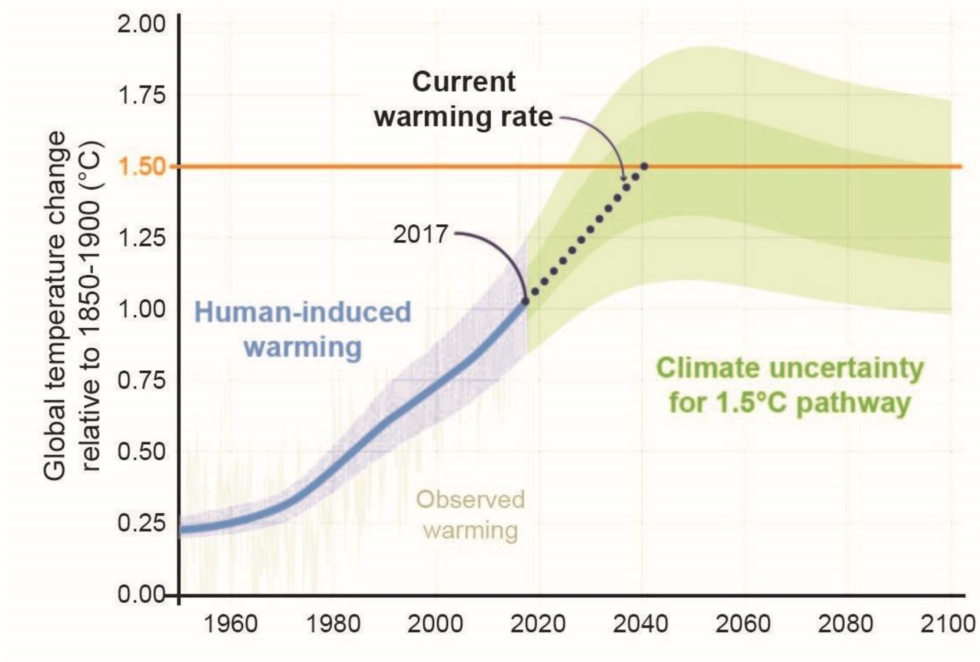


Figure 1-1 Observed warming rate against the 1.5 ℃ and 2.0 ℃ temperature thresholds Source: IPCC (2018)

rise in 2017 and 2018 after a short period of stagnation (2014-16), recording higher-than-average growth rates (IEA, 2019c). Based on observed trends, it is highly uncertain whether national carbon budgets will be satisfied by the end of century bringing the coveted 1.5 ℃ and 2 ℃ warming outcome. Furthermore, a set of moderate and extreme GHG emissions pathways have been developed by scientists with a range of plausible outcomes regarding the long-term evolution of weather characteristics, such as that of temperature, precipitation, and extreme events. Economic impacts on different sectors are expected to vary significantly under each climatic pathway.

As concerns about climate change impacts are growing with time, identification and quantification of the risks borne by economic sectors has become an established research field. Energy is a prime example of sector being vulnerable to changing climatic conditions, which is also responsible for the largest share of GHG emissions (74% in 2015 according to IEA (2019a)). Climate-related impacts are identified across all branches of energy systems; from energy supply and resource potential, through transmission and distribution networks performance to end-use energy demand (Schaeffer et al., 2012). Negative impacts on energy systems can then be translated as economic damage, quantified in terms of Gross Domestic Product (GDP) loss. According to Warren et al. (2018)[1], the economic damage under a business-as-usual scenario would be equal to a 2.6% global GDP loss in 2100, while that loss is predicted to be much lower at 0.5% and 0.3% under the 2 ℃ and 1.5 ℃ scenario, respectively.

Climatic impacts on future energy supply and demand could also create some unintended feedbacks on the climate system. Weather-driven increases of fossil fuel consumption, or a reduction of energy systems' efficiency and renewable technologies' potential would undermine climate change mitigation efforts (Cronin et al., 2018). Reducing final energy demand in buildings has a critical role in these mitigation strategies (Lucon et al., 2014; Sorrell, 2015), as improving the efficiency of end-use services helps to achieve the decarbonisation of the energy system (Lowe, 2007). Furthermore, this thesis sheds light on the potential consequences of climate change and socio-economic developments on end-use energy demand, and most specifically on evolving space cooling demand.

1.2 The role of residential space cooling demand

In this research, the focus is placed on the buildings sector, as it generates a substantial portion of global CO_2 emissions and consists of energy services described by a strong "climate-sensitive" component. I hereby define the term "climate-sensitive" energy use, which covers sectoral end-uses whose energy

[1] The detailed figures of the referenced research are sourced from IPCC (2018).

demand is strongly dependent on changing weather conditions. Amongst economic sectors, industry is globally responsible for the largest share of CO_2 emissions (Figure 1-2). The buildings and transport sector come in the second place each producing a quarter of global CO_2 emissions, after indirect emissions from electricity and heat production are re-allocated to consumption end-points (IEA, 2019a). Despite sectoral differences in the size of CO_2 emissions, the buildings sector has been overwhelming the focal point of demand-side climate change impact assessments due to its vulnerability to varying weather. On the other hand, there is weak evidence concerning the degree of climate-sensitivity in industrial and transport activities and the scale of future economic impacts under potential climatic pathways (Wilbanks et al., 2008).

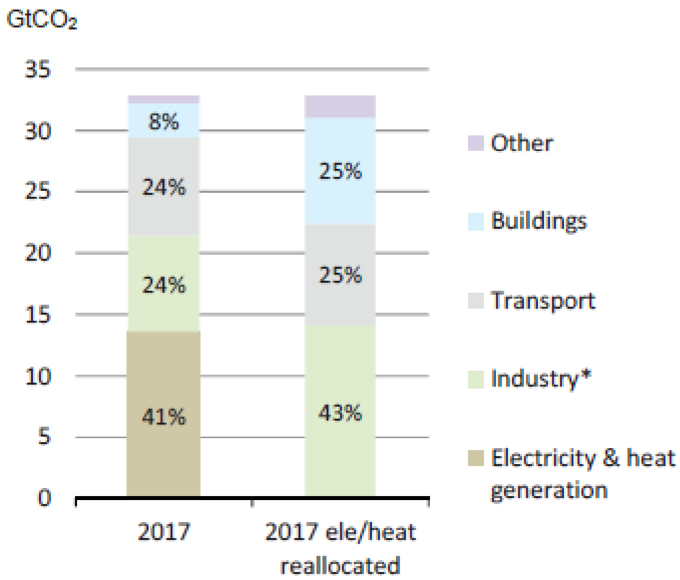


Figure 1-2 Allocation of global CO_2 emissions to different economic sectors in 2017 Source: IEA (2019a)

Many of the channels through which weather interacts with the demand side of the buildings sector are well-documented in the literature (Schaeffer et al., 2012; Ciscar and Dowling, 2014). The most profound example of climate-sensitive energy demand in buildings (residential and commercial) is for comfort heating and cooling services. Variation of space heating and cooling demand depends heavily on regional weather conditions, most importantly on outdoor temperature. Naturally, in a warming world characterised by hotter summer seasons and milder winter seasons, the need for air-conditioning (AC) will increase, while demand for space heating[2] will decrease. The sign of overall effect on future energy

[2] This would typically also include energy allocated to water heating, but evidence about its climate-sensitivity is more scarce (Kaufmann et al. (2013) is one rare example).

consumption and associated CO_2 emissions is expected to vary significantly between regions and warming pathways (Arnell et al., 2018).

Besides global temperature increase, future demand increases for space cooling will be boosted by population and income growth, especially in emerging economies (Akpinar-Ferrand and Singh, 2010). High urbanisation rates contributing to the heat island effect and fast electrification rates enabling diffusion of electric devices, which help the build-up of internal heat gains in households, add to this issue (IEA, 2018). Societal trends comprising increased household investments in thermal insulation, as well as consumers' decreased tolerance towards heat further amplify AC-related energy demand (Hekkenberg, Moll, et al., 2009). It is often the case that air-conditioners are regarded as a component of healthcare for reducing the risk for heat-related illnesses and lowering mortality rates (Barreca et al., 2016).

On a global scale, space heating is responsible for about a third of current final energy use (FEU) in the buildings sector, whereas water heating's and space cooling's share is much lower at 19% and 5%, respectively (IEA, 2017). When these figures are re-allocated to individual sub-sectors in Figure 1-3, space heating accounts for a greater proportion of FEU in the commercial relative to the residential sector. Despite the small contribution of space cooling to both residential (3%) and commercial (11%) FEU levels, a dramatic increase in AC diffusion and use is expected in the future, especially for the former sector, where AC markets have a large growth potential (IEA, 2018). This will have profound consequences on the energy system which go beyond the final energy demand side, as unlike heating most space cooling devices require electric power input.

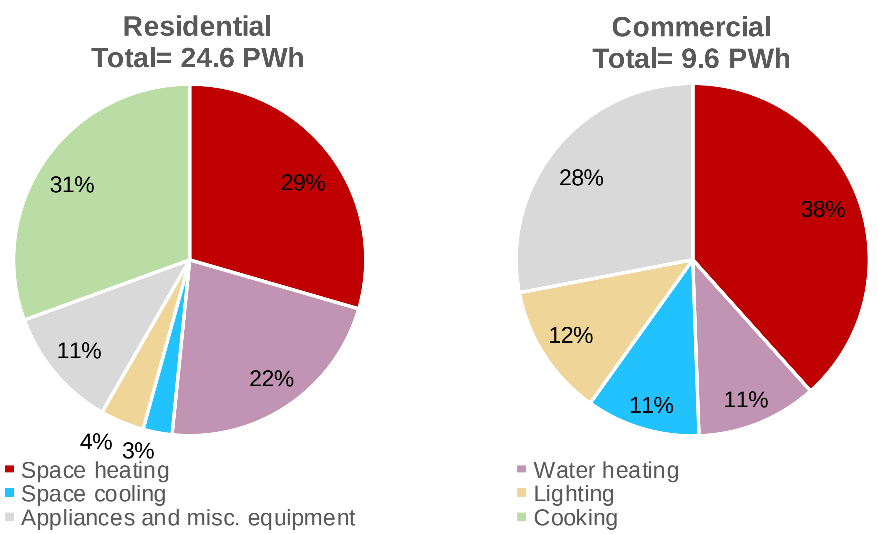


Figure 1-3 Final energy use in residential and commercial buildings per end-use in 2014 Source: IEA (2017)

Since space cooling is typically supplied through electric air-conditioners, soaring AC demand will add pressure on the global power sector in primary energy terms through increased electricity generation requirements. Space cooling already accounts for a significant share of residential electricity use in a number of countries around the world: for example, it formed about 70%, 60% and 25% of 2018's residential electricity use in Saudi Arabia, the United Arab Emirates and United States, accordingly (Lapillonne, 2019). On the other hand, space heating demand is mostly satisfied through fossil-fuel based technologies, with natural gas currently being the dominant energy source (IEA, 2017). A large-scale transformation of residential space cooling markets will have other important implications for regional power sectors and the environment, if left unmitigated:

(a) In addition to increasing total residential electricity use, coincidence of peak space cooling demand with the hottest day in a year, implies that more intense use of AC units amplifies observed peak electricity loads in the power system (Chandramowli and Felder, 2014). Currently, about 30% (16%) of peak electricity demand in the United States (China) is attributable to building air-conditioning, which is twice the annual contribution of space cooling to each country's sectoral final electricity use (IEA, 2019d). This calls for better provision of reserve capacity during summer; the part of electricity grid's capacity which operates only during periods of extremely high electric demand.

(b) As an indirect consequence of increased AC consumption, additional amount of CO_2, and health-related pollutants (e.g. sulphur dioxide (SO_2), nitrogen oxide (NO_x)) will be emitted during the electricity generation phase, depending on the fuel mix of regional power sectors (Meier et al., 2017; IEA, 2018). Moreover, growth of refrigerants stored in stationary air-conditioners in the form of hydrofluorocarbons (HFCs) could exacerbate climate change due to their high global warming potential (Velders et al., 2015). Although many nations have ratified the Kigali Amendment to the Montreal Protocol with a pledge to significantly reduce consumption of HFCs in the future (UNEP, 2016), major HFC producers like China, India and United States have yet to commit to the targets of this treaty.

Furthermore, this PhD thesis focuses on past and future trends of space cooling energy demand in residential buildings, given its (a) susceptibility to varying weather conditions, (b) adverse effect on power generation and peak electricity demand during the summer season, and (c) negative environmental impacts.

1.3 Past and future trends of space cooling energy use

Static description of FEU levels, as the one depicted in Figure 1-3, does not provide any insights into the relative growth rate of different end-use service demands in buildings. In order to display that difference, the long-term (indexed) historical variation of energy demand for individual building services is shown in Figure 1-4 (IEA, 2017). Demand for building space cooling grew on average by 2.9% and 6.8% per year in the time period 1990-2015 across the group of Organisation for Economic Co-operation and Development (OECD) and Non-OECD countries, respectively, surpassing the growth rates recorded by all other end-uses. Expansion of space cooling was much faster for lower-income, Non-OECD, nations as AC demand showed a five-fold increase between 1990 and 2015. On the other hand, demand for space heating recorded the slowest annual growth among building end-uses in the historical period (0.39%/0.45% per year for OECD/Non-OECD countries).

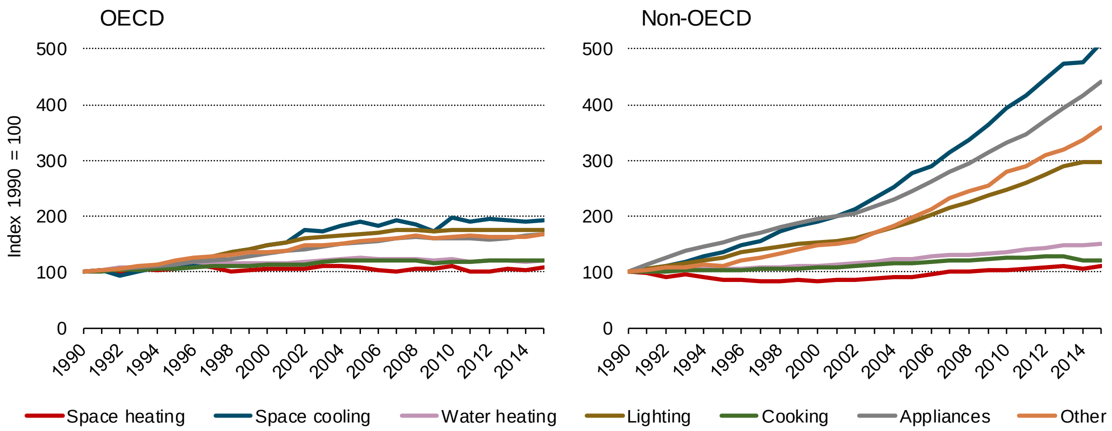


Figure 1-4 Indexed evolution of past building energy demand for OECD and Non-OECD countries Source: IEA (2017)

With respect to its long-term evolution, space cooling is projected according to IEA (2018) to follow a steep ascending trajectory, tripling its energy use levels by 2050 (6.2 PWh/yr), relative to 2016, in case no strict efficiency measures are imposed (Figure 1-5). Under the International Energy Agency's (IEA's) baseline case, space cooling is going to shape 14% of buildings FEU level in 2050, thereby becoming globally the single largest electricity consuming service. Moreover, about 70% of the projected increase of global AC consumption in 2050 is attributed to residential buildings. The foreseen increase of residential AC consumption is largely the result of the widespread adoption of air-conditioners, which is accelerated by climate change and economic development (Santamouris, 2016). While air-conditioning is currently viewed as a luxury good in many low-income areas, global average AC ownership rate under this IEA's scenario could increase from less than 30% in 2016 to 66% in 2050 (IEA, 2018).The strongest growth is expected to occur in emerging economies with hot and humid climate (e.g. India and China) (IEA, 2018; IEA, 2019d).

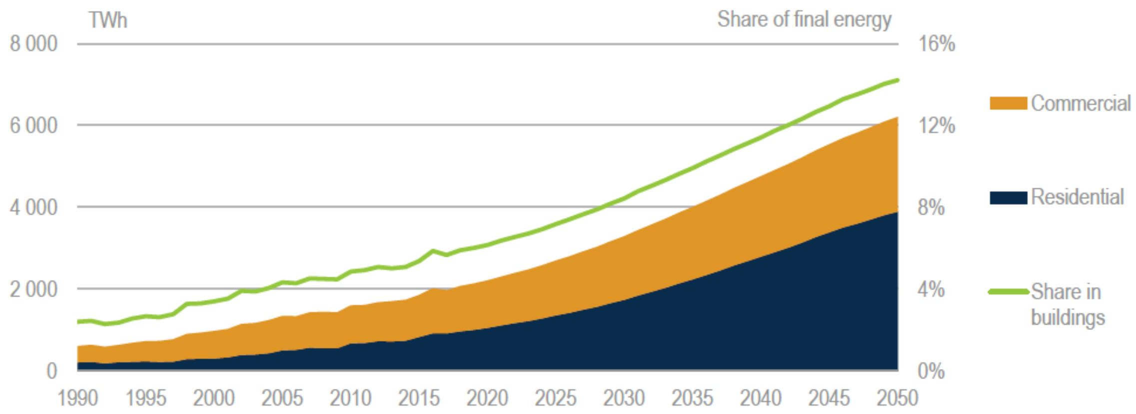
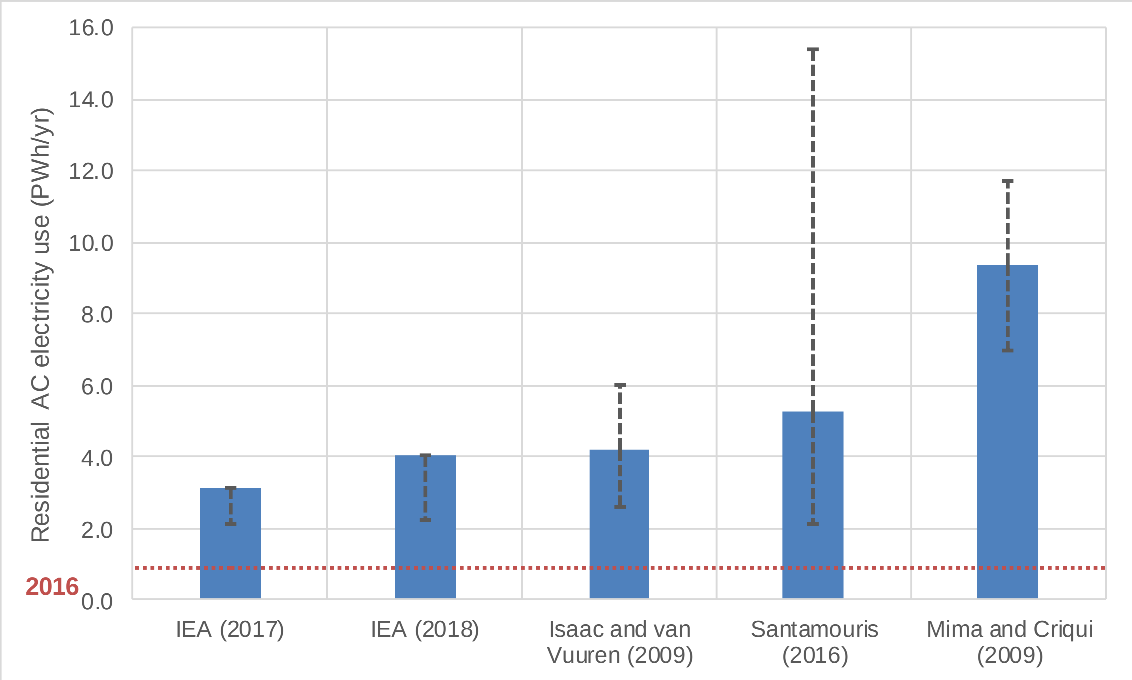


Figure 1-5 Baseline projections of global AC energy use to 2050 for residential and commercial buildings Source: IEA (2018)

Besides IEA (2018), other studies exist which report projections for the long-term evolution of global AC electricity consumption in the buildings sector, with all models predicting a significant increase in space cooling demand. Despite the general agreement in predicted trends, the developed trajectories of AC electricity consumption in the mid-21st century are surrounded by a great level of uncertainty, as it can be deduced from the important spread of published estimates. This is particularly evident in residential space cooling model projections; reference scenario estimates in 2050 were shown to vary from 3.2 PWh/yr in IEA (2017) to 9.4 PWh/yr in Mima and Criqui (2009), which is equivalent to an increase in the range 256-944% relative to 2016 levels (0.9 PWh/yr). Mid-range projections are summarised in Figure 1-6, along with respective high- and low-range trajectories, created by either testing sensitivity of AC demand to modelling input parameters (Isaac and van Vuuren, 2009; Santamouris, 2016), through enforcing stricter efficiency measures (IEA, 2017; IEA, 2018), or adding/removing the potential effect of climate change (Mima and Criqui, 2009). In the upper bound of uncertainty, residential AC electricity use could grow as high as 15.4 PWh/yr in 2050, which represents about 70% of worldwide final electricity use in 2017 (IEA, 2019f). An increase in space cooling electricity use of that magnitude could seriously hamper policies aiming to conserve energy in the residential sector, thus undermining global efforts to mitigate climate change.

Important discrepancies between scenario modelling outputs emerge since space cooling trajectories in 2050 are highly sensitive to the methodology followed to model the sensitivity of residential energy use to weather fluctuation.



Note: Error bars indicate the range of high/low scenario values

Figure 1-6 Existing projections of global residential AC electricity use in 2050

Moreover, bottom-up projections depend on the historical relationships built between different space cooling demand components (e.g., AC equipment diffusion and intensity of use) and a range of exogenous parameters, whose future evolution is also clouded by important uncertainties. Finally, residential AC energy use models constructed for specific regions are based on oversimplified assumptions about the future evolution of AC markets, since they are calibrated based on low-quality, patchy, data.

1.4 Research aims and questions

Given the large array of anticipated impacts (section 1.2) from growing space cooling needs across the globe and the important variability of future projections (section 1.3), this PhD project intends to improve the existing approaches to model the evolution of residential space cooling energy consumption. In doing so, this research aims to answer the following overarching research question:

> *With increasing residential energy demand allocated to space cooling how can AC-driven impacts be better modelled to understand the potential future implications for electricity systems in a carbon-constrained world?*

The overarching question is tackled by evaluating current modelling approaches and applying identified improvements to two separate case studies, namely that of United States (USA or U.S.) and the European Union (EU-28). Case studies are selected in such way to permit comparisons of space cooling-related impacts for two regions with important differences in the (a) current size and (b) future growth potential of their residential AC market. USA is globally the leading air-conditioning market in terms of installed output capacity and annual energy use levels for space cooling (IEA, 2018), despite being approached quickly by China. Almost 9 out of 10 of U.S. households currently use some form of air-conditioning (U.S. EIA, 2017b), in an extremely intensive manner as illustrated by the high per household AC consumption value reported in Table 1-1. Due to the widespread application of AC technologies, space cooling accounts for about a fifth of aggregate electricity use in the residential sector. However, AC energy use growth has been slowing down recently, mainly due to space cooling market saturation and efficiency improvements. Based on IEA (2019b), annual residential space cooling electricity consumption in the 2011-15 period was only 4% higher than in the 2000-10 period.

Table 1-1 Current (2015) status of residential space cooling sector in USA and the EU-28 region

Indicator	USA	EU-28
Installed cooling capacity (GW)[a]	2295	192
Residential AC electricity use (TWh/yr)	214	16
Per household AC electricity use (kWh/hh•yr)	1812	72
AC equipment diffusion rate (%)	87	9
Share in electricity consumption (%)	17	2

[a] Figure taken from IEA (2018b) represents 2016 value instead.

On the other hand, the space cooling market is very limited at present in the EU-28 region with much less capacity distributed across residential buildings (Table 1-1). While space cooling accounts for about 17% of U.S. domestic final electricity use (2015 values), the respective share for EU's residential cooling is significantly lower at 2% (JRC, 2017). This is mainly attributed to the much lower penetration rate of AC equipment in European households, which is approximately 10% in contrast to 90% for U.S. residences. EU-28 households also consume space cooling energy in a more conservative way compared to U.S. ones, as reflected by the extremely low levels of average per household consumption. Despite the low consumption levels, the future trajectory of residential AC market is expected to be high in the EU-28 region, given the small share of floor area being currently cooled. Contrast to the U.S., average annual residential energy consumption for space cooling was 60% higher in 2011-15, relative to 2000-10 levels. In this context, USA denotes the case of an enormous, nearly *saturated*, residential AC market, while the EU-28 region is an example of a small, yet quickly *growing*, space cooling market.

Parallel assessment of a saturated (USA) and un-saturated (EU-28) AC market primarily provides the benefit of differentiating between the two channels through which energy use for space cooling responds to weather variation: At a fist stage, warmer summer seasons lead people making more use of their existing AC equipment to keep indoor thermal levels within an acceptable range. In the short-term, households adjust their AC-based electricity use according to changing weather conditions, without investing in more space cooling devices. This channel is formally named in the literature as the *intensive margin* (Auffhammer and Mansur, 2014) and explains *direct* climatic impacts on usage patterns of residential space cooling, as illustrated in Figure 1-7. Understanding the mechanisms underlying this channel is a very important research topic for nearly-saturated residential AC markets, like the U.S. one, where variation of future space cooling electricity use heavily depends on how often and intense households make use of their AC units.

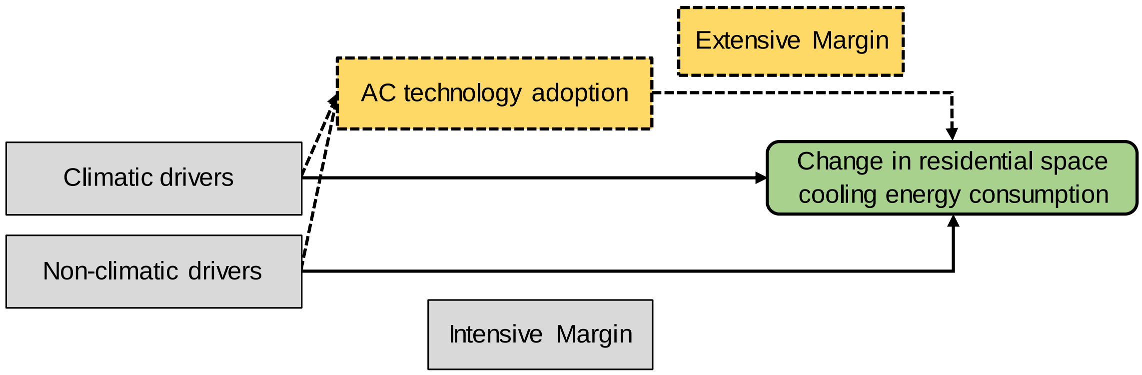


Figure 1-7 Schematic representation of intensive and extensive margin responses of space cooling energy consumption

At a second stage, households experiencing a warmer climate are also more willing to purchase additional space cooling units. Furthermore, climate change induces an increase in the size of capital stock accumulated in households with regards to air-conditioning equipment. This channel is formally known as the *extensive margin* (Li et al., 2018), which comprises indirect climatic impacts on space cooling electricity use through growing AC penetration rates, as shown in Figure 1-7. As the U.S. space cooling market approaches saturation, *extensive margin* responses of AC electricity consumption are of much less importance compared to *intensive margin ones*. On the other hand, the future evolution of space cooling electricity use in the EU-28 region will be largely determined by the future growth rate and potential saturation level of the regional residential AC market. As a result, the case study of EU-28 residential sector provides the basis of assessing *extensive margin* impacts on electricity consumption for space cooling, alongside with *intensive margin* ones. Under the framework presented in Figure 1-7, one could also examine the impact of non-climatic factors on space cooling electricity use and technology adoption.

The PhD project's specific research questions are cited below:

Research question 1 (RQ1): *What set of metrics could be designed which would improve modelling the relationship between residential electricity use and weather, and what are their implications for long-term projections of space cooling and heating loads?*

Initially, this research aims to scrutinise current approaches in modelling the variation of residential space cooling electricity use based on different climatic metrics. Existing indicators of climate-sensitive energy consumption are evaluated on a theoretical basis, about the degree to which they are able to reproduce complex weather effects on seasonal AC electricity use. A set of alternative climatic indicators is then developed which attempt to encompass some of the features of climate-sensitive energy use not currently described via current metrics. Advanced climatic metrics, which aim to improve degree day metrics and parameterise attributes of extreme temperature events and of air humidity, are then inserted into traditional econometric models describing historical residential electricity use in the (warm) south U.S. climatic region. The objective of this task is to quantify the benefits for model fit and forecasting accuracy emerging from incorporating the new climate-sensitive metrics in regional models of residential electricity use. Finally, RQ1 seeks to assess the implications for long-term projections of seasonal space cooling and heating electricity loads from modelling these more complex weather effects.

Research question 2 (RQ2): *How can climatic impacts be integrated into projections of future residential electricity use for a saturated AC market and how do they compare with the impacts of non-climatic drivers?*

The next objective of this research is to generalise findings in RQ1 regarding the value of alternative climatic metrics in explaining past residential electricity use variation for a region with different climate characteristics. This is achieved by testing the reviewed climatic metrics developed under RQ1 in models of residential electricity use, this time applied in the (cold) north U.S. climatic region. Based on the degree to which results from RQ1 can be generalised, RQ2 aims to improve projections of future residential electricity use for the saturated AC market of the whole of contiguous United States. The conducted case study econometrically estimates responses of residential electricity use with respect to changes in weather, socio-economic and energy price variables for the time period 2000-18. The constructed historical model is used together with multiple scenario data to project the impacts of climatic metrics on U.S. residential electricity consumption in the mid-21st century (2046-55). The climate-based effects on residential electricity use are subsequently compared with the magnitude and uncertainty of impacts from changes in the socio-economic and fuel price variables during the same time period. Using data with monthly resolution allows comparing climatic and non-climatic influences on future residential electricity use on an annual and seasonal basis.

Research question 3 (RQ3): *How can climatic and non-climatic metrics be integrated into models of residential space cooling diffusion in a non-saturated AC market, and what are the implications for long-term projections of residential electricity use?*

While RQ1 and RQ2 focus on climate-sensitive electricity demand across the nearly-saturated U.S. market, RQ3 aims to assess the past and future evolution of residential AC electricity use across the non-saturated EU-28 market, facilitated primarily via the growing diffusion of AC technologies. The historical (2000-15) variation of space cooling electricity use in the EU-28 residential sector is decomposed into the effects of individual factors to identify its most influencing driver in the past. This is only made possible after the recent publication of detailed end-use service demand data for the EU-28 residential sector (more details are provided in Chapter 3). The components of space cooling electricity use with a climate-sensitive component, including that for the diffusion of air-conditioners in households, are further modelled to understand the relative importance of climatic and non-climatic factors. At a final stage, a range of AC diffusion and efficiency scenarios are developed to 2050, which are translated into space cooling impacts on EU-28 residential electricity use and potential peak electricity demand.

1.5 Thesis structure

Figure 1-8 provides a schematic representation and short description of the thesis structure. In more detail, the rest of this PhD thesis is organised as follows:

Chapter 2 elaborates on previously identified research challenges in modelling demand for residential space cooling and its impact on residential electricity use, which are then aligned with the proposed research questions. More specifically, this chapter first describes the current state of knowledge from bottom-up assessments regarding the size of past and future demand for space cooling in

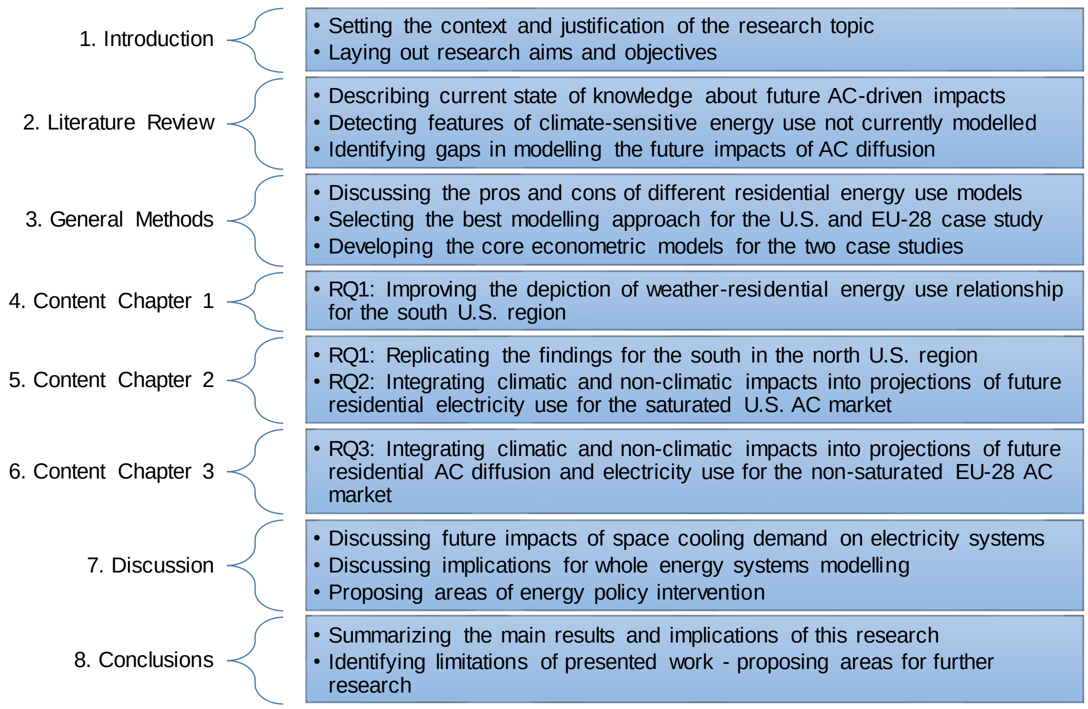


Figure 1-8 Schematic diagram of the PhD thesis structure

the residential sector. It then reviews current approaches and tools (e.g., degree days, temperature bins) used to understand the variation of space cooling demand based on weather statistics (i.e., the intensive margin). Following that, it identifies features of residential climate-sensitive energy use which are not represented through the current climatic metrics using lessons from top-down assessments. The scope of literature review is then broadened to cover non-direct impacts on residential space cooling electricity use, most importantly through the adoption of air-conditioners. Lastly, this chapter proposes improvements to current approaches in modelling the impacts of growing AC diffusion on regional electricity use requirements (i.e., the extensive margin).

Chapter 3 reviews existing residential energy use models and compares the relative strengths and weaknesses of bottom-up and top-down approaches. Furthermore, this chapter identifies the combination of modelling approaches which are most appropriate for tackling the research question for the case studies in the residential sector of the U.S. (RQ1 and RQ2) and EU-28 (RQ3) region. Chapter 3 develops the general modelling framework for assessing residential AC impacts in the U.S. and EU-28 region. Finally, it presents the mathematical formulation of the key models for each investigation, that is the residential model of electricity use and AC diffusion for the U.S. and EU-28 region, respectively.

Chapter 4, Chapter 5 and Chapter 6 include the content for the empirical analysis conducted in this PhD thesis, by tackling the specific research objectives outlined in this chapter. Chapter 4 develops a set of theoretical criteria based on which the significance of different features of climate-sensitive energy use (identified in Chapter 2) for long-term projections of residential energy use is assessed. The most important features are used as the basis for modifying current and developing new of climatic metrics, which are then fitted into traditional models of residential electricity use for the south U.S. region. The chapter assesses the extent to which these new indicators (a) improve the depiction of weather-energy use relationship and (b) have practical implications for long-term projections of residential space cooling and heating electricity loads.

Chapter 5 replicates the historical analysis of south U.S. residential electricity use in the north U.S. climatic region to generalise findings about the performance of the proposed climatic metrics. Based on the generalisability of findings, this chapter constructs an econometric model of historical residential electricity use, which extends to the whole of the contiguous United States. A sensitivity analysis is then performed to understand the interaction of uncertainties between the future impact of climatic and non-climatic trajectories on mid-21st century residential electricity use levels for a saturated AC market.

Conversely, Chapter 6 employs the case study of the EU-28 region to understand the variation of past residential space cooling electricity use according to the effect of different components. The component relating to increasing AC diffusion is further modelled in order to understand its climatic and non-climatic drivers. The chapter also presents different narratives for the potential evolution of the AC market in the mid-21st century and the corresponding impacts on residential electricity use and potential peak cooling electricity demand.

Chapter 7 synthesizes findings from the literature review (Ch. 2) and the general methods (Ch. 3) chapter, and results from the three empirical chapters to highlight the wider implication of this research. First, this chapter analyses the type and magnitude of forecasted impacts on the electricity system of the U.S. and the EU-28 region from increasing residential space cooling demand. Second, this chapter highlights the importance of adapting general modelling frameworks to the state of AC diffusion in a country or region. Third, it proposes routes through which the most important features of residential climate-sensitive electricity use can be better incorporated into whole energy system models, for a saturated and an un-saturated AC market. Finally, recommendations are made about energy policies which would be more effective in mitigating the impacts of growing residential space cooling demand according to the state of diffusion in a country or region.

Finally, Chapter 8 concludes by highlighting the contributions of this research to expert knowledge regarding future projections of residential space cooling electricity demand for a saturated and un-saturated AC market. It also revisits and answers the overarching and specific research questions developed in this chapter. Some of the limitations of this research project are identified and potential areas of future research are highlighted.

Chapter 2

Literature review

2.1 Structure of the literature review

Space cooling demand is becoming an important issue for energy conservation efforts in the buildings sector, as global energy consumption for AC purposes is projected to increase by 3-fold from 2016 to 2050 (IEA, 2018). There are various approaches towards analysing space cooling demand trends in the residential sector which fall into two main categories, namely top-down and bottom-up methodologies (Swan and Ugursal, 2009). This literature review first covers findings obtained from bottom-up assessments about the current and future size of residential space cooling electricity demand and some of the implications for the power sector. This review focuses only on bottom-up studies conducted on a macro scale, namely at the country, regional and global level. Moreover, it identifies the most important uncertainties and challenges in modelling the different components which determine the future evolution of space cooling residential electricity use. The discussion about the size of residential space cooling demand in different countries and regions, and the limitations of bottom-up models is presented in section 2.2.

The chapter then focuses on issues relating to the applicability of existing climatic metrics, like conventional degree day variables, in depicting the climate-sensitive component of building energy consumption by reviewing a number of top-down assessments. Different theoretical qualities and potential practical shortcomings of the degree day approach and of equivalent temperature-based metrics of climate-sensitive electricity use are discussed in section 2.3.

Finally, this chapter presents (section 2.4) the main findings and conclusions from top-down studies which have facilitated a distinction between intensive and extensive margin responses of past and future residential space cooling electricity use. That is the stream of papers which account for the amplifying effect of the changing stock of AC equipment on residential electricity use, either in an explicit or implicit manner. The chapter then concludes in section 2.5 by recommending ways to move the literature forward.

In summary:

- Section 2.2 evaluates the current and future size of residential space cooling demand in different regions/ countries according to various bottom-up assessments, while also discussing the gaps/ opportunities for future research.

- Section 2.3 reviews climatic metrics used to understand the past and future relationship between residential energy use and weather (i.e., intensive margin responses), and discusses how these can be improved and integrated to a more comprehensive top-down model of residential electricity use.
- Section 2.4 reviews the studies facilitating a distinction between intensive and extensive margin responses of residential electricity use and identifies the need for improved models of residential AC diffusion.
- Section 2.5 concludes by summarising the findings of this literature reviews and by reaffirming the research questions of this research.

2.2 Modelling approaches towards building space cooling demand

2.2.1 Major categories of building energy use models

Top-down and bottom-up methodologies have been extensively used to model energy use in the residential sector (Kavgic et al., 2010). Top-down generally refers to models which use high-level variables to *attribute* changes of aggregate energy consumption to characteristics of the whole residential sector. Bottom-up models on the other hand use detailed technological data to *calculate* energy consumption for individual end-uses, such as space cooling and heating, before extrapolating this amount to the entire sector (Swan and Ugursal, 2009). A third more sophisticated category is that of hybrid models which combine the macro-economic detail of top-down approaches with the technological features found in bottom-up ones (Krysiak and Weigt, 2015). A detailed description of the methodological differences between the three modelling approaches is provided in Chapter 3, as this remains outside the scope of this chapter. Instead, section 2.2.2 discusses findings from studies using the bottom-up (engineering-based) approach to simulate the future size of national/ regional/ global residential space cooling demand, while also accounting for market forces and technological progress (Dowling, 2013). In section 2.2.3, gaps/ opportunities are identified for improving the explanatory power of models of residential space cooling demand.

2.2.2 Lessons from bottom-up assessments

Thermal end uses, comprising space heating and cooling, and water heating, together account for a sizeable portion (currently around 60-70%) of global building energy use and their demand is expected to grow significantly in the future, in case of no policy intervention (Urge-Vorsatz et al., 2013; Ürge-Vorsatz et al., 2015). In a warming climate, the growing relevance of space cooling as a coping mechanism for increased heat constitutes a challenge for climate change mitigation strategies (Li et al., 2012). On the other hand, space and water heating requirements will decrease as the climate becomes warmer. The contribution of space cooling to final energy use levels in the global buildings sector grew from 3% in 2000 to 6% in 2016, and is forecasted to reach 14% by 2050 according to projections from the IEA's Energy Technology Perspective's (ETP's) model (IEA, 2018). These projections of AC-based final energy use mostly comprise electricity consumed by space cooling units and a very small percentage (~1%) of natural gas consumed by larger systems, of which the vast majority are installed in commercial buildings. Furthermore, increasing demand for space cooling together with that for household appliances is expected to cause a radical change in the buildings sector, as these services will dominate over more traditional ones and accelerate its deep electrification in the future (Levesque et al., 2018). The share of space cooling in global electricity use could rise from 10% in 2016 to 30% in 2050, overtaking the share of other end-uses (IEA, 2018).

Most of the forecasted increase in space cooling electricity use is attributed to the residential sector, where a huge penetration potential exists for AC technologies (Santamouris, 2016). Baseline projections, summarised in Figure 1-6, forecast that global residential electricity use for space cooling could increase in 2050 by a factor of 4-10 compared to 2016 levels, reaching an absolute consumption level of 3.2-9.4 PWh/yr. At the high-end of projections uncertainty, global space cooling electricity consumption in 2050 is equivalent to the current size of final electricity use in United States and China combined (IEA, 2019f). When these projections are compared to the forecasted 13.4 PWh/yr of global residential electricity use in 2050 from the IEA's Reference Technology Scenario (RTS) (IEA, 2017), space cooling's share could range from 24% up to 70%. On the other hand, the contribution of space heating to global residential electricity consumption is projected to be much lower at 4% in the mid-21st century.

Bottom-up studies strongly agree about the important influence of climate on the future growth of electricity use requirements for residential space cooling purposes. For a 3.7 ℃ surface temperature increase scenario, Isaac and van Vuuren (2009) estimated global space cooling electricity use levels in households to be 72% higher in 2100, relative to a constant climate case. Under the same climatic pathway, Mima and Criqui (2009) projected residential electricity-based AC consumption to increase by 72% in 2050, compared to the reference climate case in the Prospective Outlook for Long-term Energy Systems (POLES) model. The same study reports a smaller 19% difference between a scenario with and without a description of climate change impacts in 2050 for the EU. Mima and Criqui (2015) forecasted substantial increases in future space cooling electricity consumption via the POLES model for western and southern EU countries as a result of climate change, which agrees with findings from Dowling (2013) and Wenz et al. (2017). Labriet et al. (2015) performed an assessment of global adaptation to climate change through space heating and cooling using the TIMES[3] Integrated Assessment Model (TIAM-World). They showed that India's domestic sector will face substantial increases in AC-driven electricity use requirements due to climate change.

In addition to global-level projections, a number of regional assessments also exist, with the majority of them predicting significant increases of space cooling electricity consumption among developing countries, in absolute and relative terms. A summary of these projections is provided in Table 2-1. McNeil and Letschert (2008) combined a global logistic growth curve of AC diffusion with a simple equation of specific AC household energy use to model residential AC electricity use for a cross-section of developing countries. Both the saturation level of space cooling diffusion and unit AC electricity consumption depend on the climate expressed through degree days (a discussion about degree days is provided in section 2.3.1.1). Moreover, income determines the level of affordability of space cooling. They projected total space cooling electricity use to increase from 0.12 PWh/yr in 2005 to 0.76 PWh/yr in 2030 (6-fold increase), with the largest contributors being India (0.11 PWh/yr), southeast Asian countries (0.17 PWh/yr), the Middle East (0.12 PWh/yr) and Mexico (0.10 PWh/yr). Based on projections from IEA (2017), space cooling's share to residential electricity use in 2030 could vary from 12% for India, through 30% for southeast Asian countries to 73% for Mexico. They also note that these future AC consumption estimates could be conservative if other developing countries tracked the exceptionally historical high growth rates observed in China's AC market.

Sivak (2009) evaluated potential space cooling demand for the 50 largest metropolitan areas worldwide and found that highest AC potential exists in developing countries. Van Ruijven et al. (2011) developed a bottom-up simulation model for India which calculates demand functions in a similar fashion to McNeil and Letschert (2008) for various household end-uses, including that for fans, air coolers and air-conditioners. Their analysis predicts final residential electricity use increasing 19-22 fold between 2005 (0.10 PWh/yr) and 2050 (1.82-2.15 PWh/yr), that is 1.0-1.4 PWh/yr higher than a previous model projection, ascribing half of the excess electricity load to increased AC demand. Daioglou et al. (2012) extended this modelling framework to a set of developing countries and found that by 2030 space cooling will shape an important share of (per capita) urban residential electricity use in India (32%) with 212 kWh/pop, South East Asia (16%)

[3] TIMES stands for The Integrated MARKAL-EFOM System.

Table 2-1 Summary of regional/ national projections of future residential AC electricity use (excluding the EU-28 region)

Country or region	Study	AC electricity use (PWh/yr)	Year	% change from base year[a]
China	McNeil and Letschert (2008)	0.07	2030	-43%
	Isaac and van Vuuren (2009)	1.39	2050	+1034%
	IEA (2017)	0.28-0.49	2050	+129%
India	McNeil and Letschert (2008)	0.11	2030	+64%
	Isaac and van Vuuren (2009)	0.83	2050	+1140%
	Akpinar-Ferrand and Singh (2010)	0.22-0.28	2050	+229 to +318%
	IEA (2017)	0.60-1.06	2050	+796 to +1483%
Southeast Asia	McNeil and Letschert (2008)	0.17	2030	+432%
	IEA (2019a)	0.21	2040	+557%
	IEA (2017)	0.18-0.31	2050	+463 to +870%
USA	Scott et al. (2008)	0.16-0.25	2050	-25% to +17%
	Isaac and van Vuuren (2009)	0.37	2050	+73%
	IEA (2017)	0.11-0.17	2050	-49% to -21%
	U.S. EIA (2020)	0.39	2050	+82%
Mexico	McNeil and Letschert (2008)	0.10	2030	+1285%
	IEA (2017)	0.04-0.06	2050	+454 to +731%
Middle East	McNeil and Letschert (2008)	0.12	2030	+190%

[a] Base year values for China, India, Southeast Asia and Mexico are from IEA (2017) for year 2014, for Middle East from McNeil and Letschert (2008) for year 2010 and for USA from U.S. EIA (2017) in year 2015

with 47 kWh/pop and Brazil (22%) with 109 kWh/pop. The corresponding shares in 2007 were lower at 12%, 4% and 12%, respectively for India, South East Asia and Brazil.

There is also strong agreement about the countries – China and India – which will be responsible for the majority of residential AC electricity consumption increases by 2050. Increased diffusion of air-conditioning in households, coupled with population growth and high urbanisation rates, will lead China and India to surpass the United States and become the largest AC energy consumers by 2050 (IEA, 2018). According to Isaac and van Vuuren (2009), of the predicted 4.17 PWh/yr for global final electricity use for residential air-conditioning in 2050, 1.39 PWh/yr and 0.83 PWh/yr is respectively allocated to China and India, while just 0.37 PWh/yr originates from the United States. IEA (2019a) predicts that AC penetration rates in Chinese households will be 85% by 2030. Akpinar-Ferrand and Singh (2010) applied the methodology from McNeil and Letschert (2008) to the case of India's residential AC demand. They demonstrated that by 2050 about half of India's households will be equipped with air-conditioning, raising energy demand for space cooling at 0.22-0.28 PWh/yr. The lower modelled AC energy use estimate for 2050 relative to Isaac and van Vuuren (2009) is possibly due to the lower assumed growth rate of personal income across India. Substantial increases in space cooling electricity use are also expected in southeast Asian countries, where AC adoption rates can grow 3-fold between 2018 and 2040 (~60%) (IEA, 2019e).

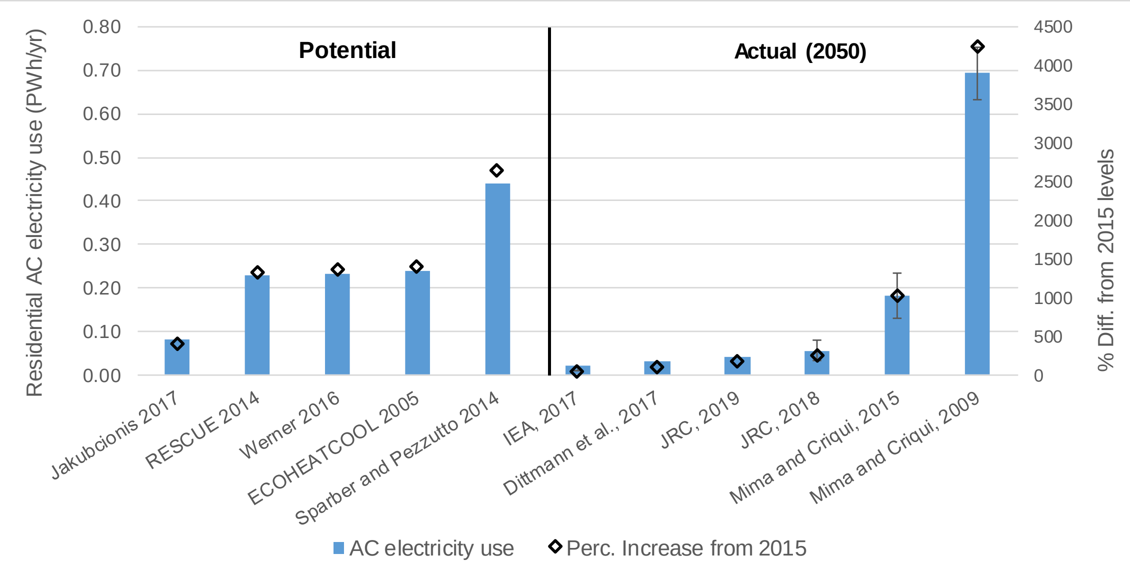
Eom et al. (2012) developed a technologically-oriented, serviced-based, energy model for China to calculate service demand for different residential end-uses. Their methodology deviates from McNeil and Letschert (2008), by using a more complex function for calculating residential space cooling demand which is composed of two parts: (a) a function for satiated AC demand which accounts for climatic (degree days) and building (efficiency of building shelf and internal gains) characteristics, and (b) a function which describes the portion of satiated demand that is actually met based on personal income and the price for providing space cooling services. Modelled scenarios show that useful demand per unit of household area for urban space cooling could increase to 25.2-28.9 MWh/m^2 in 2050, representing a 240-290% relative change from 2005 levels. The same methodology was subsequently adopted by Zhou et al. (2014) and Clarke et al. (2018) to respectively model the effect of climate change on U.S. state-level building energy use and the impact of climate change on energy expenditures for heating and cooling services at the global level.

Despite the large potential for AC electricity use growth in developing countries, the highest level of space cooling demand is currently recorded in the United States, both in total and per capita terms (Table 1-1). Waite et al. (2017) provided evidence that the cooling signal of electricity use in many U.S. urban areas, defined as its sensitivity to marginal temperature increase, is currently far stronger than across developing areas. Moreover, although the AC market in the U.S. is almost saturated, a number of sources predict an important rise of residential space cooling electricity requirements in the future, as a result of warmer temperatures and due to the population migrating from north to the south U.S. regions. Henderson (2005) and Jakubcionis and Carlsson (2017) also demonstrated the strong correlation between specific AC electricity use levels in different states and long-term cooling degree days (*CDDs*).

Scott et al. (2008) evaluated the climate-driven changes of future climate-sensitive energy use in the U.S. residential sector, by integrating a simulation with a bottom-up accounting model. They estimated residential electricity use for space cooling to range from 0.16 to 0.25 PWh/yr in 2050, representing a 19-85% relative increase from 2005 levels, without accounting for evolving building stock characteristics. IEA (2017) forecasted AC electricity use in U.S. households to reach 0.17 PWh/yr in 2050 under the RTS case, which lies within the range of estimates from Scott et al. (2008). On the other hand, the U.S. Energy Information Administration (EIA) assesses scenarios of future sectoral end-use demand through their established National Energy Modeling System (NEMS) tool (U.S. EIA, 2019c). In their 2020's annual energy outlook, they projected residential AC energy consumption to grow from 0.24 PWh/yr in 2019 to 0.39 PWh/yr in 2050 in the reference case, recording the strongest future increase amongst all household end-uses (U.S. EIA, 2020a). Their projection for 2050 agrees strongly with the value predicted by Isaac and van Vuuren (2009).These projections are also summarised in Table 2-1.

The situation in the EU-28 residential sector is markedly different. Despite its current small contribution to residential final electricity use (Table 1-1), the EU-28 market for residential air-conditioning is expanding rapidly (JRC, 2012). Moreover, space cooling demand is characterised by an enormous growth potential, since less than 10% of household floor area is currently cooled (RESCUE, 2014). The literature is therefore rich in bottom-up assessments aiming to establish an upper limit of useful and final AC residential electricity demand for the EU-28 region (ECOHEATCOOL, 2005; Sparber and Pezzutto, 2014; RESCUE, 2014; Werner, 2016). Modelled national values of useful space cooling demand (kWh-usef/m^2) are multiplied by the proportion of total residential buildings' floor area which is assumed to be cooled. Potential useful space cooling demand (PWh-usef/yr) is then calculated based on the assumption of a 100% AC saturation rate in households. The sole exception to this approach is the work published by Jakubcionis and Carlsson (2017), who assumed that AC diffusion rates in EU-28 households will not saturate at 100% but will eventually converge to those currently recorded in U.S. regions with similar climatic characteristics. Based on their assumption, the saturation level for residential AC equipment in the EU-28 region will be just over 50%, with notable differences between north (cold) and south (warm) EU countries.

Figure 2-1, which summarises existing estimates of potential space cooling electricity use (PWh/yr) for the EU-28 residential sector, demonstrates the significant variation between projected values which in the extreme case can exceed 0.44 PWh/yr. This value of potential EU-28 space cooling electricity use represents a massive 27-fold increase from present-day levels (Table 1-1) and compares with half the size of total residential electricity use as projected in 2050 for the EU-28 region. However, satisfied (actual) residential space cooling electricity demand is expected to be lower than potential demand according to most of the EU-level projections in 2050, also shown in Figure 2-1, as full AC saturation is never achieved.



Note: Column bars represent mid-range scenario values, while error bars denote respective high and low-range cases.

Figure 2-1 Projections of potential vs. actual (2050) residential space cooling electricity use at the EU-28 level

Dittmann et al. (2017) developed an AC penetration model based on a function which takes into account changes in the number of *CDDs* and personal income and predicted that the fraction of residential floor area which will be cooled in 2050 is just 23%. When combined with data on building end-use energy demand and technology stock, their model predicts EU-level residential AC electricity use to reach 0.03 PWh/yr in 2050, for a moderate climate change trajectory. JRC (2019) found that by 2050, a quarter of EU-28 households will be air-conditioned which translates to an electricity use requirement of 0.04 PWh/yr, with the Policy-Oriented Tool for Energy and Climate Change Impact Assessment (POTEnCIA) model. JRC (2018) projected EU-average AC penetration rate to increase to 60%

by 2100, with climate change being the main driver of space cooling adoption. Mima and Criqui (2009) and Mima and Criqui, (2015) also agree that EU-28 residential space cooling electricity use is mainly driven by warming temperatures and growing AC penetration rates. In the former case, their estimate of actual AC electricity use for 2050, exceeds all projections of potential space cooling electricity demand in the EU-28 region.

Studies also forecast an important increase in residential space cooling demand for individual EU-28 countries in the mid-21st century. Gouveia et al. (2012) projected energy service demand for different residential end-uses in Portugal, considering different types of houses. Space cooling was the end-use experiencing the strongest increase during the 2005-40 period, both in terms of useful AC demand (~+ 200%) and final energy use (~+100%). Olonscheck et al. (2011) similarly modelled past and future useful and actual space heating and cooling demand for the German housing stock. They found that varying assumptions about the future penetration rate of air-conditioning in households has the largest influence on future projections of national space cooling energy demand. Under the low diffusion (1%) scenario, actual space cooling electricity demand was projected to actually be lower in 2060 (0.05 TWh/yr) than in 2010 (0.07 TWh/yr). On the other hand, actual AC electricity demand was projected to increase from 0.26 to 0.86 TWh/yr between 2010 and 2060, when assuming that 13% of German households will own an air-conditioner.

2.2.3 Limitations of bottom-up models

(a) Climatic impacts are restricted to the effect of degree days

As shown previously, there are two main streams of bottom-up studies. The first category is populated with studies applying the methodological framework from McNeil and Letschert (2008) which decomposes total space cooling electricity use into three components, namely that for unit AC energy use, AC diffusion and the number of households. The first decomposition component, which section 2.3 refers to as the intensive margin, is assumed to depend linearly on cooling degree days and logarithmically on personal/household income. The second parameter, which section 2.4 refers to as the extensive margin, is further split into a saturation and an affordability sub-component: saturation is determined by an exponential function of long-term *CDDs* and affordability is a logistic “s-shaped” function based on income changes. Then total AC residential electricity use is estimated by multiplying the first two components with the number of households or total residential floor area. The second category of papers includes assessments following the more complex bottom-up model specification from Eom et al. (2012). While AC demand requirements are influenced by a number of aggregate housing stock characteristics, these papers also assume that degree days represent the climate-sensitive component of space cooling and heating electricity use. Actual AC demand is determined by the level of affordability of space cooling services in a region through a logistic growth curve, as with the first stream of papers.

The main conclusion drawn based on this review is that bottom-up models represent climatic impacts on residential AC electricity use levels which are currently limited to the effect of degree days on unit AC electricity use and space cooling diffusion. In their simplest form, degree day metrics capture the deviation of daily mean outdoor temperature from pre-determined thresholds, which represent the temperature above which space cooling devices are switched on. Section 2.3.2 elaborates on the reasons why dry-bulb degree days are not a comprehensive measure of climate-sensitive electricity use in households, based on lessons from top-down assessments, and how omission of specific modelling features could bias future projections of residential space cooling electricity use.

(b) Uncertainty in models of residential space cooling diffusion

Despite AC diffusion being the key driver of space cooling electricity use at the global level and across regions with small AC markets, its amplifying effect on residential space cooling electricity use is not yet well understood. Santamouris (2016) performed a sensitivity analysis to gauge the relative impact of various factors on global residential AC electricity consumption in 2050. He found that uncertainty in future AC penetration levels is the largest source of variability in projections, as AC electricity consumption in 2050 varies by 360% between the low and high development case. Uncertainty in global AC diffusion projections is in turn highly sensitive to the impact of future trajectories of personal income according to Isaac and van Vuuren (2009).

A common modelling feature amongst bottom-up studies, which has strong influence on future projections of national residential AC electricity use, relates to the approach followed in establishing the future saturation rates for space cooling diffusion and demand. The “climate maximum” approach, for which a detailed description is provided in Chapter 3 (section 3.6), matches future saturated AC diffusion/demand levels for a country with the current demand/diffusion observed in the United States, after adjusting for differences in the number of cooling degree days. While this approach offers the benefit of using readily-available data for the USA as a proxy for the future residential AC behaviour of other countries, there is little evidence to support that national AC saturation rates will indeed follow this trend in the future.

The important uncertainty in future estimates of AC diffusion is also evident in Figure 1-6 which summarises existing global-level projections of residential AC electricity use in 2050. It also justifies the wide range of future estimates of residential space cooling electricity use for regions which currently have low AC equipment penetration rates, as demonstrated for China and India in Table 2-1 and for the EU-28 region in Figure 2-1. On the other hand, the variability of devised projections for the nearly-saturated AC market of the U.S. residential sector is smaller (Isaac and van Vuuren, 2009; U.S. EIA, 2020a), despite the one study predicting that U.S.-wide AC electricity use actually decreases in the future, possibly due to improved efficiency standards and the omission of climatic effects (IEA, 2017). A principal objective for my research is thus improving current models of AC diffusion and the representation of extensive margin responses in models of residential space cooling electricity use. A detailed discussion about how top-down empirical assessments can help improve modelling the effects of AC diffusion on future residential AC electricity use is provided in section 2.4.

2.3 Modelling intensive margin responses

In this section, observation-based (top-down) econometric and regression studies are detected which analyse historical aggregate residential electricity use in relation to the variation of climate-sensitive metrics, so as to separate space heating and cooling effects. These empirical relationships are then used to project the partial impact of climate change on residential electricity use. Section 2.3 and 2.4 discuss the main findings from top-down assessments seeking to estimate the past and future effects of climatic and non-climatic factors on residential electricity use, respectively via the intensive and extensive margin.

2.3.1 Current climatic metrics and applications

The literature of intensive margin responses of residential energy use mainly consists of studies analysing electricity use, since unlike other residential fuels it provides the basis for distinguishing between space heating and cooling behaviours (Ranson et al., 2014). Natural gas, coal and heating oil on the other hand find mainly application on space heating activities in households (Sailor and Muñoz, 1997; Amato et al., 2005; Ruth and Lin, 2006; Petrick et al., 2010). Multi-fuel space heating effects can be superimposed on patterns of electric-based space cooling effects to examine the climate-sensitivity of aggregate energy demand in the residential sector. Outdoor temperature is considered by many studies to be the single most important weather-based factor for space heating and cooling demand (Mirasgedis et al., 2006; Apadula et al., 2012; Hong and Kim, 2015).

The theoretical relationship between residential energy demand and outdoor air temperature is believed to be non-linear, which can be portrayed through a continuous “U-shaped” curve containing a heating and cooling component (Gupta, 2012; Li et al., 2018). As illustrated by Figure 2-2, minimum energy demand occurs at the so called threshold temperature; a point on the curve coinciding with the outdoor temperature at which internal (i.e. equipment, light and people) and external (i.e. solar) heat gains have equal magnitude with heat loss from a building’s envelop. Under these conditions, there is no requirement for mechanical heating or cooling output to sustain indoor thermal comfort levels (Day, 2006; McGilligan et al., 2011). The level of demand at the threshold temperature, under this theoretical model, therefore depends on energy requirements for residential climate-insensitive services. An instantaneous positive (negative) deviation of outdoor temperature from that cut-off point induces an increase of the space cooling (heating) effect, as a result of the induced indoor-to-outdoor thermal energy disequilibrium. In practice, expressing the temperature- energy demand relationship requires explicit information about (a) the threshold temperature at which space heating demand switches to cooling, and (b) the variation in the sensitivity of climate-sensitive energy demand at different temperature ranges.

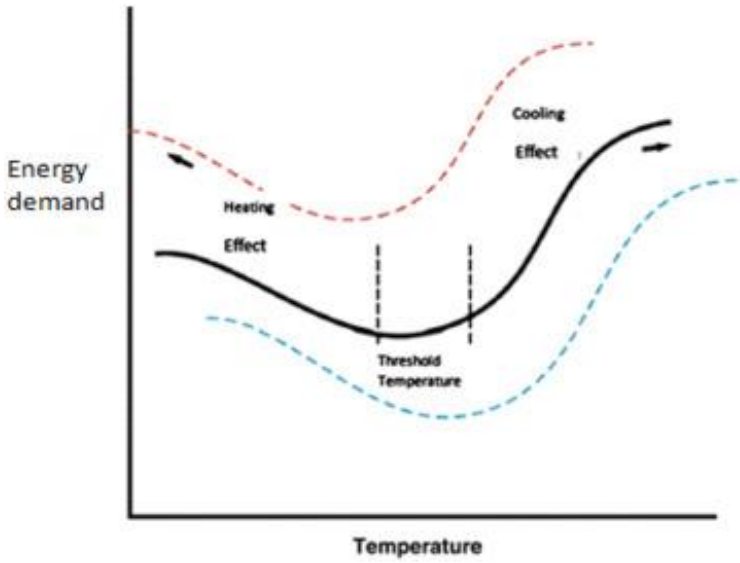


Figure 2-2 The U-shaped relationship between building energy demand and outdoor air temperature Source: Li et al. (2018)

2.3.1.1 Degree days

Degree days is the climatic metric broadly used in the literature to analyse the climate-sensitivity of electricity use in residential buildings (Fazeli et al., 2016). Heating (*HDD*) and cooling (*CDD*) degree days in their simplest form respectively measure the negative and positive difference between daily outdoor air temperature, TMP_{out}, and a pre-specified set-point temperature, TMP_{bh} and TMP_{bc}, as demonstrated by eqn. (2-1) and (2-2) (Mourshed, 2012):

$$HDD = \min(0, TMP_{out} - TMP_{bh}) \tag{2-1}$$

$$CDD = \max(0, TMP_{out} - TMP_{bc}) \tag{2-2}$$

Degree days are then aggregated on the temporal and spatial scale at which electricity use data are collected and serve as a proxy for space heating and cooling demand. Degree days impose a “V-shape” structure on the residential electricity use-temperature relationship, which simplifies the estimation of marginal temperature effects, as they are assumed to be invariant of initial TMP_{out} level. Use of a separate indicator for *HDDs* and *CDDs* offers the benefit to capture potential asymmetrical space heating and cooling effects on past and future residential electricity use.

Amato et al. (2005) and Ruth and Lin (2006) analysed past (1990-2001) residential monthly electricity use in the U.S. state of Massachusetts and Maryland, respectively, employing simple regression models and a set of degree day, electricity price and daylight hours metrics. The performance of the regression models was optimised by iteratively changing the temperature set points based on which *HDDs* and *CDDs* are calculated until they fit best the historical electricity use data. Both papers predict the impacts of future climate change on per capita electricity use to be stronger during the summer season. A similar conclusion was obtained in Ahmed et al. (2012), which found that increasing temperatures will most affect future residential electricity use in summer, but also during spring. However, Ruth and Lin (2006) also stress that assumptions about the development of future electricity prices and local population may have greater influence on residential electricity use than increasing temperatures. Mirasgedis et al. (2007) found that future (2071-2100) changes in GDP, population and energy intensity will be responsible for a 2-6 fold increase in the annual level of electricity demand in Greece from current levels, while the corresponding effect of climate change ranges from 4 to 6%.

Eskeland and Mideksa (2010) estimated a historical (1994-2005) residential electricity use model for 31 European countries using fuel price, income and degree day metrics. Annual *HDDs* and *CDDs* were calculated based on an arbitrary threshold temperature t_{bh}=18 ℃ and t_{bc}=22 ℃, respectively. For a medium-high GHG emissions scenario, they projected end-of-century annual residential electricity use to increase across warmer south European countries relative to current levels (by up to 19% for Turkey), due to higher space cooling requirements. However, the net effect of climate change on European residential electricity use was found to be small and negative, due to important heating-related electricity demand reductions across colder south countries. Moreover, the authors note that non-climatic factors (e.g., socio-economic and demographic changes) will have a greater impact on residential electricity use than climate change alone.

Zachariadis and Hadjinicolaou (2014) used autoregressive distributed lag models to estimate past (1996-2013) electricity use for different sectors in the Mediterranean island of Cyprus, based on income, fuel price and degree day variables. The definition of degree day temperature thresholds followed that from Eskeland and Mideksa (2010). They concluded that climate change will affect most future electricity demand in residential buildings, by increasing annual electricity use levels by 7.7% in 2050, compared to the constant climate scenario. They note that the percentage increase between future and current electricity use levels could be up to 35% in summer months due to climate change, calling for additional installations of electricity generating capacity.

Huang and Gurney (2016a) used simple regression models to relate historical state-level building electricity use in the contiguous United States with monthly *HDD* and *CDD* metrics. Degree day metrics for each state were associated to a unique base temperature which was selected empirically according to a segmented regression method. However, non-weather variables, such as income and fuel price indicators, were not included in the historical analysis of building energy use. Annual source electricity use in the U.S. building was projected to increase by 9.4% in the 2080-99 period above present-day values due to an extreme climate change scenario. More importantly, they stressed that this growth can be much larger (up to 27%) during the cooling season. Likewise, they found important differences between the projected impact of climate change on annual building electricity use for different states, ranging from a 3% reduction in Washington to a 14% increase in Massachusetts.

2.3.1.2 Temperature bins

An alternative measure of climate-sensitive energy use to degree days is the temperature bins (Fazeli et al., 2016). This concept first requires dividing the observed range of mean daily temperatures into bins, whose size is determined either through equidistant cut-off points or temperature percentiles (Auffhammer and Aroonruengsawat, 2011). Instead of measuring degree days relative to a threshold, this method involves counting the number of days whose average temperature falls into a specific bin over a time period. Furthermore, this approach imposes a flexible functional form whereby marginal temperature effects on electricity use vary with the bin in which TMP_{out} belongs. An example of the temperature bins method is shown in Figure 2-3, which was applied for the case of Mexican residential electricity use (Davis and Gertler, 2015).

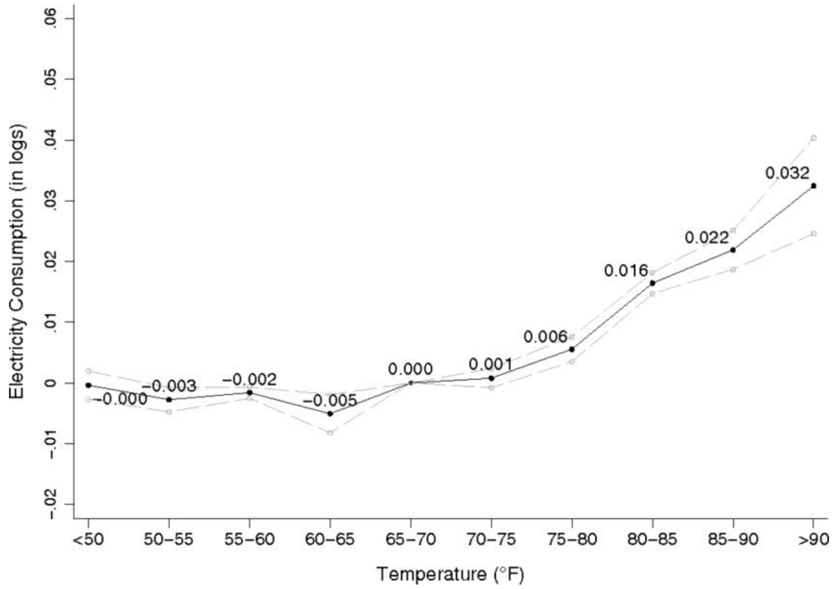


Figure 2-3 Application of temperature bins method for Mexican residential electricity consumption Source: Davis and Gertler (2015)

Temperature bins, often resembling the characteristics of a "U-shaped" model, are believed to be better than degree days in capturing the non-linearity of climatic effects on residential energy use at very warm or cold temperatures (Deschênes and Greenstone, 2011). However, statistical accuracy remains an important issue, as an adequate number of data points is required to empirically identify differential day impacts on residential energy use at the upper and lower tail of temperature distribution. Moreover, more assumptions need to be made about the sensitivity of electricity use to the range of temperatures not observed in the present, but will be recorded in the future as a result of climate change.

Deschênes and Greenstone (2011) used the temperature bins approach to model the dependency of annual state-level U.S. residential energy consumption (1968-2002) to outdoor temperature variation. They then projected end-of-century U.S. annual residential energy consumption to increase by 11% compared to current levels, under a "business as usual" climate trajectory. They also demonstrated that positive space cooling effects on residential energy use outweigh negative heating effects mostly for the warm south U.S. region, resulting in net positive increases of end-of-century energy use.

De Cian and Sue Wing (2019) modelled the influence of weather on energy use for different sectors and energy carriers in tropical and temperate countries, based on bins capturing the days with very high (>27.5 ℃) and low (<12.5 ℃) outdoor temperatures. They then found that moderate (extreme) climate change would increase global residential electricity use by 3% (5%) in 2050, on top of a 384% growth relative to present-day consumption levels under a business-as-usual socio-economic pathway. Van Ruijven et al. (2019) extended previous work by demonstrating the important size of uncertainty in future energy use projections, based on the variation found in socio-economic pathways and Earth System climate model simulations.

2.3.1.3 Raw temperature variables

A third, less widely-applied, approach for assessing space cooling behaviour is linking the variation of residential energy use with raw monthly, seasonal or annual temperature variables (Fung et al., 2006; Asadoorian et al., 2008; Mansur et al., 2008; De Cian et al., 2013). This method has easier application compared to the two previous ones, since it does not require any weather data transformations or any assumptions concerning space cooling and heating thresholds prior to model estimation. Despite its simplicity, using mean temperature variables as predictors of climate-sensitive energy use often masks space heating and cooling effects which work in a different direction (Sailor and Muñoz, 1997). Hor et al. (2005) showed that models of monthly electricity use using degree days overall perform better than those employing untransformed temperature variables, for the case of the United Kingdom.

De Cian et al. (2013) analysed short-run and long-run responses of annual residential electricity use to mean seasonal temperatures for 31 OECD/non-OECD countries. They demonstrated that the variation in residential electricity use in 2085 due to climate change will be positive (negative) for hot (cold) countries due to increasing (decreasing) space cooling (heating) electricity demand.

2.3.2 Critique of current climatic metrics

Although degree days and temperature bins, and to a lesser extent raw temperature variables, are the established methods in the literature, both methods present some drawbacks. These drawbacks relate to their ability to model different features of residential climate-sensitive energy use. Omission of the features which are summarised in this section below may compromise the practical usefulness of these metrics to project the impact of climate change on the future variation of space cooling and heating demand in the residential sector.

(a) Choosing degree day set points based on empirical research

The degree day approach is often criticised for the arbitrary choice of threshold temperatures, which represent the outdoor temperature levels at which space heating and cooling devices are switched on. The vast majority of global and regional studies analysing climate-sensitive residential energy use estimate past and future *HDD* and *CDD* values based on a uniform base temperature of 18.3 ℃ which is kept constant across space (Isaac and van Vuuren, 2009; Labriet et al., 2015; Salari and Javid, 2016). In reality, however, various factors have an influence on heating and cooling set-points, including building stock characteristics, household affluence levels, lifestyle and cultural attributes and non-temperature weather factors (Fazeli et al., 2016).

Strong evidence particularly from top-down studies employing national (Valor et al., 2001; Mirasgedis et al., 2007; Blázquez et al., 2013), city/state (Sailor and Muñoz, 1997; Psiloglou et al., 2009; Ahmed et al., 2012; Lee et al., 2014; Vu et al., 2015) or city-block/building-level (Fikru and Gautier, 2015; Guan et al., 2017) data suggests that degree day temperature thresholds indeed vary across space. Moreover, space cooling is often associated with a different cut-off temperature from space heating demand (Valor et al., 2001; Blázquez et al., 2013; Yi-Ling et al., 2014; Wang and Bielicki, 2018; Li et al., 2018), strengthening evidence for the validity of the *comfort zone* model (Figure 2-4) over the single base temperature one. Moreover, availability of disaggregated U.S. energy statistics helped to demonstrate that degree day base temperatures differ also between residential and commercial buildings. Households tend to have a higher threshold temperature than commercial buildings due to lower internal heat gains (Amato et al., 2005; Ruth and Lin, 2006). All in all, degree day temperature thresholds were demonstrated to be place, technology and sector-specific.

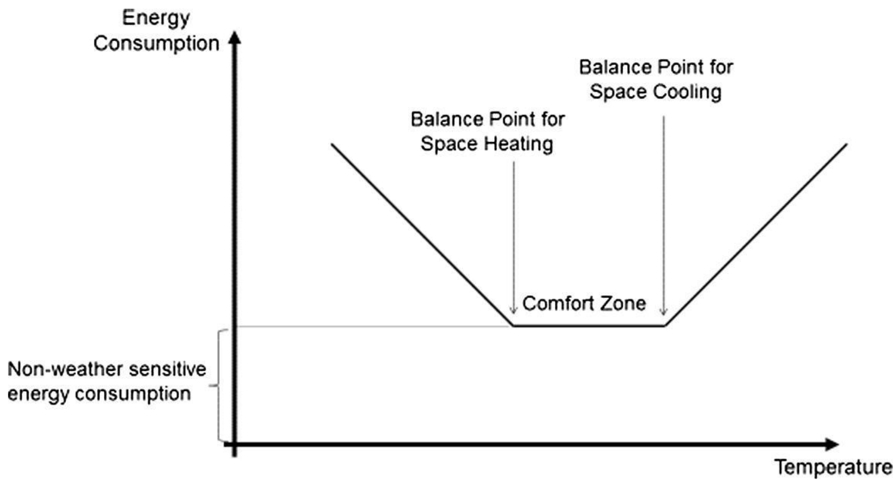


Figure 2-4 Comfort zone model of climate-sensitive energy use in buildings Source: Fazeli et al. (2016)

While the procedure for choosing heating and cooling set-points calculations has not been standardized yet (Azevedo et al., 2015), a well-practiced method involves an ad-hoc optimisation of degree day thresholds according to past energy use observations. This is achieved via an iterative process which identifies the combination of degree day definitions which maximise model fit (Amato et al., 2005; Ruth and Lin, 2006; Huang and Gurney, 2016a; Brown et al., 2016). Less commonly the iterative process finds the model producing the most accurate out-of-sample energy use forecast (Kaufmann et al., 2013). These approaches are believed to more effectively capture the real shape of the temperature-energy demand relationship. However, there is little evidence to suggest that optimised degree day variables perform better than traditional ones, when these are utilised in top-down econometric models of residential electricity use also utilising a set of non-weather exogenous factors (e.g. personal income, fuel price).

(b) Describing extreme weather impacts

Indicators of climate-sensitive energy use (degree days and temperature bins) have been criticised for merely parameterising the variation of mean outdoor temperature, while neglecting the potential effects of temperature extremity on residential electricity use. For example, under extreme weather conditions where diurnal temperature fluctuation is large enough, averaging the maximum and minimum temperature could yield a value belonging in the climate-insensitive zone of the degree day or temperature bins model (Chang et al., 2016). Traditional climate-sensitive indicators would therefore measure a very small effect on space cooling electricity use, which is unrealistic. Degree days and temperature bins also do not account for the effect of persistently high or low temperatures on residential electricity use. As Mansur et al. (2008) explains, the effect of 10 *CDDs*/*HDDs* x 3 days practically is not equal with the impact of 3 *CDDs*/*HDDs* x 10 days, as in the former case households respond to extreme temperatures over a consecutive number of days. In the latter case, small number of degree days distributed over a long time period could have a negligible impact on residential electricity use levels.

Extreme temperature effects on energy use become more relevant when studying the occurrence of heat waves in the summer, namely of extended periods of unusually hot weather (IPCC, 2012). These events intensify the need for space cooling which leads to considerably higher energy consumption levels and peak electric demand. Heat waves are projected to become more important in the 21st century, as a result of climate change, both in terms of increasing duration, frequency and intensity (Meehl, 2004). Insufficiently capturing the impacts of temperature abnormality could lead to an undervaluation of seasonal AC electricity use requirements under different climate change trajectories.

The impact of extreme air temperatures has been traditionally studied using daily time series of total-system’s electricity demand. Historical records of statistically-smoothed peak load are regressed against daily maximum temperature (Miller et al., 2008; Wenz et al., 2017; Auffhammer et al., 2017). Some studies choose to complement model specifications with a mixture of non-temperature weather variables, such as precipitation and wind speed. Model coefficients are then enacted with future simulations of air temperature data to obtain the future distribution and intensity of peak load events under climate change trajectories. Auffhammer et al. (2017) showed that extreme climatic events will affect peak electricity demand more than average load consumption in the United States. However, linking total electricity use with high-frequency climatic data comes at the cost of omitting important socio-economic and energy price variables, which are generally available with coarser temporal resolution. Models of aggregated daily electricity demand also do not allow isolating AC consumption behaviours observed specifically in the residential sector.

There is lack of top-down studies with identification strategies aiming at a first stage to isolate the effect of extreme weather on monthly or annual residential electricity consumption from that of mean temperature, and at a second stage from that of non-climatic factors. Considine (2000), Fu et al. (2015), Lee and Loveridge (2016) and Lee et al. (2017) are the only identified exceptions.

Considine (2000) was the first to assess the effects of random weather surprises on U.S. fuel-specific and aggregate energy consumption, using a demand system of shared equations. Instead of employing a traditional set of degree day metrics, the study uses measures of degree day deviation above 30-year climatological normal to capture temperature abnormality. Warm weather shocks were found to have a positive effect on residential energy demand, through increased AC-driven electricity consumption in summer months. An additional *CDD* deviation per day over the course of a month increases aggregate residential energy use by 0.8%. However, the effect of *HDD* deviations on U.S. residential energy use and carbon emission was shown to be much larger than *CDD's* one.

A more sophisticated definition of extreme temperature events was adopted by Fu et al. (2015) to estimate models of energy consumption for three U.S. metropolitan areas (New York, Chicago, Los Angeles). They identified *heat wave years* by applying a set of criteria on daily records of maximum air temperature. However, they did not find heat waves years having a statistically-significant effect on annual electricity consumption in all 3 cases via the Ordinary Least Squares (OLS) model. Annual population and mean electricity price were instead the most important predictors of electricity use. This may suggest that the effect of heat waves cannot be precisely identified using annual energy use statistics since they mask the seasonal variation of space cooling energy consumption with respect to warm temperatures.

The latest examples in the literature (Lee and Loveridge, 2016; Lee et al., 2017) study the complex temperature impacts on past residential electricity use for a panel of U.S. states. Lee and Loveridge (2016) extended the model of annual electricity use from Deschênes and Greenstone (2011) to include attributes of short-term temperature fluctuation and abnormality. Their empirical analysis demonstrated the improvements in overall model fit achieved through interacting conventional temperature bin variables with other temperature metrics. The marginal impact of abnormally warm days on U.S. residential electricity use was found to be positive, only when the number of hot days in a year is high enough, a condition which as the authors admit is *counterintuitive*. The ambiguous sign of some model coefficients could reflect the fact that seasonal effects of extreme temperature events on space heating and cooling demand are hidden in the inter-annual variation of electricity consumption data.

Lee et al. (2017) built on the previous work by utilising monthly electricity use data for the U.S. residential sector. Their preferred econometric specification included mean temperature and two extreme heat and cold metrics capturing the number of days in a month exceeding the 95th percentile of historical temperature distribution. They concluded that abnormally hot weather in the winter (summer) season leads to a decrease (increase) of monthly residential electricity use, with the former effect being greater than the latter one in hot years. While their model accounts for the frequency of unusually hot and cold days in a month, it does not control for other attributes linked with the duration and intensity of extreme heat events which can also affect AC energy use. Moreover, their analysis is limited on the effect of temperature abnormality on past electricity use, neglecting potential consequences of future climate change.

(c) Modelling acclimatisation effects

Studies utilising degree days to depict the weather-driven changes of space cooling electricity consumption may rely on temperature thresholds chosen either arbitrarily or through post-estimation analytics. While the second method is preferable since it optimises the choice of regional degree day set-points, it still imposes the assumption that these base temperatures are *time-invariant*. This also applies for the time-invariant distribution of cut-off points adopted in the temperature bins approach. While this assumption could hold true with AC electricity demand behaviours the short-run, it is highly questionable whether this would also be the case in the long-run.

In the context of long-term climate change, occurrence of higher-than-average outdoor temperatures over lengthy time periods can increase residents' resilience towards heat. This phenomenon is formally known as *acclimatisation* which has the potential of reducing space cooling electricity use in households, as people begin to feel comfortable with even higher outdoor temperatures (Azevedo et al., 2015; Wang and Bielicki, 2018). Adaptation to climate change may result from causes other than physiological ones (acclimatisation); building archetypes being modified in accordance with changing climatic conditions, as well as declining expectations for thermal comfort and other behavioural responses could also limit the growth of AC energy use (Halawa and Van Hoof, 2012). In practical terms, acclimation to higher TMP_{out} levels increases the acceptable range of indoor temperatures (TMP_{ind} from eqn. (2-5)), which consequently reduces AC-driven electricity demand. Neglecting impacts of acclimatisation on *CDD* temperature set points could therefore lead to an overestimation of projected increases in residential AC electricity consumption under future climate change.

Past assessments have shown that regional set points of climate-sensitive electricity use show strong correlation with long-term mean temperature levels, which is attributed to the acclimatisation of residents (e.g. Lee et al. (2014) demonstrated that for South Korea, and Brown et al. (2016) and Huang and Gurney (2016) for United States). Still, no studies exist yet which have attempted to extrapolate this trend in the future and incorporate its effect in projections of residential electricity use.

Some evidence also suggests that some kind of acclimatisation is exhibited by electricity consumers on a daily basis. This causes the base temperature for space heating and cooling to vary hourly, with both showing a peak in the warmest hours of the day and a minimum in the coolest ones (Wang and Bielicki, 2018). However, modelling the diurnal acclimatisation of residents to heat is more applicable to projections of space cooling electricity use over short time scales (less than a decade). For studies, devising projections of residential AC electricity use on a decadal timescale, modelling regional acclimatisation to long-term weather conditions is a more influential feature.

(d) Capturing non-temperature climatic influences

Degree days and other temperature transformations (e.g., temperature bins) used to explain residential energy demand for space cooling and heating rely solely on statistics of *dry-bulb* temperature (Schaeffer et al., 2012). Variation of building energy use has been previously modelled on the basis of non-temperature weather factors such as humidity, wind speed and cloudiness. Assessments of complex weather effects can be divided into those plugging raw meteorological variables as independent factors in regression models (Sailor, 2001; Apadula et al., 2012; Barreca, 2012; Vu et al., 2015; Chapagain and Kittipiyakul, 2018) and those which develop metrics as a combination of different weather variables. Examples of the latter approach comprise wet-bulb degree days (Krese et al., 2012), enthalpy days (Sailor and Muñoz, 1997; Sailor, 2001; Hor et al., 2005), wind chill/ heat index (Apadula et al., 2012) and *CDDs* adjusted for residual temperature and humidity (Guan et al., 2017).

The strongest evidence revolves about the benefits of encapsulating attributes of air humidity in degree day-based models of electricity use, whose prediction accuracy shows improvements during summer months (Hor et al., 2005; Apadula et al., 2012; Guan et al., 2017; Chapagain and Kittipiyakul, 2018; Xie et al., 2018). This is because dry-bulb degree days restrict the application field of this metric to *sensible* cooling; the load component responsible for removing heat from air thereby lowering room temperature, without altering the absolute humidity content of air (Krese et al., 2012; Friedrich et al., 2014). *Latent* cooling, on the other hand, which is the load reducing indoor air humidity to acceptable levels, is omitted from degree day calculations. However, omission of non-temperature weather controls, especially of air's humidity can introduce bias in identifying temperature's response coefficient, since the two variables are closely related. Nevertheless, temperature is still considered the single most important weather-based predictor of space cooling electricity use, especially when the temporal scale of analysis is longer than a decade (Hor et al., 2005; Mirasgedis et al., 2006; Fung et al., 2006; Mirasgedis et al., 2007; Hong and Kim, 2015).

(e) Representing continuous heating and cooling demand

The weather dependence of continuous cooling processes (e.g. food processing and storage), whose demand does not exhibit a clear seasonal pattern like that for comfort cooling, is not fully embodied in existing residential energy use models. In the context of climate change, prolonged periods of warm weather may cause electricity demand for refrigeration to increase alongside with that for air-conditioning, as the temperature gap fridges need to bridge would be larger. Hekkenberg, Moll, et al. (2009) proposed a theoretical model of building energy use which determines the climate-sensitivity of continuous cooling processes based on an absolute air temperature metric. Wang and Bielicki (2018) analysed past hourly electricity consumption across two U.S. transmission zone and found that a comfort zone exists between the set points for space heating and cooling. Moreover, this comfort zone branch was shown to exhibit a small positive slope, implying that electricity demand increases with temperature even when it is not used for space cooling purposes. Instead, this temperature-sensitive load could be attributed to continuous cooling processes.

(f) Capturing effects on other residential end-use services

The effect of changing degree days, as quantified through an econometric model, does not necessarily portray changes in space cooling and heating demand, as demand for other residential end-use services may also correlate with outdoor temperature (Hekkenberg, Moll, et al., 2009). A prime example of a climate-sensitive end-use is lighting, whose demand increases during winter months as occupants tend to spend more time indoors, when use of space heating equipment is also higher. A seasonal change of residential energy use stimulated by an increase in *HDDs* could in reality hide a small portion of demand attributed to lighting. A way for resolving this identification issue is to include daylight hours as an extra variable in the econometric model's specification, as this could reduce the bias in the coefficient for *HDDs* (Amato et al., 2005). As demonstrated by Bašta and Helman (2013), electricity use in Prague is more responsive to sunshine duration than to temperature when analysing inter-day electricity demand variation. Nevertheless, on longer time scales the predictive power of the temperature variable becomes again superior.

(g) Dynamically changing temperature response function

Intertemporal dynamics driven by socio-economic and technological developments in the residential sector influence both the threshold and slope of the temperature response function. The dynamic nature of climate-sensitive electricity use functions is rarely treated through econometric models using static approaches (Hekkenberg, Moll, et al., 2009). Belzer et al. (1996) is a rare example of research in which the reference temperature and response coefficients for space heating and cooling electricity loads were not assumed to be static for a cross-section of U.S. commercial buildings. These parameters were instead modelled as a function of specific building characteristics and regional climatic conditions. However, this approach requires a significant amount of surveyed bottom-up data, thereby hindering the applicability of dynamic methods over extended political or geographical regions. In these cases, bottom-up techno-economic tools provide more flexible functional forms for capturing the evolving parameters of climate-sensitive electricity use, as in Isaac and van Vuuren (2009).

2.3.3 Saturated AC market – the need for alternative metrics of climate-sensitive energy use

Unlike other household end-uses, space cooling and heating demand exhibits substantial seasonal and spatial variability. Moreover, in the context of future climate change, increases (decreases) of residential space cooling (heating) electricity use as a result of rising temperatures show great spatial (Zhou et al., 2014; Huang and Gurney, 2016b) and temporal heterogeneity (Huang and Gurney, 2016b; Huang and Gurney, 2016a). Moreover, as demonstrated in section 2.3.2, current climatic metrics do not encompass all the features of residential climate-sensitive energy use. This may undermine their role for assessing the full range of climatic impacts on future residential electricity use. In the case of the U.S. residential sector, my first research objective is therefore to improve understanding about the direct relationship between residential electricity consumption and weather variation. The use of a top-down model helps capture the variation of residential electricity use on fine temporal and spatial scales, in contrast to large-scale, technologically-driven, bottom-up modelling tools.

In addition to climate, evidence from section 2.3.1 shows that socio-economic and energy price factors shape occupant behaviours in relation to residential energy use practices (Eskeland and Mideksa, 2010; Blázquez et al., 2013; Salari and Javid, 2016; Fan et al., 2019). As a consequence of this, the anticipated response of residential space cooling and heating demand to climate change, will also depend on the interplay between residential electricity use and these non-climatic factors. Top-down models can be extended to include the broader non-technological factors that bottom-up, process-based, tools may not be able to incorporate (Swan and Ugursal, 2009). Furthermore, the second research objective of this thesis is to accommodate the effect of non-climatic factors in the U.S. model of residential electricity use and compare its size and uncertainty with that of climatic metrics in the mid-21st century.

2.4 Modelling extensive margin responses

The *extensive margin* expresses the socio-economic trend observed in the residential sector, whereby higher outdoor temperature levels encourage more residents to install mechanical air-conditioners in their households. Future adaptation to warmer weather in the residential sector may be expressed in other forms, as households could opt for alternative space cooling sources or invest in building materials with advanced thermal properties (Auffhammer and Mansur, 2014). In this thesis the focus is placed on climate change adaptation expressed through increased AC penetration due to its proven positive feedback effect on residential electricity use that can be flexibly incorporated in top-down econometric models. A larger share of households acquiring an AC unit over time implies that an equal outdoor temperature increase during the summer season would gradually have a stronger marginal impact on residential electricity use.

In practical terms, *extensive margin* adjustments as a result of rising AC ownership rates would cause the temperature response function of residential energy demand displayed in Figure 2-2 to have a steeper space cooling branch. Bessec and Fouquau (2008) detected a progressively sharper space cooling effect when analysing past electricity use of 15 European countries through 5-year rolling regressions. Hekkenberg et al. (2009) demonstrated that to be also true for the case of Netherlands, where the temperature sensitivity of electricity use in specific summer months became more distinct over successive years, possibly reflecting the more widespread use of AC technologies.

2.4.1 Distinguishing extensive from intensive margin responses

The following paragraphs provide a simple description of the economic theory behind the distinction between intensive and extensive margin responses of residential electricity use. In the context of household production theory (Filippini, 1999; Alberini and Filippini, 2011), households are thought to produce different "commodities" by purchasing goods, which include an energy source (e.g. electricity, natural gas, petroleum products) that fuels an energy-using durable good (e.g. boilers, air-conditioners, washers). Household commodities are classified into three categories, as motivated by De Cian and Sue Wing (2019): (a) climate-sensitive energy services (E_{cs}), (b) climate-insensitive energy services (E_{ci}), and (c) a numeraire composite commodity (S). Category, E_{cs}, represents thermal end-uses requiring the input of an array of fuels, $\overrightarrow{Fl_{cs}}$, and a stock of heating, ventilation and air-conditioning (HVAC) technologies, $\overrightarrow{St_{cs}}$. On the other hand, E_{ci}, comprises baseload energy services that combine a set of fuels $\overrightarrow{Fl_{ci}}$ with capital stock, $\overrightarrow{St_{ci}}$. These can be used as direct arguments in the household's utility function via eqn. (2-3):

$$U = (\overrightarrow{Fl_{cs}}, \overrightarrow{St_{cs}}, \overrightarrow{Fl_{ci}}, \overrightarrow{St_{ci}}, S; W, NW) \tag{2-3}$$

According to this utility function, consumption preferences for various commodities are shaped by an array of weather and non-weather based factors, labelled as W and NW. Households then seek to maximise their utility function conditional on their income level (INC), as well as the price of fuels ($\overrightarrow{P_{Fl}}$) and durable goods ($\overrightarrow{P_{ST}}$), as demonstrated through eqn. (2-4):

$$\max_{\overrightarrow{Fl_{cs}}, \overrightarrow{St_{cs}}, \overrightarrow{Fl_{ci}}, \overrightarrow{St_{ci}}, S} U(\,; W, NW) \text{ subject to } \overrightarrow{P_{Fl}}.(\overrightarrow{Fl_{cs}} + \overrightarrow{Fl_{ci}}) + \overrightarrow{P_{St}}.(\overrightarrow{St_{cs}} + \overrightarrow{St_{ci}}) + S \leq INC \tag{2-4}$$

The optimisation problem presented in eqn. (2-4) is solved by demand functions $\overrightarrow{Fl_{cs}}^{*}(W, NW)$, $\overrightarrow{St_{cs}}^{*}(W, NW)$, $\overrightarrow{Fl_{ci}}^{*}(W, NW)$ and $\overrightarrow{St_{ci}}^{*}(W, NW)$ which maximise U, given a set of expectations about the weather and non-weather parameters. For the sake of simplicity the parameter W is replaced with the distribution of outdoor air temperature, F(TMP_{out}), as in Auffhammer and Mansur (2014). At a given outdoor temperature level, households would ideally maximise utility by adjusting their consumption for climate-sensitive energy services (both $\overrightarrow{Fl_{cs}}$ and $\overrightarrow{St_{cs}}$) to achieve the desired indoor temperature level.

However, short-run fixation of capital stock causes households to depart from this behaviour. As a result of this, variation of outdoor temperature leads households in the short run to adjust their demand for climate-sensitive fuels ($\overrightarrow{Fl_{cs}}$), through increased or decreased use of the current stock of HVAC technologies ($\overrightarrow{St_{cs}}$). A positive deviation of TMP_{out} from TMP_{ind} drives up residential electricity use for AC purposes, known as the "cooling effect". For a fixed stock of durables, the amount of heat removed via AC technologies is proportional to the absolute difference between *TMP*$_{out}$ and *TMP*$_{ind}$ (Auffhammer and Mansur, 2014), as shown by eqn. (2-5):

$$\overrightarrow{Fl_{AC}^{elc}} = \overrightarrow{Fl_{AC}^{elc}}\left(|TMP_{out} - TMP_{ind}|; \overrightarrow{St_{AC}}\right) \tag{2-5}$$

In the long-term, however, households are capable of satisfying thermal comfort needs by adjusting energy use for climate-sensitive services via two separate channels. In addition to directly changing the utilisation rate of the existing equipment, households also indirectly control electricity consumption levels via the extensive margin by choosing to modify their stock of AC units. Long-term preferences for the demand of climate-sensitive energy services are further complicated via the warming climate. Climate change will manifest its effects on global and local climatic conditions essentially by modifying the distribution of observed outdoor temperatures, $F(TMP_{out}^{cc})$. This will involve a shift of the distribution's mean towards hotter temperatures, but could also have an impact on its variability and asymmetry properties (IPCC, 2012). Extensive margins are of particular importance for the evolution of AC stock in the residential sector, as warming climate will increase consumers' propensity for buying new units. Estimating future increases in space cooling electricity use therefore requires demand functions which accommodate both the response of fuel usage (Fl_{AC}^{elc}) and AC stock (St_{AC}) to changing climatic conditions, as shown in eqn. (2-6):

$$\Delta E_{AC}^{cc} = \overbrace{\overrightarrow{Fl_{AC}^{elc}}^{*}(TMP_{out}^{cc}) - \overrightarrow{Fl_{AC}^{elc}}^{*}(TMP_{out})}^{1} + \overbrace{\overrightarrow{St_{AC}}^{*}(TMP_{out}^{cc}) - \overrightarrow{St_{AC}}^{*}(TMP_{out})}^{2} \tag{2-6}$$

Capturing extensive margin adjustments of space cooling electricity use, namely the second component of eqn. (2-6), is essential for regions in which AC ownership rates are currently low, but are expected to grow significantly in the future, like in the case study for the EU-28 region.

2.4.2 Practical applications in the literature

Efforts to explicitly or implicitly describe extensive margin feedback loops were identified in papers analysing electricity demand at the global and regional (European) level, or focusing on individual countries like the United States, Canada, Mexico, Brazil, China and India. The main characteristics of top-down studies addressing intensive margin responses, previously reviewed in section 2.3, and those also quantifying extensive margin adjustments are summarised in Table 2-2. The main distinguishing characteristic between the papers in the second category of assessments is in the method through which extensive margins are incorporated in traditional top-down models of residential electricity consumption, i.e. whether these are treated as *exogenous* or *endogenous* factors.

In the *exogenous* case, an independent model of AC diffusion is first developed, based on a set of exogenous parameters, which is subsequently *soft-linked* to a model of residential electricity use. Projections devised via this approach require adjusting the parameters in the reference model of electricity use to account for the changing response of space cooling electricity consumption to higher AC penetration rates. In the *endogenous* case, a single model aims to partially capture the effect of growing AC diffusion on residential electricity use through an approximate measure of the stock of household durables. While exogenous assessments are typically more data demanding as they require detailed – often difficult to find - AC stock statistics with a long time span, endogenous studies rely on cruder assumptions about the nature of extensive margin responses.

The first general finding emerging from the literature on extensive margins is that part of the growing climate-sensitivity of residential energy use in the past was attributed to the increasing stock of air-conditioners in households. Asadoorian et al. (2008) employed a two-stage regression model to first show that, besides personal income and equipment price, seasonal temperature is an important determinant of AC stock size in urban Chinese households. At a second stage, they found that the number of installed AC units as predicted through the first-round regression can explain annual differences of urban domestic electricity use, with an elasticity value close to 0.1. Still, urban electricity use is much more elastic with respect to changes in mean summer temperature (η_{tmp}=2.1), signifying the dominance of intensive over extensive margin responses.

Rapson (2014) developed a dynamic discrete-choice model to analyse AC adoption behaviours in U.S. households and electricity use for space cooling using annual data from the EIA's Residential Energy Consumption Survey (RECS). In the consumer optimisation problem, households are given the option at each time step to purchase a central AC system or individual room units (i.e. extensive margin) and then select the amount of space cooling electricity production (i.e. intensive margin). Along the intensive margin, the marginal effect of exogenous parameters like *CDDs*, income and household square footage on space cooling energy consumption was compared. More importantly, along the extensive margin, AC unit demand elasticities were calculated with respect to the <u>efficiency</u> and <u>price of AC units</u>, as well as <u>electricity prices</u>. The paper finds the demand for air-conditioners to be more responsive to changes in energy efficiency relative to changes in AC unit and electricity prices, with an elasticity value ranging from 0.6 to 1.0 for central units and from 0.2 to 0.3 for room units.

Table 2-2 Summary of top-down studies with a description of intensive and/without extensive margin adjustments

			Study period			
No.	Paper	Study location	Historical	Projections/ Simulations	Int. margin specification	Ext. margin specification
1	Sailor and Muñoz (1997)	8 U.S. states	1984-1994	N/A	Raw temperature, Degree/ enthalpy days, Wind speed	N/A
2	Considine (2000)	United States	1983-1997	+10% CDD and +10% HDD	Degree day deviations	N/A
3	Sailor (2001)	8 U.S. states	10-15 years	+1/+2/+3 ℃ and $2xCO_2$ case	Degree/ Enthalpy days, Wind Speed	N/A
3	Sailor and Pavlova (2003)	12 cities in 4 U.S. states	10-15 years	+ 20% CDD	Degree days, Wind speed	Exogenous
4	Amato et al. (2005)	Massachusetts	1990–2001	2010/2020/2030	Degree days	N/A
5	Hor et al. (2005)	England and Wales	1989-1995	1996-2003	Raw temperature, Degree/ enthalpy days, Wind speed, Sunshine hours, Relative humidity	N/A
6	Fung et al. (2006)	Hong Kong	1990-2004	+1/+2/+3 ℃	Raw temperature	N/A

7	Mirasgedis et al. (2006)	Greece	1993-2002	2003	Degree days, Relative humidity	N/A
8	Ruth and Lin (2006)	Maryland	1990-2001	2005/2015/2025	Degree days	N/A
9	Mirasgedis et al. (2007)	Greece	1993-2003	2071-2100	Degree days	N/A
10	Asadoorian et al. (2008)	Chinese provinces (rural and urban)	1995-2000	N/A	Raw temperature	Exogenous
11	Mansur et al. (2008)	U.S. households	1990	N/A	Raw temperature, Precipitation	N/A
11	Miller et al. (2008)	California	2002-2012	2035-2065, 2070-2099	Extreme heat days, Degree days	N/A
12	Psiloglou et al. (2009)	Athens, London	1997-2001	N/A	Raw temperature, Degree days	N/A
13	Eskeland and Mideksa (2010)	31 European countries	1994-2005	2100	Degree days	N/A
14	Auffhammer and Aroonruengsawat (2011)	California's households	2003-2006	2020-2100	Temperature bins, Precipitation	Endogenous
15	Deschênes and Greenstone (2011)	Contiguous U.S. states	1968-2002	2070-2099	Temperature bins, Precipitation	N/A
16	Valor et al. (2001)	Spain	1983-1998	N/A	Raw temperature, Degree days	N/A

17	Ahmed et al. (2012)	New South Wales	1999-2010	2030/2050/2100	Degree days	N/A
18	Apadula et al. (2012)	Italy	1994–2009	N/A	Degree days, Heat index, Wind chill, Cloud Cover	N/A
19	Krese et al. (2012)	Office building in Slovenia	2009-2010	N/A	Dry and wet-bulb degree days	N/A
20	Blázquez et al. (2013)	47 Spanish provinces	2000-2008	N/A	Degree days	N/A
21	De Cian et al. (2013)	31 OECD/non-OECD countries	1987-2000	2085	Raw temperature	Endogenous
22	Lee et al. (2014)	South Korea (urban and rural cities)	2001-2010	N/A	Raw temperature, Degree days	N/A
23	Rapson (2014)	Contiguous United States (Non-California)	1990-2005	N/A	Degree days	Endogenous
24	Yi-Ling et al. (2014)	Shanghai	2003–2007	2011-2050	Raw temperature, Degree days	N/A
25	Zachariadis and Hadjinicolaou (2014)	Cyprus	1960-2013	2020/2030/ 2040/2050	Degree days	N/A
26	Davis and Gertler (2015)	Mexican households	2009-2012	2070-2099	Temperature bins, Precipitation	Exogenous

27	Fikru and Gautier (2015)	2 Texas households	2012-2013	N/A	Degree days, Solar radiation, Humidity, Precipitation, Wind speed, Pressure	N/A
28	Fu et al. (2015)	New York, Chicago, and Los Angeles	1973–2013	N/A	Raw temperature, Heat wave year	N/A
29	Vu et al. (2015)	New South Wales	1999–2010	N/A	Degree days, Humidity, Rainy days	N/A
30	Barreca et al. (2016)	U.S. households	1980	N/A	Temperature bins	Endogenous
31	Brown et al. (2016)	2003–2012	2003–2012	2015-2040	Degree days	N/A
32	Gupta (2016)	28 Indian states	2000-2009	2030/2050	Degree days, Rainfall	Endogenous
33	Huang and Gurney (2016)	Contiguous U.S. states	2008-2012	2020-2099	Degree days	Exogenous
34	Lee and Loveridge (2016)	Contiguous U.S. states	1968-2002	N/A	Temperature bins, Precipitation bins, Temp. abnormality/ fluctuation metrics	N/A
35	Salari and Javid (2016)	Contiguous U.S. states	2005-2013	N/A	Degree days	N/A

36	Auffhammer et al. (2017)	Contiguous U.S. load zones	2006–2014	2086-2099	Temperature bins, Precipitation	N/A
37	Guan et al. (2017)	Adelaide’s sub-zones/ households	2010-2015	N/A	Raw/ residual temperature, Specific humidity	N/A
38	Wenz et al. (2017)	35 European countries	2006-2012	2013-2099	Temperature bins	Endogenous
39	Auffhammer (2018)	California’s households	1999-2009	2020-2099	Temperature bins, Rainfall	Endogenous
40	Li et al. (2018)	30 Chinese provinces	2009-2014	N/A	Temperature deviations	Exogenous
41	Rivers and Shaffer (2018)	Canadian provinces/ households	2001-2015	2041-2060, 2081-2100	Degree days, Temperature bins	Exogenous
42	Wang and Bielicki (2018)	2 U.S. transmission zones	1999-2007/ 2004-2009	2008-2014/ 2010-2014	Raw temperature, Relative humidity	N/A
43	Forrester (2019)	Brazilian municipalities	2000, 2009-2011	N/A	Heat index, Degree days	Exogenous
44	De Cian and Sue Wing (2019)	Global (204 countries)	1974-2014	2050	Temperature bins, Humidity bins	Endogenous
45	van Ruijven et al. (2019)	Global (204 countries)	N/A	2050	Temperature bins, Humidity bins	Endogenous

Li et al. (2018) utilised panel data for 30 Chines provinces in the 2009-14 period to show that a 1 ℃ deviation of temperature above a pre-defined comfort zone leads to an 9% average increase of monthly electricity consumption during the summer. Of that 9% aggregate temperature effect on provincial electricity consumption, merely 0.5% was due to growing AC stock levels (i.e. the *extensive margin*) and the rest 8.5% was attributable to increased fuel use given a fixed AC stock (i.e. the *intensive margin*). AC penetration rates for the southern Chinese region were found to be less responsive to temperature shocks compared to the northern region. This was attributed to residents in the South being more adapted to warm weather conditions during summer.

De Cian and Sue Wing (2019) analysed sectoral fuel use for different countries to identify the impact of temperature on energy consumption, within an error-correcting framework (first employed by De Cian et al. (2013)) which controls for capital stock changes in the long-run. Similar to Li et al. (2018), their methodological design allows decomposition of the long-run temperature elasticity into an intensive and extensive margin component. Their results regarding temperate countries' residential sector suggest that while the impact of hot days (> 27 ℃) on annual electricity use via the intensive margin has a negative sign, that is counterbalanced by a positively signed extensive margin effect. Above large enough capital stock volumes, the net effect (i.e. intensive and extensive) of hot days on residential electricity use turns positive. This highlights the amplifying effect that residential AC adoption has on space cooling electricity consumption for temperate countries.

This group of top-down studies has developed elegant ways to link the gradual accumulation of capital stock in households with the growing climate-sensitivity of residential electricity use. However, the studies also attempting to project future residential electricity use under various climate change trajectories do not fully embody extensive margin adjustments.

De Cian and Sue Wing (2019) and van Ruijven et al. (2019) acknowledge that their projections are "silent" on the impact of future AC diffusion on residential electricity use in a warming world. Rather they only partially quantify their potential effect on domestic electricity use endogenously, via the estimated long-run temperature elasticity. This has 3 implications for the interpretation of results: First, endogenously estimating extensive margins does not allow constructing detailed scenarios of future AC penetration rates. Second, non-characterisation of future extensive margin responses could underestimate the impact of AC stock accumulation on residential electricity use in the long-run. Third, the identified long-run temperature coefficient based on which extensive margin responses are calculated contains effects which are working in a different direction: the stock of

AC units changing in accordance with warmer temperatures, thereby **increasing** electricity-based final energy use in households. On the other hand, more efficient space cooling units becoming available in the market over time, which **reduces** final residential AC electricity use. These counteracting effects cannot be adequately separated within this modelling framework.

Next, the literature review examines assessments which have included a more comprehensive description of extensive margin responses in projections of future residential electricity use. The core finding from this set of studies is that the evolution of space cooling electricity consumption in small residential AC markets will heavily depend on future extensive margin adjustments. If impacts of AC diffusion are neglected these could lead to a serious underestimation of future household electricity requirements in the summer. Sailor and Pavlova (2003) quantified future extensive margins by adjusting seasonal residential electricity use, modelled through degree day variables, to the proportionate increase of AC diffusion in 12 U.S. cities. Diffusion rates were expressed, as shown in eqn. (2-7), as a non-linear function of long-term *CDDs*, which represent the regional climate:

$$Diff = 0.994 - 1.17 \times \exp(-0.00298 \times CDD) \tag{2-7}$$

Their results showed that with an assumed uniform 20% *CDD* growth across the U.S., climatic impacts on monthly electricity consumption are more pronounced when long-term AC diffusion effects are considered. For example, Los Angeles would face a 5% increase in July's electricity use if AC diffusion levels remained unchanged; if extensive margins are instead incorporated to projections the relative load increase in July for a 20% *CDD* change rises to 8%. In a more recent study, Huang and Gurney (2016) used a corrected form of eqn. (2-7) from McNeil and Letschert (2008) to estimate the change in state-level building electricity use occurring under an extreme climate change trajectory. In contrast to Sailor and Pavlova (2003), the paper concludes that expansion of AC capacity in the residential sector as a result of climate change has a *minor contribution* to future increases of source electricity consumption in the U.S. building sector.

Auffhammer and Aroonruengsawat (2011) and Auffhammer (2018) are two closely-related studies which use microdata for California's households to assess the spatially-heterogeneous effects of weather on electricity use. The former paper demonstrated that the temperature response functions of electricity consumption vary in shape with climate zone. Under a high emissions scenario, the paper projected an aggregate 1-2% increase of California's electricity use in 2040-59, relative to 1961-90 levels, that is attributed to intensive margin responses. Adaptation to warmer weather expressed through AC diffusion is assessed under a hypothetical scenario under which all households are assigned with the steepest temperature response function observed across all climate zones. In this **worst case hypothetical case,** California's electricity use was shown to grow by 3.3-6.2% in 2040-59, indicating the small additional impact of AC diffusion on space cooling electricity demand requirements.

Auffhammer (2018) adopted a similar approach as in Auffhammer and Aroonruengsawat (2011) to estimate temperature response coefficients of electricity use at the California's zip code level. In a second stage, the paper develops a function which relates these empirically-determined temperature response coefficients, with long-term summer temperature statistics. Findings from that part point that households in warmer climates tend to have steeper temperature response functions, as a result of higher AC penetration rates. Without accounting for extensive margin adjustments, moderate (extreme) climate change leads to a 2.2% (3.2%) increase of California's residential electricity use in 2040-59, relative to 2000-15 levels. When extensive margin effects are also added, this percentage increases to 3.2% (4.8%) during the same time frame under the moderate (extreme) climate change case. As the author concludes, this is a small increase for California's electricity system which could be counterbalanced via modest technical efficiency improvements.

Results concerning the significance of extensive margins in the evolution of residential space cooling electricity consumption are more robust for developing and emerging economies. Gupta (2016) analysed the climate-sensitivity of electricity consumption between 2005 and 2009 for a panel of 28 Indian states[4]. This research implicitly controls for AC adoption practices by assuming that Indian states with hotter climate and higher income levels are more inclined to have an air-conditioner installed, and thus their electricity consumption is more climate-sensitive. Under a climate change case of 1 ℃ uniform temperature increase in 2030, total Indian electricity consumption was projected to increase by 6.9% (8.7%), relative to a constant-climate scenario, for a 4% (6%) GDP annual growth rate. Extensive margin adjustments dominate over intensive margin ones in this case, since they were responsible for about 57% of the aggregated climatic effect on electricity consumption in 2030.

Davis and Gertler (2015) used household-level data to model responses of daily electricity consumption in Mexico along the intensive and extensive margin. Diffusion of air-conditioning was found to be sensitive to changes of personal income, whose positive effect becomes more pronounced across warm municipalities. Imposing end-of-century temperature predictions under a moderate (extreme) emissions scenario, while holding AC penetration at present-

[4] AC ownership rate in Indian households was about 5% in 2011 (Shah et al., 2015).

day levels[5], increased annual residential electricity use by 7.5% (15.4%) relative to 2010. Extensive margins were embedded to projections by altering the slope of the temperature response function in a region with a higher future level of AC diffusion, to match the shape of the relevant response function in another region which has the same diffusion level at present times. In this case, end-of-century Mexican electricity use was projected to grow by 64.3% (83.1%) relative to 2010 for the corresponding climatic scenarios. The same qualitative findings regarding the strong interplay between income and climate were obtained by Forrester (2019), who modelled AC diffusion for a cross-section of Brazilian municipalities[6]. This report also demonstrated that when accounting for the spatial distribution of air-conditioners across households, electricity consumption is more climate-sensitive in the wealthier regions.

Barreca et al. (2016) developed a discrete-continuous model to understand the differences in electricity consumption levels between households with and without an air-conditioner for a cross-section of U.S. households. In their model, household AC ownership is controlled via an indicator variable based on 1980's survey values. Their findings show that households with an AC technology consume annually 11% more electricity, compared to non-air-conditioned ones. However, identification of the impact of AC diffusion on residential electricity use is solely based on a single cross-section of data. Rivers and Shaffer (2018) extended the work undertaken by Barreca et al. (2016) by exploring different waves of household survey data. Also, improving on the work in Davis and Gertler (2015) they explicitly modelled the future change in the slope of the temperature response functions for different Canadian provinces[7] as a result of the projected increases in the stock of AC equipment. However, they accounted only for the impact of warmer temperatures on future AC diffusion levels and not for that of growing personal income.

Wenz et al. (2017) performed the only assessment of extensive margin responses of electricity use in Europe. The paper implicitly controls for future adaptation to warmer climates, through assuming a common temperature response function of daily electricity demand/ peak load between European countries. This in essence allowed the authors to assess the potential impact of higher temperatures on electricity demand/ peak load, for cold European countries who currently make very little use of space cooling technologies. This

[5] This paper reports a nationwide residential AC ownership rate in Mexico of 13% in 2010.

[6] This paper reports a nationwide residential AC ownership rate in Brazil of 11.8% in 2010.

[7] This paper reports a nationwide residential AC ownership rate in Canada of 55% in 2013.

is based on the assumption that in the future cold European countries will mimic the behaviour of warm ones. Increased demand for space cooling as a result of long-term climate change caused peak load in many European countries to shift from winter to summer months. While this study endogenises extensive margins responses, it does not identify the specific factors which drive AC diffusion, thereby limiting understanding about future adaptation in households. Moreover, similar to the other studies it does not investigate the magnitude of energy demand reductions which could be achieved through efficiency improvements.

2.4.3 Non-saturated AC market – the need for improved AC diffusion models

In contrast to the U.S. case study, future space cooling demand in the EU-28 region will be determined to a great extent by the gradual diffusion of AC technologies in households. Measuring the direct (i.e. the intensive margin) relationship between residential electricity use and climatic/non-climatic drivers, based on historical observations would mask increases attributed to the adoption of AC equipment: Electricity use in many cold EU-28 countries has a very weak cooling signal, as the use of AC units is currently limited (Bessec and Fouquau, 2008; Damm et al., 2017). Projections of future electricity consumption in this group of countries based on historical load data would be biased, since they do not account for the gradual penetration of air-conditioning in households. Focus is therefore placed on modelling past and future diffusion-driven increases of space cooling electricity consumption across the EU-28 region (i.e. the extensive margin), while controlling for specific climatic and non-climatic influences. Representing different technology options is not a particular strength of top-down modelling specifications. Nevertheless, top-down econometric models with a technological module can describe general appliance characteristics, like ownership rates, as it will be explained in Chapter 3.

2.5 Conclusions from the literature review

From this literature review, the following conclusions can be drawn:

First, there is unanimous evidence that global demand for residential space cooling will increase significantly in the future, albeit at varying growth rates between developed and developing regions. The growth of space cooling demand will be accompanied with substantial increases in electricity use requirements for residential buildings, which in turn put additional stress on regional electricity systems. Additional investments in baseload and peak electricity generating capacity will therefore be required in order to meet AC-driven increases of seasonal residential electricity use. However, existing projections of future residential space cooling demand at the global, regional and national level show important variability, due to the large uncertainties involved in the energy modelling process relating to the representation of climatic and AC diffusion effects. This makes any evaluation about the size of growing cooling-driven impacts on electricity systems an uncertain task. This research is aimed at improving projections of space cooling electricity demand, in order to advance knowledge about the future implications on regional electricity systems from growing AC demand:

Overarching research question: *With increasing residential energy demand allocated to space cooling how can AC-driven impacts be better modelled to understand the potential future implications for energy systems in a carbon-constrained world?*

Second, while the strongest increase in future AC residential electricity use is expected in developing regions, the United States is currently the country with the highest energy demand for space cooling, which is projected to keep rising in 2050. Intensive margins will continue to constitute the major mechanism through which households will adapt to higher temperatures in the future. Given its almost saturated AC market, the U.S. residential sector constitutes an ideal case study for studying the direct relationship between residential electricity use and weather. In section 2.3.1, a number of features of climate-sensitivity of residential electricity use were identified, which are not captured by current climatic indicators. These modelling features will form the basis for developing a new set of climatic metrics in Chapter 4 which improve the model fit and prediction accuracy of historical models of residential electricity use, when applied to different U.S. regions. This leads to the first research question of this thesis:

RQ1: *What set of metrics could be designed which would improve modelling the relationship between residential electricity use and weather, and what are their implications for long-term projections of space cooling and heating loads?*

Third, there is strong evidence that climate change impacts on future residential electricity use will be much stronger on a sub-annual and sub-national scale. At the same time, these climate-driven effects on space cooling and heating electricity demand will interact with the dynamic nature of socio-economic, fuel price and technological developments. Non-climatic drivers, such as personal income and energy prices, which are generally not available at the sub-national spatial and seasonal temporal level, may have an equal or even larger impact on future residential AC electricity use than the climate itself. Chapter 5 brings all these elements together in improving projections of residential electricity use for a saturated AC market in 2050, while quantifying the uncertainty in both climatic and non-climatic impacts at different time scales. This leads to the second research question of this thesis:

Research question 2 (RQ2): *How can climatic impacts be integrated into projections of future residential electricity use for a saturated AC market and how do they compare with the impacts of non-climatic drivers?*

Fourth, compiled evidence points to the direction that the gradual increase in the stock of air-conditioners can partly explain the growing climate-sensitive component of historical residential electricity use in non-saturated AC markets. Moreover, the future level of residential space cooling electricity consumption in these markets will heavily depend on future AC adoption rates. However, availability of consistent annual AC stock data in the residential sector is an important prerequisite for differentiating between extensive and intensive margin adjustments of past residential electricity use. This was found to be rarely the case, except for the China's residential sector. Besides Davis and Gertler (2015), not any work was identified which has assessed the impact of climatic and non-climatic factors on future residential electricity use for a non-saturated AC market, via an explicit model of AC diffusion.

Last, there is a large gap in the literature concerning the potential role of technological efficiency improvements in mitigating the diffusion-driven increases of residential electricity use. While many econometric papers address the effect of accumulating AC stock on growing residential electricity use, no research has directly examined the impact of the diffusion of *more efficient* units in the AC market, as these top-down approaches often lack the technological detail of bottom-up models. This leaves a significant room for improvement in the literature of extensive margins; a topic which is dealt with via Chapter 6 in assessing past and future trends of space cooling electricity use for EU-28 households to 2050. This has formed the third research question of this thesis:

Research question 3 (RQ3): *How can climatic and non-climatic metrics be integrated into models of residential space cooling diffusion in a non-saturated AC market, and what are the implications for long-term projections of residential electricity use?*

Chapter 3
Methods

3.1 Structure of the Methods chapter

Chapter 2 on literature review highlighted the requirements for further research on areas relating to the characterisation of the climate-sensitive component of residential energy use. It also demonstrated the need for projections of future residential electricity use to more effectively integrate climatic with non-climatic impacts at different temporal scales. The previous chapter identified opportunities for additional studies not only addressing direct climatic and non-climatic effects on residential electricity use, but also the indirect impacts on space cooling electricity use through AC technology adoption. This chapter covers an overview of the methodological approaches adopted in this research. The more specific methodological details are included in the content chapters that follow.

The Methods chapter first examines the families of residential energy use models from a methodological standpoint, and provides the rationale for adopting top-down type of approaches (section 3.2). Second, section 3.3 develops the general modelling frameworks which form the basis for the U.S. (Chapter 4 and Chapter 5) and EU-28 (Chapter 6) case studies. Third, it justifies the choice of panel data econometric techniques for estimating the core model modules used for future scenario analysis in both assessments (section 3.4). Finally, section 3.5 and 3.6 formulate the mathematical specifications used to model residential electricity use and AC diffusion for the U.S. and EU-28 region, respectively.

3.2 Review of residential energy use models

3.2.1 Top-down, bottom-up and hybrid approaches

According to Swan and Ugursal (2009), the main distinguishing characteristic between models explaining energy use in the residential sector is whether they have a top-down or bottom-up orientation. In a top-down setting, the focal point of investigation is total energy consumed for all residential end-use services and modelling input typically consists of macro-level variables aggregated across the entire sector. In a bottom-up setting, modelling tools aim at describing energy consumption for individual or a sample of housing units, sometimes disaggregated to different final end-uses. Data input in this case involves micro-level variables regarding building, equipment and occupancy characteristics. Hybrid modelling constitutes a “grey area”, as these models share features with both top-down and bottom-up techniques. Top-down and bottom-up specifications can be further divided into a number of sub-categories, as shown in Figure 3-1, where the main distinguishing characteristic is the general method adopted in modelling residential energy use.

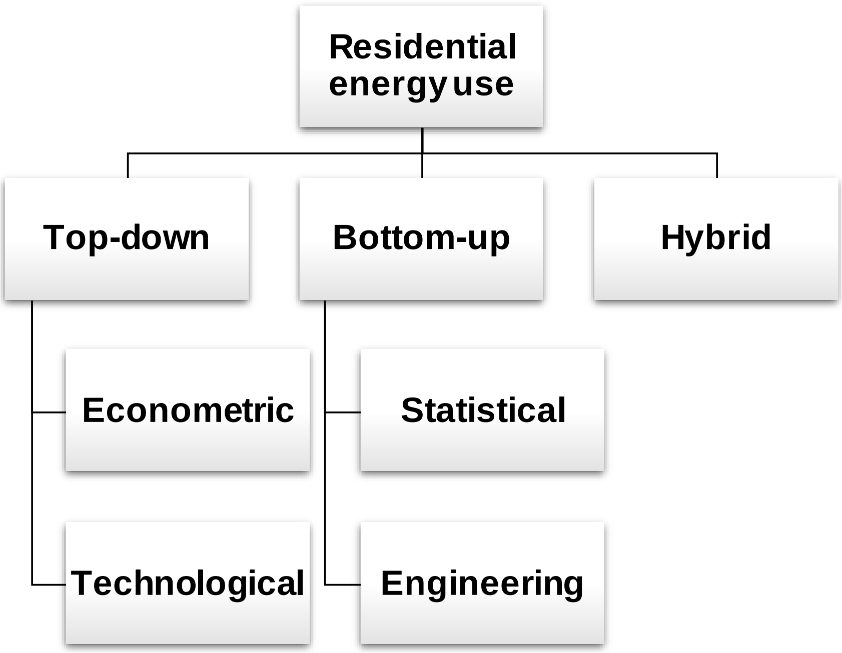


Figure 3-1 Classification of residential energy use models Adapted from Swan and Ugursal (2009)

Top-down is the first major class of residential energy use models, which can be divided into those employing econometric and technological-type approaches. In the former case, reduced-form econometric equations are built to explain the short-run and long-term response of historical building energy use to variables relating to income, fuel price, consumer expenditures and climate characteristics (Eskeland and Mideksa, 2010; De Cian et al., 2013; van Ruijven et al., 2019). Technological top-down models expand the scope of purely economic models by incorporating information about the evolution of housing and capital stock, such as household construction/ renovation and equipment ownership rates (Saha and Stephenson, 1980; Haas and Schipper, 1998; Gonseth et al., 2017).

On the other hand, bottom-up models of residential energy use are classified as statistical or engineering ones. Models belonging in the first category analyse historical household billing information via different statistical routes (i.e., regression, conditional demand analysis and neural networks) to identify the drivers of dwelling energy use. Consumption statistics are often combined with data about weather (Fikru and Gautier, 2015) and socio-economic parameters (Yu et al., 2011; Auffhammer, 2018) building characteristics and occupant behaviour (Ndiaye and Gabriel, 2011) or the presence of appliances (Fan et al., 2017). On the other hand, engineering bottom-up is the only category of models which do not rely on historical statistics, but instead simulate end-use energy consumption for dwelling types representative of the national housing stock. Calculations are primarily based on physical building variables and thermodynamic equations, as well power ratings for various equipment classes. Some examples of assessments using building physics models are Dirks et al. (2015), Huang and Gurney (2016) and Reyna and Chester (2017). Engineering models can be further divided into models using archetypes, distribution and sample techniques.

Finally, ad-hoc hybrid approaches are developed to complement the economic dimension of top-down models with the technological detail of bottom-up tools. This can be achieved by either "soft-linking" a large-scale bottom-up with a top-down model or integrating a bottom-up/top-down model with the "reduced-form" version of another tool (Krysiak and Weigt, 2015). A third way for directly combining a top-down with a bottom-up energy use model is through a mixed complementarity problem framework (Böhringer and Rutherford, 2009).

3.2.2 Model selection: comparison of the strengths and weaknesses of top-down and bottom-up approaches

This section explores the main features of top-down and bottom-up philosophies and identifies the modelling qualities which are most appropriate for addressing the three principal research objectives of this study. Assessment of the general performance (i.e., strong, fair, weak) of top-down and bottom-up approaches according to a number of categories is presented in Table 3-1. The content of this table presents the view of the author of this thesis and is based on information compiled from various modelling reviews in the literature (e.g., Swan and Ugursal (2009), Kavgic et al. (2010), Zhao and Magoulès (2012) and Fumo (2014). Top-down econometric and technological models are considered as a single model family as they often complement each other (Swan and Ugursal, 2009).

Chapter 4 seeks to improve understanding about the relationship between residential energy use and weather for the south U.S. region, through the application of different climate metrics. Modelling attributes which would be particularly appealing for the objectives of Chapter 4 is flexibility to capture the effect of various climatic and non-climatic factors (e.g., demographic, socio-economic, fuel price) on historical residential electricity use at various temporal and spatial scales. While both top-down and bottom-up techniques exist which can measure the statistical effect of weather variability on residential energy consumption, only top-down econometric and bottom-up statistical tools may encompass non-climatic influences, which is a prerequisite for Chapter 4's historical analysis. On the other hand, physically-based, bottom-up, energy models do not facilitate an interaction between end-use demand and external

Table 3-1 Performance of top-down and bottom-up models in various categories

Categories	Top-down	Bottom-up	
	Econometric-Technological	Statistical	Engineering
Incorporate multiple climatic effects	S	S	S
Include socio-economic and price effects	S	F	W
Capture human behaviour	F	S	W
Simulate energy consumption of individual end-uses	W	F	S
Describe technological detail	F	S	S
Are computationally efficient/ not data intensive	S	F	W
Account for discontinuities	W	W	S

Note: Strong (S), Fair (F), Weak (W)

market forces as macroeconomic feedback effects are not adequately modelled (Kavgic et al., 2010).

Chapter 5 extends findings about the statistical performance of various climate metrics in the south and north U.S. region to the national level and aims to build a state-level model of residential electricity use for the contiguous U.S. region. The model is then used to project annual and monthly U.S. residential electricity use in 2050 under different climatic and non-climatic trajectories. Top-down models can more easily expand the scope of analysis over larger regions compared to bottom-up ones as they rely on high-level economic variables. While the higher granularity of micro-data utilised in statistical bottom-up estimations helps model occupant behaviours more effectively than top-down ones, statistical models require input from large household surveys; a task which is more computationally efficient for city or state-level studies. In the context of long-term projections of residential energy use, top-down econometric models are also typically preferred over bottom-up ones “as a computationally efficient alternative” method (Esteves et al., 2015; van Ruijven et al., 2019).This is due to top-down modes allowing to quantify the uncertainty of future climatic and non-climatic impacts on residential electricity use without the need of imposing any assumptions considering technological and behavioural change.

Chapter 6 alternatively studies the evolution of space cooling demand in the EU-28 region and aims to understand past and future impacts of weather and non-weather factors on residential electricity use through increased AC diffusion. As a result, a separate technological module needs to be built to explain the historical and future growth of residential AC penetration and efficiency rates in EU-28 households. Bottom-up models and in particular engineering-based ones, are ideal for simulating dwelling energy use for individual end-use services, due to their rich technological detail. Bottom-up models therefore outperform top-down ones when the objective is to identify the most cost-effective combination of competing technologies to reach specific energy or emissions reduction targets (Reyna and Chester, 2017).

However, the current AC market in the EU-28 region is homogeneous since it is fully dominated by electricity-driven room air-conditioning (RACs) units (Pezzutto et al., 2017), in contrast to U.S. households where central air-conditioning has been more widely adopted (Rapson, 2014). In assuming that no future “discontinuities” occur on the technology side, electric RAC will continue to constitute the main supplier of space cooling in EU-28 households without competing with other technologies, with an efficiency conversion factor which increases incrementally. Under these conditions, a top-down model with a simplified technology module, which adjusts past and future EU-28 space cooling electricity use to changes in the diffusion and efficiency of AC units, would provide more flexibility and transparency than a technologically-detailed bottom-up model. Moreover, the quality of bottom-up engineering simulations is said to be sensitive to potential bias resulting from any inaccurate description of physical properties concerning different equipment or dwelling parts (Kavgic et al., 2010).

Given the above, a traditional top-down econometric model is chosen to examine the direct relationship between household energy use and weather in Chapter 4 and assess the past and future trends of electricity consumption in the contiguous U.S. residential sector in Chapter 5. Moreover, a combination of top-down econometric and technological-type methods is selected to study the evolution of AC electricity consumption in the EU-28 region, in accordance with the growing AC adoption in households.

3.3 General modelling framework

This section expands on the combination of top-down econometric-technological approaches needed in order to achieve the specific research objectives. More importantly, this section explains the demand for differentiated modelling frameworks, each designed in accordance with the maturity stage of regional residential AC markets. The modelling framework adopted for the U.S. case study in Chapter 4 and Chapter 5, tailored to applications for saturated AC markets, is explained in section 3.3.1. The model structure for the EU-28 case study in Chapter 6, adapted to a small, but quickly growing AC markets, is then provided in section 3.3.2.

3.3.1 The U.S. case study

An adapted version of the modelling framework developed in Wadud (2014) for research in transport/cycling is utilised here for analysing energy use patterns in the U.S. residential sector. The model structure shown in Figure 3-2 applies to Chapter 4, where improvements to climate-sensitive metrics are proposed, as well as to Chapter 5, where electricity use model projections are generalised to the whole of the U.S. domestic sector. The U.S. case study is built around an econometric model which balances historical data of monthly state-level electricity sales between 2000 and 2018 with that estimated based on climatic and non-climatic explanatory parameters. At a first stage, traditional degree day metrics are used to depict the climate-sensitive component of monthly electricity use. Non-climatic variables are also included in the model specification to identify the response of electricity use to socio-economic (i.e. personal income) and fuel price (i.e. electricity price) effects. At a second stage, alternative climate metrics are adopted so that the model more accurately portrays the seasonal variation of space cooling and heating demand for a number of U.S. climatic regions. The exact steps followed to improve the estimation and forecasting accuracy of the U.S. electricity use model are elaborated in Chapter 4 (section 4.2.2.1).

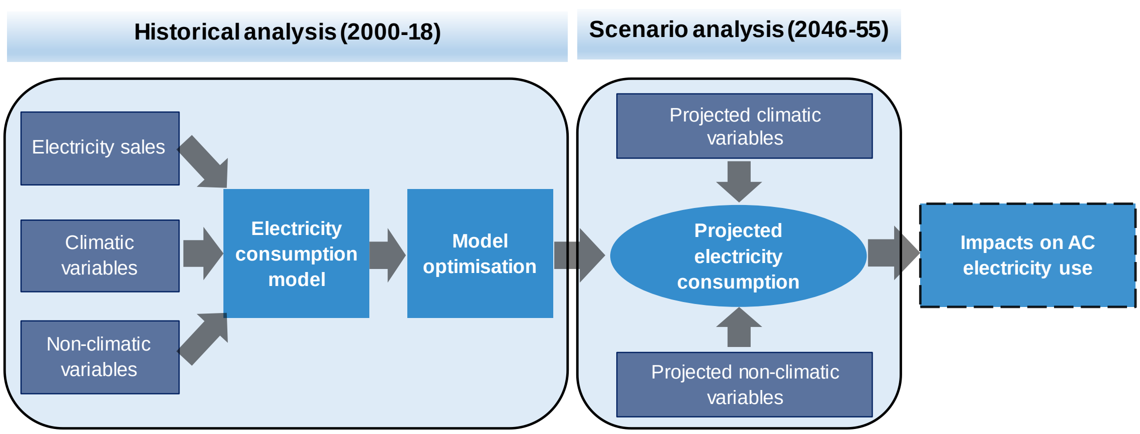


Figure 3-2 Modelling framework for the U.S. case study

Based on the generalisability of Chapter's 4 findings with respect to the performance of different climate metrics, Chapter 5 utilises available climatic and non-climatic data to devise mid-21st century projections for U.S. residential electricity use. In order to determine future consumption levels, the coefficients econometrically estimated via the optimised historical model are enacted with scenario values of population, GDP, electricity prices and temperature in the time period 2046-55. Future changes of residential AC electricity use are determined by the relative change in the climate-sensitive metric for space cooling multiplied by the corresponding model parameter. The seasonal and annual effect of climate change on space cooling is then compared with the effect of growing personal income and electricity prices on overall residential electricity use, under various climatic and non-climatic trajectories in 2050. The assessment is also focused on how the uncertainty of temperature, income and electricity price impacts on residential electricity use varies on an annual and sub-annual basis. Due to the late maturity stage of the U.S. space cooling market, the electricity model does not control for potential changes in AC diffusion rates, as these are assumed to have a small influence on future projections.

3.3.2 The EU-28 case study

Assessing space cooling electricity demand in the EU-28 region requires a different approach as residential AC markets are at an early stage of development and growing diffusion of AC units is thought to be the most important driver. Modelling total residential electricity use and indirectly quantifying demand for space cooling through proxy climatic variables, similar to the U.S. case study, is deemed problematic for two reasons:

(a) Due to the low present-day AC saturation rates in the residential sector, the climate-sensitivity of electricity use at high temperatures is weak in many cold European countries (Damm et al., 2017). Econometric approaches based on historical electricity use observations would generally fail to obtain a statistically meaningful effect of warm weather on space cooling electricity use, as long-run adaptation to a warmer climate through AC diffusion is not captured.

(b) Given the strong seasonality of space cooling demand, analysis would require electricity use data measured on a sub-annual basis. Eurostat, which is the main supplier of the EU’s energy supply and consumption statistics, publishes final electricity use data in the residential sector only on an annual basis (ESTAT, 2015). Moreover, availability of monthly data is limited to total electricity available for the internal market (i.e., electricity available for internal market = net production + imports – exports – used for pumped storage), which does not permit sectoral decomposition of final demand.

The novel modelling framework developed to address the research objectives of the EU-28 case study is presented in Figure 3-3. It is primarily based on annual data for the residential space cooling sector of EU-28 countries sourced from the novel Integrated Database of the European Energy Sector (IDEES), which was published by the European Commission's Joint Research Centre (JRC) in 2018 (JRC, 2017; JRC, 2018b). Historical analysis is performed across two overlapping layers: Traditional index decomposition analysis (IDA) (Achão and Schaeffer, 2009; Nie and Kemp, 2014; Reuter et al., 2019) is first employed to quantify activity, structural and intensity effects on space cooling electricity consumption during the time period 2000-15. More specifically, the historical variation of EU-28 residential AC electricity use is decomposed into the effect of changes in different components, namely household numbers, unit AC efficiency, useful specific cooling demand and AC diffusion. While this stage of analysis employs consumption data obtained at the end-use level, it is still considered as "top-down" in the sense that all input variables represent country-level aggregates. The sensitivity of national AC penetration rates and useful specific cooling demand to climatic and non-climatic influences is then individually studied using two econometric models.

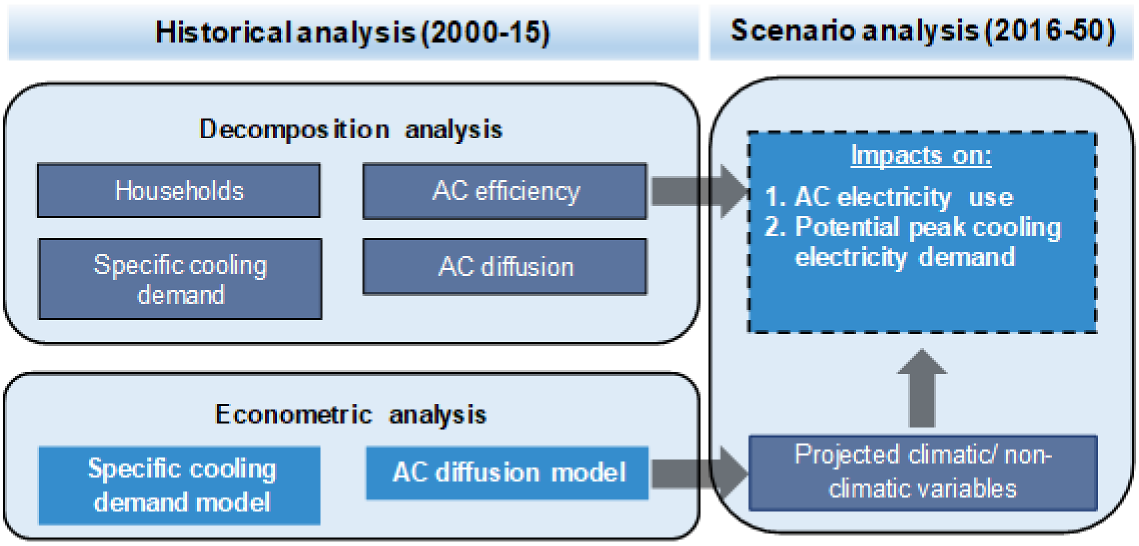


Figure 3-3 Modelling framework for the EU-28 case study

Finally, scenarios are developed to analyse the impact of distinct AC diffusion trajectories on EU-28 sectoral space cooling electricity consumption in the time period 2016-50, as well as on potential peak cooling electricity demand. Future baseline AC diffusion estimates are derived from the econometric model developed in the previous stage, when enacted with country-level projections of climatic and socio-economic data. These are benchmarked against two alternative scenarios concerning future unit efficiency improvements and diversified AC installation rates in new and renovated buildings, for which the assumptions are presented in Chapter 6 (section 6.2.3).

3.4 Panel data econometric models

This section identifies the specific econometric approach which can help develop the major model components comprising the general framework for the U.S. (3.3.1) and EU-28 (3.3.2) case studies; that is respectively an econometric model of residential electricity use and space cooling diffusion. The adopted approach is based on panel data estimation techniques, whose advantages relative to more simplified cross-sectional and time series methods are presented in section 3.4.1. Section 3.4.2 explores the suitability of different panel data estimators in the context of the U.S. and EU-28 case study and finally section 3.4.2 provides the mathematical formulation for the selected panel data method.

3.4.1 Treatment through panel data analysis

While the modelling frameworks developed for the objectives of the U.S. and EU-28 case study focus on different aspects of space cooling demand, they both require application of an econometric technique which accounts for spatial and temporal heterogeneity. In both cases the structure of compiled data is 'panel', meaning that observations for different cross-sections (*N*) are repeated over many time periods (*T*). For the first case study, observations concerning contiguous U.S. states are collected over several months (2000-18), while for the EU-28 case study country-level data are obtained over a number of years (2000-15). It should be noted that in the contiguous U.S. example, the number of cross-sections is larger than the number of time periods (N=49, T=228), while the opposite holds true in the EU-28 case (N=28, T=16).

The simplest way for treating these data would be to pool them together and estimate a residential electricity use and an AC diffusion model, respectively for the U.S. and EU-28 region, using OLS regression. However, estimating these models through standard OLS regression would raise important misspecification issues, since this method disregards the temporal and spatial dimension of data. Ignoring the potential heterogeneity of household consumption and purchasing behaviours between states/countries essentially deems the generated OLS coefficient estimates unreliable (Gujarati and Porter, 2009). As a result, a more sophisticated approach is required for developing the core econometric models for the two case studies.

Panel data econometric approaches, on the other hand, acknowledge the uniqueness of behaviours exhibited by different individuals over time since they can exploit data structures containing a cross-sectional and temporal dimension. More importantly, controlling for individual heterogeneity through panel data techniques reduces the bias in estimated statistical effects, relative to conventional time series and cross-sectional methods (Auffhammer and Mansur, 2014). This is primarily achieved by implicitly controlling for individual-specific factors which remain constant with time and for which no quantifiable information is available. Moreover, more efficient estimates are generated as a result of the increased information and variability stored in panel data and the resulting higher number of degrees of freedom (Baltagi, 2008).

In general panel data estimators fall under two major categories: static and dynamic ones. In the static case, variation in the response variable is solely explained through the estimated effect of selected explanatory factors. In the dynamic case, the response variable is modelled based on the effect of the independent parameters, as well as on the lagged term of the dependent variable which essentially captures its “history”. While the second class of models is said to be better in capturing the long-run adjustments of electricity use (De Cian and Sue Wing, 2019), static estimators are instead adopted for the U.S. and EU-28 case study. This is because the main aim of this research is to devise projections up to 2050 based on future scenario climatic and non-climatic data, rather than on producing accurate predictions or forecasts of electricity use. In the saturated U.S. market, these projections investigate the potential impact on today’s electricity system, if the historical model was re-run with input data for 2050. In the un-saturated EU-28 market, long-run adaptation of residential space cooling electricity use is also partly captured through a separate model for AC diffusion.

3.4.2 A fixed, random or between-effects model?

The most widely applied static panel data estimators are fixed (FE), random (RE) and between effects (BE). The FE class estimates effects based on the temporal variation of observations within each entity (“within-group”), whereas the BE one exploits the cross-sectional variation of observations between entities (“between-group”). The RE class on the other hand estimates a weighted average of “within-group” and “between-group” effects (Greene, 2012). Although a number of statistical tests exist, the choice between a FE, RE and BE model is sometimes subjective as it depends on the nature of the conducted experiment.

When the aim of the investigation is to measure the response of the variable of interest (i.e., residential electricity use/ AC diffusion) to the month-to-month (or year-to-year) variation in selected variables the FE and RE estimators are more appropriate. When on the other hand, the research interest lies on the response of the variable of interest to the long-average value of an explanatory factor the BE approach is preferable. In the U.S. case study, the interest lies in measuring the effect of weather on monthly residential electricity use through application of different climate metrics, while also controlling for short-run responses to socio-economic and energy price variables. Similarly, in the EU-28 case study the aim is to econometrically estimate the sensitivity of AC diffusion to annual changes in weather and non-weather parameters. Due to the focus of my analysis being on the within-group variation of data, the BE estimator is dismissed.

The next step involves choosing between a FE or RE model. In the FE case, inference is conditional on the effects of *N* entities comprising the sample, whereas in the RE case the sample is thought to be representative of a larger population for which unconditional inference is made (Hsiao, 2003). While the FE approach has the major advantage of identifying intercepts which vary with entity, this comes at the cost of reducing available degrees of freedom. This could raise an efficiency issue in the case of a very large N dimension (Baltagi, 2008). The RE model instead assumes that all individual-specific effects are randomly drawn from a common population and thus can be reduced down to a single intercept. Furthermore, deciding on an appropriate estimator requires recognition of whether the tested relationship applies merely to the selected sample or to a larger population; since my investigation is built around data pertaining to all states (countries) of the contiguous U.S. (EU-28) region, the choice of a FE estimator over a RE could be justified.

As Wadud et al. (2019) explains, what makes an FE model appealing for energy policy making is its ability to depict the direction of “change” in the dependent parameter. Generated FE model coefficients resemble the effect on the dependent variable – on average across the panel groups – from a unit change in the independent variables along the temporal dimension. This is a crucial pre-requisite for constructing the scenario analysis for the U.S. and EU-28 case study, whereby predicted changes in climatic and non-climatic variables are used to project future residential electricity use and AC diffusion, respectively. Finally, guidance about the suitability of an RE or FE model is provided through application of a Hausman test, whose null hypothesis is that unit-specific effects are not correlated with independent variables (Hausman, 1978). Potential rejection of the Hausman test is suggestive of the inconsistency of the RE model and the superiority of the FE estimator. Considering the above discussion points, the FE method is adopted when estimating a model of residential electricity use and AC diffusion for the contiguous U.S. and EU-28 region, subject to validation through application of the Hausman test.

3.4.3 Mathematical formulation of the FE estimator

The starting point for estimating a panel data model is specifying a hypothetical one-way regression model, adopting variables notation with a double subscript for the spatial (*i*) and temporal (*t*) unit as in eqn. (3-1):

$$y_{i,t} = \alpha_0 + \alpha_1 x_{i,t} + \alpha_2 z_i + \mu_i + \varepsilon_{i,t} \quad (3\text{-}1)$$

where *y* and *x* are respectively the dependent and (time-varying) independent variable, *z* and denotes the time-invariant explanatory variable, *μ* is the individual-specific intercept and *ε* the idiosyncratic disturbance term.

In the FE case, econometric estimation is based on "within-group" data variation, or in other words on the temporal change in variables for individual states/ countries (Bell and Jones, 2015). The first step for performing a FE estimation is to take the time average of eqn. (3-1):

$$\overline{y_i} = \alpha_0 + \alpha_1 \overline{x_i} + \alpha_2 z_i + \mu_i + \overline{\varepsilon_i} \quad (3\text{-}2)$$

and then subtract eqn. (3-2) from (3-1), to obtain eqn. (3-3):

$$(y_{i,t} - \overline{y_i}) = \alpha_1 (x_{i,t} - \overline{x_i}) + (\varepsilon_{i,t} - \overline{\varepsilon_i}\ ) \quad (3\text{-}3)$$

This data transformation allows estimating the temporal ("within") effect of independent variables (*x*) on the parameter of interest (*y*) via OLS estimation. This is alternatively called the least-squares dummy-variable estimation method, since a series of dummies are added in the model specification to represent unit-specific intercepts (μ_i). In the example of the contiguous U.S. residential sector, 49 unique fixed effects are estimated corresponding to individual states, while 28 country-specific intercepts are generated for the EU-28 region. Furthermore, unit-specific effects are allowed to be correlated to the past, current and future values of the independent variable, which is often true thereby leading to unbiased OLS estimates (Hsiao, 2003). This assumption is formally expressed as the expectation value of μ_i conditional on *x*, given by eqn. (3-4):

$$E\left[\mu_i \middle| x_{i,t}\right] \neq 0 \quad (3\text{-}4)$$

3.5 A FE model of electricity use for the U.S. residential sector

As already discussed in section 2.4.1, electricity use in households can be split into two major categories: *baseload* consumption which refers to the operation of electric appliances that does not vary considerably during the year and *climate-sensitive* consumption which shows great variation between different seasons. In order to model temperature-driven changes of seasonal space cooling (and heating) demand, while also accounting for non-climatic influences, empirical relationships are determined using state-level data obtained with monthly resolution. The **reference** specification described in eqn. (3-5) forms the basis for estimating a state-level model of residential electricity use (*EL*) covering the contiguous U.S. region.

$$EL = f(POP, INC, INCSQ, EP, CDD, HDD, Year, Month) \tag{3-5}$$

The explanatory parameters selected in analysing the past variation of U.S. residential electricity use can be split into socio-economic (*POP*, *INC*, *INCSQ*), energy price (*EP*) and climate-related ones (*CDD*, *HDD*). Dummy variables (*Year*, *Month*) are also added to capture additional unobserved variation. Justification about the choice of individual variables is discussed below:

(a) Population (*POP)*

Perhaps amongst the important determinants of residential electricity use is the size of resident population. Population has been shown to exert a statistically significant influence on annual electricity use in the domestic sector (Blázquez et al., 2013; Burke and Abayasekara, 2018), as well as on economy-wide monthly electricity demand (Mirasgedis et al., 2007; Ahmed et al., 2012). Total residential electricity use can be expressed in *per capita* terms (i.e., *EL_PC=EL/POP*) before entering the model as the dependent variable, so that the population trend is removed. In that regard, while per capita electricity use may remain unchanged between two time periods, total consumption levels would still rise as a result of growing population (Emodi et al., 2018).

(b) Personal income (*INC/INCSQ*)

Evidence shows that there exists a uni-directional causal relationship between income and residential electricity use (Joyeux and Ripple, 2011). Increasing personal income and wealth, stimulate higher energy use in households, which may be partly attributed to consumers purchasing additional air-conditioning and other electricity-consuming devices (Asadoorian et al., 2008). As a result, the elasticity of residential electricity use with respect to income is often found to be significant and positive (Paul et al., 2009; Eskeland and Mideksa, 2010; Alberini and Filippini, 2011; Salari and Javid, 2016). A quadratic *INC* term is also included in the specification to capture diminishing marginal effects of income (Wadud et al., 2019). This additional variable is believed to be especially vital for long-term energy use projections since after demand for household energy services reaches a point of satiation, it does not grow further with higher income levels (Eom et al., 2012).

(c) Electricity price (*EP*)

Economic theory dictates that consumers move along their demand curve following a change in the price of a supplied good according to an own-price elasticity value (Bernstein and Griffin, 2006). Households similarly adjust their demand for electricity as a reaction to a price increase by reducing the use of electricity-intensive equipment or invest in more energy-efficient devices (in the long-run). Furthermore, climate policies aiming to discourage energy consumption in buildings often apply price-based mechanisms, such as a carbon tax (Alberini and Filippini, 2011; Salari and Javid, 2016). Price of electricity has been therefore shown to be a significant driver in models of annual (Eskeland and Mideksa, 2010; Alberini et al., 2011; Burke and Abayasekara, 2018) and monthly (Amato et al., 2005; Paul et al., 2009) residential electricity consumption.

(d) Cooling and heating degree days (*CDD*/*HDD*)

As explained in section 2.3.1.1, degree days have been used extensively as a measure of heat (*CDD*) and cold (*HDD*) stress in buildings and are similarly adopted here as a proxy of space cooling and heating electricity use. In addition to externally sourced degree days, this research employs customised sets of *HDD* and *CDD* metrics calculated at the county level from high-resolution climatic data. This is to ensure that spatially-aggregated *CDD* and *HDD* indicators better capture the variability of outdoor temperatures recorded across each state. *CDDs* (*HDDs*) measure the sum of positive (negative) deviations of daily mean outdoor temperature (TMP_{out}) from a pre-specified base outdoor temperature TMP_{bc} (TMP_{bh}) over a month, as shown through eqn. (3-6) and (3-7):

$$CDD_{county,mo} = \sum_{i=1}^{d} \begin{cases} (TMP_{out} - TMP_{bc}), & TMP_{out} > TMP_{bc} \\ 0, & TMP_{out} \leq TMP_{bc} \end{cases} \tag{3-6}$$

$$HDD_{county,mo} = \sum_{i=1}^{d} \begin{cases} (TMP_{bh} - TMP_{out}), & TMP_{out} < TMP_{bh} \\ 0, & TMP_{out} \geq TMP_{bh} \end{cases} \tag{3-7}$$

where *d* is the number of days in a specific month, *mo*. Under the reference specification of the residential electricity use model, the base temperature for both *CDD* and *HDD* calculations is set at 18.3 ℃. Use of 18.3 ℃ as the reference outdoor temperature in energy use calculations via degree days for U.S. dwellings was established back in the 1920s (Day, 2006). It was based on the assumption that 21.1 ℃ is the acceptable indoor temperature level in U.S. dwellings at which there is no energy demand for mechanical space heating or cooling (Azevedo et al., 2015). The 2.8 ℃ difference between the base indoor and outdoor temperature level represents the heat contribution in buildings from internal gains and solar radiation. Furthermore, the same degree day outdoor temperature threshold (18.3 ℃) has been subsequently applied in building energy modelling studies in the U.S. (Sailor and Muñoz, 1997; Sailor, 2001; Sailor and Pavlova, 2003; Hadley et al., 2006; Alberini et al., 2011; Zhou et al., 2014)[8] and other regions (Valor et al., 2001; Pardo et al., 2002; Fan et al., 2019).

A change in outdoor temperature intuitively has a stronger impact on electricity use when experienced by heavily populated counties rather than less populated ones (Santamouris, 2016). Monthly *CDDs* and *HDDs* are therefore aggregated to the state level after a weighting factor is applied to account for differences in resident population between constituent counties, as given by eqn. (3-8) and (3-9) accordingly:

$$CDD_{s,mo} = \frac{\sum_{county} CDD_{county,mo} POP_{s,county}}{\sum_{county} POP_{s,county}} \tag{3-8}$$

$$HDD_{s,mo} = \frac{\sum_{county} HDD_{county,mo} POP_{s,county}}{\sum_{county} POP_{s,county}} \tag{3-9}$$

where POP_{county} denotes county population in 2010.

(e) Annual dummies (*Year*)/ Time trend

Annual dummies are inserted in the model to account for year-specific effects on residential electricity use which are consistent across the U.S. region. These dummies can capture macro-level shocks on state-level electricity demand which may be the result of passed legislations promoting energy conservation programmes in buildings. Moreover, they can control for potential macro-economic trends like the gradual replacement of the old housing stock with new more energy-efficient buildings. The sub-script *k* takes any integer value from 2 to 19, representing all years from 2001 to 2018 (2000 is the reference year). If the size of annual dummies can be approximated by a linear trend, these will be replaced in the model with a single time variable.

8 The studies of Sailor and Muñoz (1997) and Sailor (2001) apply a higher temperature threshold of 21 ℃ only for Florida.

(f) Monthly dummies (*Month*)

A set of monthly dummies are also included in the basic specification to control for the seasonal variation of residential electricity use, which is not attributable to fluctuating weather, nor is induced by electricity price and personal income changes. Any unobserved variation of electricity consumption levels could arise for example from winter and summer vacation travel patterns (Mirasgedis et al., 2007). These monthly-level effects are fixed across the states and over the years in the sample. The sub-script, *l,* takes any integer value from 2 to 12, covering all months from February to December (January is the reference month).

The aforementioned variables are used to estimate and validate a linear, state-level, model of (per capita) residential electricity use for the south, north and contiguous U.S. region in the time period 2000-18. This is presented in eqn.(3-10), along with the hypothesised signs of involved effects:

$$\begin{aligned} EL\_PC_{s,mo} = \beta_s + \underbrace{\beta_1}_{(+)} INC_{s,mo} + \underbrace{\beta_2}_{(-)} INCSQ_{s,mo} + \underbrace{\beta_3}_{(-)} EP_{s,mo} + \underbrace{\beta_4}_{+} CDD_{s,mo} \\ + \underbrace{\beta_5}_{(+)} HDD_{s,mo} + \sum_{k=2}^{19} \beta_{7,k} Year_{k,yr} + \sum_{l=2}^{12} \beta_{6,l} Month_{l,mo} \\ + \varepsilon_{s,mo} \end{aligned} \quad (3\text{-}10)$$

where *EL_PC*, *INC*, *INCSQ, EP*, *CDD* and *HDD* are defined at the state (*s*) and monthly (*mo*) level and follow the definitions provided in the previous paragraphs. It is hypothesised that a unit positive change in the *INC*, *CDD* and *HDD* variables is associated with an increase of per-capita electricity use. On the other hand, an increase in *EP* is expected to have a decreasing effect on *EL_PC*. The coefficient of *INCSQ* is also predicted to carry a negative coefficient to simulate saturation effects at higher personal income levels.

For the reasons outlined in section 3.4.2, instead of estimating eqn. (3-10) via separate OLS regressions, which would yield unique sets of model coefficients corresponding to individual states, climatic and non-climatic effects on residential electricity use are estimated using the FE strategy. This is also because the research interest of this assessment does not lie in the behaviour of individual states, but rather in overall residential electricity consumption in the United States. Under this setting, panel data estimation for the south, north and contiguous U.S. region results in respectively 16, 21 and 49 state-specific intercepts (β_s) which are allowed to be correlated with the explanatory parameters. A Hausman test is also performed to confirm the superiority of the FE estimator over the RE one. The error term is assumed to follow the typical properties of zero mean and constant variance (i.e., $\varepsilon_{s,mo} \sim IID(0, \sigma_\varepsilon^2)$).

The model described in eqn. (3-10) serves as a reference point for constructing **extended** model specifications in Chapter 4 based on alternative proposed climatic metrics. The same model is used as the basis for devising mid-21st projections of residential electricity consumption for the contiguous U.S. region in Chapter 5. This is accomplished by using the equation coefficients estimated for the 2000-18 period together with new sets of climatic (i.e. *CDD* and *HDD*) and non-climatic (i.e. *INC*, *INCSQ* and *EP*) state-level variables constructed using different scenario values for the 2046-55 period.

3.6 A FE model of AC diffusion for the EU-28 residential sector

Diffusion (*Diff*) of residential air-conditioners in EU-28 countries during the baseline period 2000-15 is studied, in Chapter 6, in a panel data setting through an "s-shaped" logistic growth curve; a functional form first used by McNeil and Letschert (2008) and McNeil and Letschert (2010) to construct a global AC diffusion curve, which was later adopted by a number of global (Isaac and van Vuuren, 2009; Levesque et al., 2018), regional (Mima and Criqui, 2015; JRC, 2018a) and country-level (Akpinar-Ferrand and Singh, 2010; Auffhammer, 2014) studies. An alternative to logistic is a Gompertz-type curve which assumes that diffusion rates approach saturation at a slower pace (van Ruijven et al., 2011; Daioglou et al., 2012). The logistic s-shaped curve is finally selected here as it is the most popular approach in the literature and because a Gompertz function would better suit case studies designed for developing countries. This function simulates the fast up-take of space cooling technologies by poor households with increasing income levels, which then starts to slow down at higher affordability levels. There is no reason for imposing this restriction for future projections in developed EU-28 countries. Similar to Auffhammer (2014), the logistic growth curve is modified via eqn. (3-11) to account for intra-country data variation with a double subscript notation:

$$Diff_{c,yr} = \frac{Sat_c}{1 + \gamma_c exp(\delta X_{c,yr})} \tag{3-11}$$

Saturation (*Sat*) represents the maximum attainable penetration level of air-conditioning in residential buildings which is invariant with time, measured in years (*yr*), and can be unique for each EU-28 country (*c*). Without imposing any ad-hoc restrictions, *Sat* across the EU-28 region can theoretically vary between 0 and 100%. The horizontal position of the logistic curve is adjusted by the constant *γ*, while its slope is controlled by *X*, an array of variables expected to have a positive or negative temporal impact on AC diffusion rates.

Besides local climate, a number of studies have concluded that growing personal income has been a strong determinant of worldwide AC up-take (Biddle (2008) for United States; Auffhammer (2014) for China; Davis and Gertler (2015) for Mexico). Evidence has also shown that energy efficiency improvements and reduction in equipment prices has a reinforcing effect on consumer purchasing decisions with respect to air-conditioners (Rapson, 2014). Bringing these elements together and based on available information, my model explicitly accounts for weather and income changes and implicitly controls for evolving energy efficiency standards and AC prices through a time trend. Rearranging eqn. (3-11) and taking logarithms on both sides produces the following linear model given in eqn. (3-12):

$$\ln\left(\frac{Sat_c}{Diff_{c,yr}}-1\right) = \ln(\gamma_c) + \underbrace{\delta_1}_{(-)} trend + \underbrace{\delta_2}_{(-)} INC_{c,yr} + \sum_{r=0}^{R} \underbrace{\delta_{3yr-r}}_{(-)} TMP^{JJA}_{c,yr-r} + \varepsilon_{c,yr} \tag{3-12}$$

where *INC* denotes annual personal income in individual EU-28 countries, as approximated by per capita GDP which is adjusted to represent between-country price-level differences based on purchasing power parity (PPP). The response of AC diffusion to weather variation is captured through TMP^{JJA} which accounts for mean outdoor temperature in the summer months June-July-August (JJA). A TMP^{JJA} lag (R=1) is subsequently added to control for the delayed impact of extreme heat events on AC ownership rates (Auffhammer, 2014). Since the impact of a unit change of temperature is expected to be stronger in areas with larger population (Santamouris, 2016), the variable TMP^{JJA} is adjusted, through eqn. (3-13), to account for the heterogeneous distribution of residents across each EU-28 country. This is achieved by applying weights corresponding to 2014's population count of "Nomenclature of territorial units for statistics – level 3" (NUTS-3) sub-regions:

$$TMP^{JJA}_{c,yr} = \frac{\sum_{NUTS} TMP^{JJA}_{NUTS,yr} POP_{c,NUTS}}{\sum_{NUTS} POP_{c,NUTS}} \tag{3-13}$$

Due to the transformation of the logistic model, a positive change in one of the variables on the right-hand side of eqn. (3-12) results in a decrease of the *Diff* variable, when other terms are kept constant. Furthermore, it is expected that model coefficients pertaining to *INC*, *TMP* and *trend* carry a negative sign, in accordance with their positive effect on AC diffusion. As my interest is in overall diffusion rates in the EU-28 region, instead of running an OLS regression for eqn. (3-12), which would yield 28 unique sets of model coefficients corresponding to each EU-28 country, the income and weather effect on residential AC diffusion is identified via FE estimation. The FE estimation is also preferred over single-country regressions as there are few observations in the time dimension (T=16). The FE panel data estimator estimates 28 country-specific, time-invariant, effects (γ_c). A Hausman test is also performed to confirm the superiority of the FE estimator over the RE one. Finally, a well-behaved disturbance term is added (i.e., $\varepsilon_{c,yr} \sim IID(0, \sigma_\varepsilon^2)$).

Matching future *Sat* levels in EU-28 countries with present-day AC diffusion rates observed in regions of United States with similar climatic conditions – the so called “Climate Maximum” approach (McNeil and Letschert, 2008; Isaac and van Vuuren, 2009)– would cloud analysis with strong assumptions about the pace of evolution of regional AC markets. This approach assumes that current AC penetration rates in the United States represent the maximum attainable level of space cooling diffusion for a given climate, represented via long-term mean *CDD* levels. An exponential function is often used to describe the dependence of AC saturation rates to a region’s climate; with cooler regions having low predicted saturation levels which increase rapidly with modest changes in *CDD*s. On the other hand, warmer regions are expected to have high potential diffusion rates which move slower towards full (100%) saturation.

However, it is questionable whether in the future EU-28 populations will fully adopt the cooling intensive lifestyle observed in the U.S. residential sector. Jakubcionis and Carlsson (2017) calculated the potential saturation rate for residential space cooling in EU-28 countries using the Climate Maximum approach. They found the maximum potential AC diffusion level to be 97% for Cyprus and Malta and 85% for Spain. These represent a huge increase from the current AC diffusion levels, which were 27%, 24% and 10% in 2015 for Cyprus, Malta and Spain, respectively, according to JRC-IDEES data (JRC, 2018b). Large discrepancies between the climate maximum and current AC diffusion levels are also reported for cooler EU-28 countries, like France where only 4% of households had an AC unit installed in 2015 and the predicted saturation rate is expected to be 60%.

Instead, a different approach is followed to determine these ceiling values empirically. EU-28 countries are first split in two groups according to long-term (1995-2015) *CDDs*, each of them assumed to reach a unique saturation point: countries with higher than average *CDDs* are labelled as warm, while the rest of them are named as cold. The statistical performance of the historical *Diff* model is iteratively evaluated for various group-level *Sat* values through the adjusted-R^2 criterion. Sat_{cold} is constrained to be always smaller or equal to Sat_{warm}, while both variables are set to vary above the highest current AC diffusion level in each region. Since the highest national penetration rate for residential space cooling recorded in 2015 is respectively 48% (Croatia) and 19% (Slovenia) for warm and cold EU-28 countries, Sat_{warm} is therefore allowed to vary from 50% to 100%, while Sat_{cold} from 20% to 100%, at steps of 10%. A combination of saturation points that maximise the historical model's goodness-of-fit are finally adopted.

The model described in eqn. (3-12) is used as the basis for developing baseline projections of residential AC diffusion for EU-28 countries in the 2016-50 period. This is achieved by using the equation coefficients estimated for the 2000-15 period together with new sets of climatic (i.e. TMP^{JJA}) and non-climatic (i.e. *INC*) country-level variables built using different scenario values for the 2016-50 period. Projections of AC diffusion are then translated into future impacts on space cooling energy use and potential peak cooling electricity demand.

3.7 Summary of methods

Chapter 3 has developed the methods needed to address the research questions of this study. It begun with providing a summary of the main characteristics of top-down, bottom-up and hybrid modelling philosophies. It then proceeded with identifying the specific modelling features which are most appealing for the aims and objectives of the U.S. (Chapters Chapter 4Chapter 5) and EU-28 (Chapter 6) case study, reflecting on the relative strengths and weaknesses of top-down and bottom-up approaches. The chapter then designed two separate modelling frameworks for studying the evolution of past and future space cooling electricity use for a nearly-saturated (U.S.) and small, but quickly growing, (EU-28) AC market. The first framework is built on pure top-down econometric techniques, while the second one employs a combination of top-down econometric and technological approaches. Chapter 3 also provided the rationale for treating the core econometric models of this study through FE panel data estimation. Finally, this chapter selected the specific variables and structure of the mathematical models used in Chapter 4/5 and Chapter 6 respectively for analysing past and future trends of U.S. residential electricity use and EU-28 AC diffusion.

Chapter 4

Testing alternative metrics of climate-sensitive energy use

4.1 Introduction

4.1.1 Chapter structure

This chapter aims at upgrading metrics and developing a new set of climate indicators to improve knowledge about the relationship between weather and energy use in the residential sector. In doing so, it evaluates the implications for historic modelling performance and future projections of residential electricity use from incorporating the generated set of alternative climate metrics to traditional econometric models. Modification of existing climate indicators and construction of new metrics is guided through a selection process, explained in section 4.1.2, which evaluates the importance of identified short-comings in current approaches against a set of qualitative criteria. The chapter then proceeds with employing the metrics developed in section 4.2.2.1 to analyse the evolution of past (section 4.3.2 and 4.3.3) and future (section 4.3.4) residential electricity use using the case study of the south U.S. climatic region. This chapter also provides a discussion regarding the relative performance of alternative climatic metrics (section 4.4.1) and their implications for future generation capacity requirements in south U.S. power sectors (section 4.4.2). Finally, section 4.5 summarises the conclusions of this chapter.

4.1.2 Selecting modelling features for further investigation

From the presented critique on degree days and equivalent temperature metrics in section 2.3.2, it becomes evident that existing approaches are limited in portraying the weather–energy use relationship in a comprehensive manner. The extent to which each omitted feature from climate metrics could compromise the quality of space heating and cooling load projections is first evaluated on theoretical grounds, on the basis of 3 qualitative criteria developed for the purposes of this research: (a) their relevance for residential end-use electricity consumption, (b) their applicability to projections of climate-sensitive energy use carried out on timescales longer than a decade and (c) ease of treatment through econometric analysis.

Table 4-1 presents the correspondence between each modelling feature and the 3 qualitative criteria. Amongst features pertaining to the application of climatic metrics, setting degree day temperature thresholds through empirical analysis (**No. 1**), describing the effects of extreme weather (**No. 2**), and capturing acclimatisation processes (**No. 3**) and non-temperature weather influences (**No.

4) meet all three qualitative criteria. On practical grounds, **No. 1** is the only feature whose implications on decadal projections of residential energy use have been examined. Using optimised base temperatures in degree days formulation has been shown to result in a smaller predicted increase of building electricity use in most of the U.S. states for an extreme climate change scenario, compared to when using the conventional 18.3 ℃ value (Huang and Gurney, 2016). Empirically selecting the temperature set point for degree day calculations is therefore a first step for improving the reliability of future residential electricity use projections in this chapter.

Table 4-1 Correspondence between modelling features and qualitative criteria

No.	Modelling feature	Relevant for residential consumption	Applicable on a decadal timescale	Suitable for econometric analysis
1	Choosing degree day set points based on empirical research	Yes	Yes	Yes
2	Describing extreme weather impacts	Yes	Yes	Yes
3	Modelling acclimatisation effects	Yes	Yes	Yes*
4	Capturing non-temperature climatic influences	Yes	Yes	Yes
5	Representing continuous heating and cooling demand	No	No	Yes
6	Capturing effects on other residential end-use services	Yes	No	Yes
7	Dynamically changing temperature response function	Yes	Yes	No

* As explained in the main text, long-term acclimatisation can be only studied within a cross-sectional modelling framework.

Researchers across many disciplines have specifically focused on heat wave trends because of the significant risks they pose for natural and human systems (IPCC, 2012). Despite the attention received, there is no general agreement about the appropriate use of extreme heat metrics, since definitions are tailored to satisfy study-specific objectives. As Smith et al. (2013) further explains, definitions also vary as a result of the variety of factors involved in the calculation of extreme heat statistics; this includes the choice of a representative heat stress metric, an absolute or relative threshold above which temperature is considered as abnormal and a measure for the heat event's duration. Moreover, given climate's transformation into a future state where heat waves become longer, more frequent and intense (Meehl, 2004), projecting the additional effect of temperature extremity on seasonal electricity loads via growing space cooling demand is essential (**No. 2**).

Modelling non-temperature, weather-based influences (**No. 3**) is not considered as essential precondition in devising decadal projections of climate-sensitive energy use given the prevalence of temperature-based impacts. Nevertheless, increased humidity during periods of unusually hot weather leads to higher heat stress levels, exacerbating the thermal discomfort perceived by residential consumers (Zuo et al., 2015). The potential amplifying effect of air humidity on future residential electricity use during heat waves is also explored in this chapter.

On the other hand, parameterising long-term acclimatisation adjustments in residential electricity use projections (**No. 4**) is more plausible within a cross-sectional framework; one in which temperature set points for *CDDs*/*HDDs* derived from historical data for different regions are plotted against long-term average temperatures. This relationship could then be used to evaluate the potential magnitude of AC-based electricity use avoided due to acclimatisation, by allowing regional degree day thresholds to evolve over time with increasing mean outdoor temperatures. However, this approach has two main shortcomings: (a) it disregards the rich information hidden in the temporal dimension of data, and (b) constitutes an *ex-post* analysis of acclimatisation effects, which does not elaborate on the actual factors *driving* acclimatisation. Given the other possible routes to climate change adaptation, including through choices over different building materials and technologies, it is uncertain whether (physiological) acclimatisation will be the main driver of degree day thresholds in the future.

Continuous heating and cooling (**No. 5**) is of lesser relevance for residential end-use electricity consumption. In the U.S. residential sector for example, food refrigeration which is the most common continuous cooling service accounts only for 7% of sectoral electricity use (as opposed to 17% from air-conditioning) (U.S. EIA, 2017a). Moreover, demand for continuous cooling exhibits weaker temperature dependence compared to that for comfort cooling and heating, and consequently has minor influence on decadal projections of climate-sensitive residential electricity use.

Climatic indicators (degree days and temperature bins) may incorrectly simulate a change in electricity use that is not entirely driven by demand for space heating and cooling (**No. 6**). Thus projecting future climate-sensitive electricity use through these indicators may hide some increases attributed to lighting, whose demand correlates with cold weather as days become shorter and people spend more time indoors. While this seasonal lighting effect could be important in the short-run, long-term projections of residential climate-sensitive electricity use are more likely to be dominated by space heating and cooling loads. Lastly, controlling for structural changes which alter the shape of the residential energy use-weather relationship (**No. 7**) would require/ depend on numerous assumptions about future technology, building and behavioural characteristics. While technologically-detailed bottom-up models can model such dynamic relationships, future projections are filled with uncertainty.

In summary, degree days and other temperature-related metrics are shown to have key drawbacks which may have different implications for long-term projections of residential electricity use. This chapter therefore seeks to assess these missing features through developing alternative climatic metrics.

4.1.3 Specific research objectives

This chapter moves the literature forward by exploring methodological deficiencies discussed in the previous section relating to the use of existing climatic metrics in residential electricity use models. Alternative climate metrics are examined through a case study which analyses historical (2000-18) and future (2046-55) monthly residential electricity use for a panel of U.S. states located in the southern climatic region. The study's specific objectives are presented below:

(a) Quantify the benefits arising in terms of improved model fit and prediction accuracy from applying alternative set-point temperatures for the calculation of degree day variables (No.1 feature in Table 4-1). For the purposes of this research objective, a panel data model of residential electricity use is estimated and validated for the 16 states of the U.S. south climatic region using monthly data for the historical period 2000-15 and 2016-18, respectively. Econometric estimation is based on traditional degree day metrics and a set of socio-economic and fuel price variables. The reference econometric model uses readily-available published records of degree days, while the second base model employs degree days calculated from high-resolution temperature data with a uniform 18.3 ℃ threshold level. The third (optimised) base model version allows the threshold temperatures for heating and cooling degree days in the south U.S. region to vary until optimal fit is achieved.

(b) Assess the potential magnitude of extra improvements achieved by complementing the optimised degree day model with a combination of indicators describing various attributes of extreme heat and cold episodes (No. 2 feature in Table 4-1). These new metrics which are defined in 4.2.2 specifically control for the total and average duration and intensity, as well as the frequency and single-occurrence, of heat and cold waves during a particular month. Each model version incorporates a separate metric of extreme temperature events; this results in a total of 6 extended candidate historical models of per capita residential electricity use. Moreover, potential additional benefits for the model's fit and forecasting strength are evaluated from further extending these 6 candidate specifications to include a measure of air humidity (No.3 feature in Table 4-1). This process yields the final set of 6 humidity-based extended specifications, bringing the total number of candidate specifications up to 15.

(c) Finally, evaluate the practical usefulness for seasonal load projections of extending electricity use models to include empirically-determined degree days and controls of extreme temperature and humidity. This is assessed on the basis of monthly residential electricity use projections devised in the mid-21st century under a high-end climate change scenario and reference assumptions for the evolution of socio-economic and energy price variables. Projections in 2046-55 based on the extended model specifications are compared with those built following standard climatic metrics to evaluate the sensitivity of future climate-sensitive electricity use to extreme weather and humidity effects.

4.2 Data and Methodology

4.2.1 Modelling framework

The analysis is built around the general modelling framework which was presented for the case study of U.S. residential electricity use in Figure 3-2 (section 3.3.1). This chapter extends the general framework to address the specific steps required in optimising the performance of the historical electricity use model, as illustrated in Figure 4-1. A base panel data model of monthly, state-level residential electricity use is first estimated for the south U.S. climatic region using traditional degree days, personal income and electricity price as explanatory factors. An optimisation procedure is then followed, whereby model performance – evaluated through a series of statistical criteria – is upgraded via three successive steps: (a) allowing temperature set points to vary in heating and cooling degree day calculations, (b) incorporating measures relating to the duration, frequency and intensity of extreme heat and cold events, and (c) capturing the interaction between extreme temperature and air humidity effects.

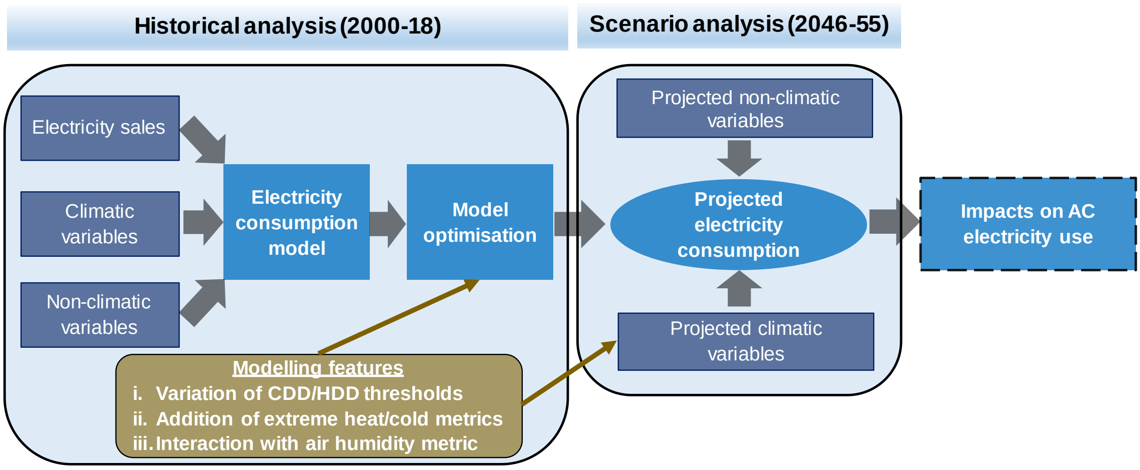


Figure 4-1 Modelling framework for the south U.S. case study

The various forms of the historical electricity use model are estimated using data collected in the 2000-15 period and subsequently validated for the 2016-18 period. The term 'base' is used to label econometric specifications depicting climate-sensitive electricity use through different definitions of dry-bulb degree day metrics from this point onwards in the chapter. 'Extended' is also a term assigned to degree day specifications which are complemented with a series of metrics capturing attributes of heat and cold wave events, and air humidity statistics. Models estimated based on both the base and extended specifications are used together with scenarios of future climatic and non-climatic data to project residential electricity use in the mid-21st century (2046-55). Finally, the projected differences of electricity use levels in the 2046-55 period between the extended and base model help assess the potential misallocation of future annual and seasonal climate-sensitive (AC and heating) loads from adopting traditional definitions of degree days and neglecting extreme weather and humidity factors.

4.2.2 Modelling historical residential electricity use for the south U.S. climatic region (2000-18)

The base econometric model presented earlier in eqn. (3-10) is used to estimate historical (per capita) residential electricity use (*EL_PC*) in the south U.S climatic region based on the effect of degree days (*CDD/HDD*), personal income (*INC*) and electricity price (*EP*):

$$EL\_PC_{s,mo} = \beta_s + \beta_1 INC_{s,mo} + \beta_2 INCSQ_{s,mo} + \beta_3 EP_{s,mo} + \beta_4 CDD_{s,mo} + \beta_5 HDD_{s,mo} + \sum_{k=2}^{19} \beta_{7,k} Year_{k,yr} + \sum_{l=2}^{12} \beta_{6,l} Month_{l,mo} + \varepsilon_{s,mo} \quad (3\text{-}10)$$

The temporal effect of the explanatory variables on monthly state-level electricity consumption is obtained through a FE panel data estimator, which also controls for state (β_s) and time-specific ($Year_{yr}$, $Month_{mo}$) fixed effects. The model's parameter coefficient's are estimated (used interchangeably with the term 'trained') using data for the 2000-15 period, while the performance of each model is tested (used interchangeably with the term 'validated') for the 2016-18 period.

In the reference case (**Base₀**), the climate-sensitive part of residential electricity use is modelled via external degree day variables, published in a public domain by the National Oceanic and Atmospheric Administration's (NOAA's) Climate Prediction Centre. NOAA derives daily temperatures for state climate divisions by relating them to nearby weather station records, which are used as the basis for calculating monthly heating and cooling degree days via a uniform 18.3 ℃ set point temperature. Degree days are then aggregated from the climate division to the state level through applying weightings corresponding to the population of each division for 2010.

4.2.2.1 Developing alternative metrics of climate-sensitive energy use

The second specification (**Base₁**) utilises degree day metrics which are constructed from gridded air temperature records being the product of a reanalysis process conducted by the National Centre for Environmental Prediction (NCEP). Daily temperatures at the population centre of each county were estimated, after matching each county's centre of population for 2010 to the 4 nearest grid points using geographical data from the U.S. Census Bureau (U.S. Census Bureau, 2011). NCEP's temperatures were interpolated between the 4 grid points following the inverse distance weighting method (Oyana and Margai, 2015), shown by eqn. (4-1):

$$TMP_{county} = \frac{\sum_{g=1}^{4} w_g \, TMP_g}{\sum_{g=1}^{4} w_g} \quad (4\text{-}1)$$

where TMP_{county} denotes the daily temperature at the centre of population of a county, TMP_g is the temperature at the adjacent grid point, g, and w is the corresponding weighting factor. The weighting is calculated as the inverse of the (great-circle) distance between the centre of population and adjacent grid point to the power of 2. Records of monthly, county-level, *HDDs/CDD*s were then constructed for the time period 2000-18 and averaged across each state, using county populations for 2010 as weightings. Similar to the reference $Base_0$ model, $Base_1$ applies a fixed 18.3 ℃ threshold temperature in the definition of monthly state-level *CDDs* and *HDDs*. Annual-mean (2000-18) levels of *CDDs* and *HDDs*, calculated with a uniform 18.3 ℃ set-point temperature, are plotted in Figure 4-2 for the 49 states comprising the contiguous U.S. region.

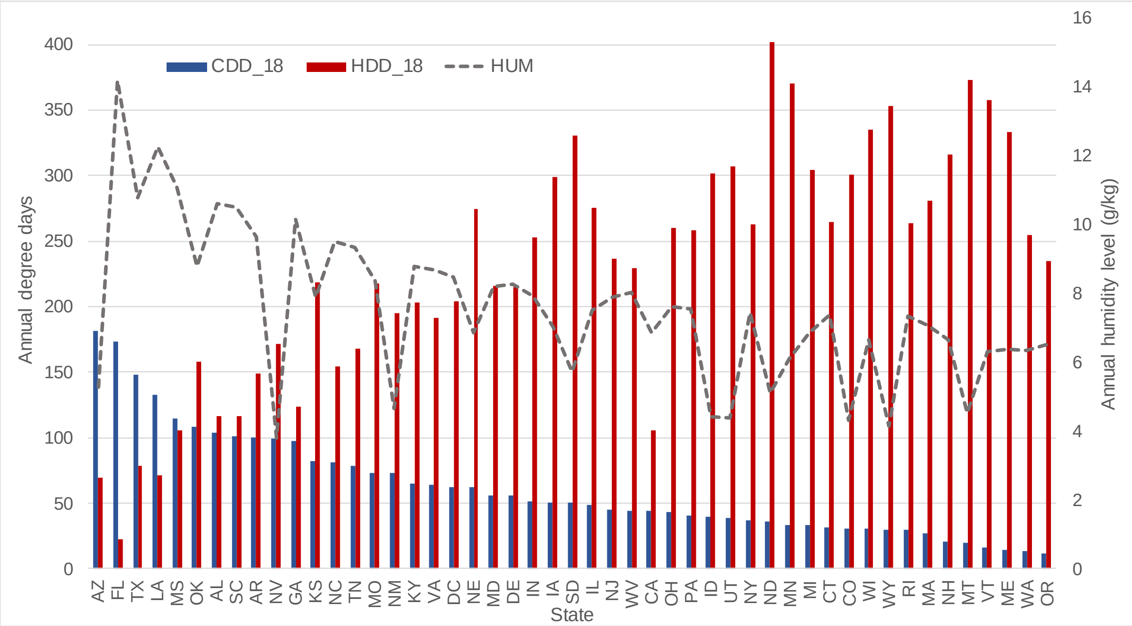


Figure 4-2 Annual-mean (2000-18), population-weighted, degree days and specific humidity level for the 49 states in contiguous United States

[AL: Alabama, AR: Arkansas, AZ: Arizona, CA: California, CO: Colorado, CT: Connecticut, DC: District of Columbia, DE: Delaware, FL: Florida, GA: Georgia, IA: Iowa, ID: Idaho, IL: Illinois, IN: Indiana, KS: Kansas, KY: Kentucky, LA: Louisiana, MA: Massachusetts, MD: Maryland, ME: Maine, MI: Michigan, MN: Minnesota, MO: Missouri, MS: Mississippi, MT: Montana, NC: North Carolina, ND: North Dakota, NE: Nebraska, NH: New Hampshire, NJ: New Jersey, NM: New Mexico, NV: Nevada, NY: New York, OH: Ohio, OK: Oklahoma, OR: Oregon, PA: Pennsylvania, RI: Rhode Island, SC: South Carolina, SD: South Dakota, TN: Tennessee, TX: Texas, UT: Utah, VA: Virginia, VT: Vermont, WA: Washington, WI: Wisconsin, WV: West Virginia, WY: Wyoming]

Based on Figure 4-2, 9 out of 10 U.S. states with the highest annual space cooling requirements (based on population-weighted *CDDs*) belong to south climatic regions (South, Southeast and Southwest sub-regions as in Figure 4-3). At the same time, 9 out of 10 states with the highest annual space heating requirements (based on population-weighted *HDDs*) belong to north U.S. climatic regions (Northeast, East North Central and West North Central sub-regions as in Figure 4-3). Despite the observed anti-correlation between the number of *CDDs* and *HDDs* across the contiguous U.S., the states with the highest (Arizona) and lowest (Oregon) space cooling requirements do not coincide with the ones having respectively the lowest and highest space heating needs.

New sets of historical degree day metrics were then calculated after allowing the temperature thresholds for *HDDs* and *CDDs* to independently vary within the range of 15.3-22.3 ℃, simultaneously for all states in the sample, each time with a step of 1 ℃. An iterative process is followed whereby the panel data model of per capita residential electricity use is estimated in the 2000-15 period under all possible combinations of *CDD* and *HDD* variables until optimal model fit is achieved ($\mathbf{Base_{opt}}$). Since this case study focuses on the south U.S. climatic region, where residents are accustomed to warmer climates and exhibit higher (lower) tolerance towards heat (cold), one would expect that better fit is achieved with *CDD* (*HDD*) set points set higher than 18.3 ℃.

In the second stage, performance of the three base models developed in the previous section is compared with that of alternative specifications, which in addition to degree days are modified to encompass different attributes of extreme temperature events. The following paragraphs outline the procedure for combining measurements of local maximum and minimum air temperature to develop an array of extreme heat and cold metrics. These metrics are specifically designed to encapsulate information about the (a) intensity, (b) duration, and (c) frequency of extreme temperature events which could have an impact on past and future space heating and cooling electricity loads.

For this exercise, local maximum and minimum air temperatures (t_{max}/t_{min}) are selected as an effective metric of heat and cold exposure, respectively, as these variables have been employed to study the impact of climate change on seasonal peak loads (Wenz et al., 2017). A common practice in utility systems planning is to size plants generating capacity according to the peak load recorded during T90 days, that is demand in days in which temperature exceeds the 90th-percentile probability of summertime daily maximum temperatures recorded for a specific region (Miller et al., 2008; Burillo et al., 2017). In the same fashion, extreme heat and cold events are defined here on the basis of relative cut-off points rather than absolute ones. This provides the advantage of accounting for regional heterogeneity in resident population's perception of "extreme" heat or cold, which depends on their adaptation to local climate. Lastly, since my main interest lies in the cumulative effect of a series of extreme heat/cold days on electricity consumption, definitions dealing with single-day events in isolation are excluded.

Amongst identified definitions, the set of rules from Lau and Nath (2012) are utilised to build an algorithm which determines whether a string of days qualifies as a heat wave event during the historical modelling period (2000-18). Inference is primarily based on two thresholds, t_1 and t_2, representing in turn the 90th and 75th percentile of state-level daily maximum JJA temperature defined over the 30-year time period 1985-2015. Daily t_{max} values (1985-2018) were derived from

3-hourly records of near-surface air temperature using NCEP's reanalysis weather data. These values were matched to each county's population centre using the interpolation eqn. (4-1) and aggregated to the state level via the application of county population weightings. Implementing the following selection criteria allows important characteristics such as the severity and duration of extreme temperature events to be taken into consideration:

(a) t_{max} must be higher than t_1 for a minimum of three consecutive days,
(b) t_{max} averaged over the duration of the event must be always higher than t_1, and
(c) t_{max} needs to be above the t_2 level for every day of the event.

The aforementioned criteria were successively applied to isolate all heat wave episodes which occurred in the 16 states comprising the south U.S. climatic region in the historical period 2000-18. In order to gauge the impact of heat wave days (*HWD*s) on residential climate-sensitive electricity use, a set of novel extreme temperature metrics is developed, which in turn parameterise the *duration*, *frequency* and *intensity* of these events. The *duration* metric (*NHW*) specifies the total number of *HWDs* in a month, during which populations residing in a specific state experienced unusually hot weather. The *frequency* variable (*FHW*) holds a count of heat wave episodes occurring during the same month. The intensity metric (*IHW*) sums the departure of daily maximum temperatures from the corresponding state-specific thresholds, t_1 and t_2, over all *HWDs* in a month. Two composite metrics are also used to capture more complex extreme temperature effects: one which measures the average duration of heat wave events occurred over a month (NHW_{av}) and another which captures the average intensity of all extreme hot days in a month (IHW_{av}). Finally, a dummy variable (*dumHW*) is created which simply controls for months during which at least one heat wave event took place.

The impact of cold wave days (*CWD*s) on state-level residential electricity use is investigated using a similar approach to the heat wave analysis, while adapting the aforementioned metrics to be compatible with statistics of daily minimum temperature instead:

(a) t_{min} must be lower than t_4 for a minimum of three consecutive days,
(b) t_{min} averaged over the duration of the event must be always lower than t_4, and
(c) t_{min} needs to be below the t_3 level for every day of the event.

In this case, t_4 and t_3 respectively stand for the 10th and 25th percentile of state-level daily minimum DJF (December-January-February) temperature distribution during the time period 1985-2015. Daily t_{min} statistics (1985-2018) were calculated at the county level and aggregated to the state level using the same procedure as with maximum air temperatures. In addition to the five continuous, a dummy variable (*dumCW*) is defined to measure consistent level differences of residential electricity use between months in which a cold wave occurred or not. A summary of the definitions of the extreme heat and cold wave metrics used in this investigation is provided in Table 4-2.

Table 4-2 Description of heat wave and cold wave day metrics

Type	Metric	Formulation
Heat Wave	Duration	$NHW_{s,mo} = \sum_{i=1}^{d} 1, \quad (i = HWD)$
	Frequency	$FHW_{s,mo} = \sum_{i=1}^{d} 1, \quad (i = HWD \text{ and } (i\text{-}1) \neq HWD)$
	Intensity	$IHW_{s,mo} = \sum_{i=1}^{d} \begin{cases} t_{max} - t_1, & (i = HWD \text{ and } t_{max} > t_1) \\ t_{max} - t_2, & (i = HWD \text{ and } t_{max} > t_2) \end{cases}$
	Mean duration	$NHWav_{s,mo} = NHW_{s,mo}/FHW_{s,mo}$
	Mean intensity	$IHWav_{s,mo} = IHW_{s,m}/NHW_{s,mo}$
Cold Wave	Duration	$NCW_{s,mo} = \sum_{i=1}^{d} 1, \quad (i = CWD)$
	Frequency	$FCW_{s,mo} = \sum_{i=1}^{d} 1, \quad (i = CWD \text{ and } (i\text{-}1) \neq CWD)$
	Intensity	$ICW_{s,mo} = \sum_{i=1}^{d} \begin{cases} t_4 - t_{min}, & (i = CWD \text{ and } t_{min} < t_4) \\ t_3 - t_{min}, & (i = CWD \text{ and } t_{min} < t_3) \end{cases}$
	Mean duration	$NCWav_{s,mo} = NCW_{s,mo}/FCW_{s,mo}$
	Mean intensity	$ICWav_{s,mo} = ICW_{s,mo}/NCW_{s,mo}$

Three extended *EL_PC* model versions, namely $\mathbf{Ext_{dur}}$, $\mathbf{Ext_{frq}}$, $\mathbf{Ext_{int}}$, are specified in such way that a linear combination of climatic metrics relating to the duration, frequency and intensity of extreme heat and cold events is added to the base specification. In practice, this is implemented in turn by adding the terms ($NHW_{s,mo}$ + $NCW_{s,mo}$), ($FHW_{s,mo}$ + $FCW_{s,mo}$) and ($IHW_{s,mo}$ + $ICW_{s,mo}$) to eqn. (3-10). In the same additive fashion, two more model specification encompass the effect of the average duration ($\mathbf{Ext_{avdur}}$) and intensity ($\mathbf{Ext_{avint}}$) of extreme temperature episodes on per capita residential electricity use. A heat and cold wave dummy variable model ($\mathbf{Ext_{dum}}$) is finally estimated.

At the final stage, the six different extreme heat metrics embedded to extended model specifications are interacted with a measure of monthly air humidity. Similar to Barreca (2012), the specific humidity variable (i.e., the mass of water vapour per unit mass of moist air parcel) is chosen instead of relative one (i.e., absolute water content of air relative to maximum water vapour before saturation) due to its lower susceptibility to measurement error. Monthly-average values of specific air humidity (g/kg) were interpolated for all counties from NCEP's reanalysis grid data (via eqn. (4-1)) and aggregated to the state level, after being corrected for within-state population distribution ($HUM_{s,mo}$). Annual specific humidity levels averaged during the 2000-18 period for the 49 states in the contiguous U.S. region are also presented in Figure 4-2. Generally, states with higher space cooling requirements (based on population-weighted *CDD* levels) have also higher annual air humidity levels, with the notable exception of states in the Southwest and West climatic sub-region (e.g. Arizona and Nevada).

The hypothesised amplifying effect of air humidity on space cooling electricity use is investigated through the addition of $HUM_{s,mo}$ variable as an interaction term in the model. This interaction allows identifying whether the *effect size* of heat waves on residential electricity use is dependent on monthly-average humidity levels. In practical terms, this is equivalent to amending the extended parts of the model specification for duration, frequency and intensity to read as ($NHW_{s,mo} \times HUM_{s,mo} + NCW_{s,mo}$), ($FHW_{s,mo} \times HUM_{s,mo} + FCW_{s,mo}$) and ($IHW_{s,mo} \times HUM_{s,mo} + ICW_{s,mo}$), respectively. This results in the final set of humidity-based extended model candidates (**Hum$_{dur}$**, **Hum$_{frq}$** and **Hum$_{int}$**), including also two developed for the composite metrics (**Hum$_{avdur}$** and **Hum$_{avint}$**) and one for the dummy variable (**Hum$_{dum}$**). Summarising the above, the total number of Base (3), Ext (6) and Hum (6) specifications tested for the historical period 2000-18 amounts to 15.

4.2.2.2 Model selection criteria

The model fit of the various candidate specifications for the residential electricity use model is evaluated through a series of statistical measures. First, each model specification is assessed on the basis of its coefficient of determination (R^2); a descriptive statistic measuring the fraction of variability in the response variable which can be explained by the selected explanatory variables. The higher R^2 is, the better the goodness-of-fit characterising a model. The adjusted version of R^2 also imposes a penalty for the addition of new independent variables in the specification which is a safeguard for model overfitting, so it is preferred over the un-adjusted version (Greene, 2012). While adjusted R^2 describes the general performance of individual models, it is criticised for its small penalty for the addition of new variables (Amemiya, 1985) and it has little value in identifying the *best* model when other candidates are available.

Akaike information criterion (AIC) and Bayesian information criterion (BIC) are metrics specifically designed to guide model selection, in the context of maximum likelihood estimation (Burnham and Anderson, 2004). These statistical criteria are suitable for ranking different candidate models according to how well simulated data approximate the distribution of real consumption data, while compensating for the number of parameters used in the estimation procedure. These criteria have only explanatory meaning in relative terms; the lowest AIC or BIC value is associated with the model that minimises the loss of information, thus depicting reality in more accuracy. Despite being formulated on the basis of different assumptions, both criteria are characterised by the same structure, as shown by eqn. (4-2) and (4-3) :

$$AIC = -2\ln\left(\hat{L}\right) + 2K \tag{4-2}$$

$$BIC = -2\ln\left(\hat{L}\right) + K \times \ln(n) \tag{4-3}$$

In both cases, the first term represents the level of model accuracy, where $\ln\hat{L}$ is the maximised log-likelihood value. The second part of AIC and BIC formulas determines the penalty imposed for model complexity, where *K* denotes the number of estimated parameters and *n* is the number of observations. Since AIC scores cannot be interpreted on an absolute scale, it is often useful to convert them into a more meaningful output through Akaike weights, w_S. For a set of *Q* candidate specifications, *w* represents the probability of model *i* being the optimal one (Wagenmakers and Farrell, 2004). Akaike weights are calculated via eqn. (4-4):

$$w_i(AIC) = \frac{exp\left\{-\frac{1}{2}\Delta_i(AIC)\right\}}{\sum_{q=1}^{Q} exp\left\{-\frac{1}{2}\Delta_q(AIC)\right\}} \tag{4-4}$$

where $\Delta_i(AIC) = AIC_i - \min(AIC)$. The same magnitude of probabilities is obtained when Schwarz weights are calculated instead, which requires simply replacing AIC with BIC scores in eqn. (4-4).

Finally, the forecasting strength of each candidate specification is assessed via the means of the mean absolute percentage error (MAPE). Past residential electricity consumption is simulated under all candidate specifications based on the historical values of input variables and FE regression coefficients. MAPE is first computed using the full range of *in-sample* data over the estimation period (2000-15), and subsequently using *out-of-sample* data gathered over the model's testing period (2016-18). The main advantage of MAPE relative to other statistics is that it has a very straightforward interpretation; it expresses the average departure of model's simulated values from real electricity consumption data in a percentage form, given in eqn. (4-5):

$$MAPE = \sum_{s=1}^{n} \left| \frac{EL\_PC_s^{Real} - EL\_PC_s^{Model}}{EL\_PC_s^{Real}} \right| \times \frac{100\%}{n} \tag{4-5}$$

MAPE is calculated and averaged over the states comprising this study's sample, using electricity use data over the whole year and subsequently restricted to the summer and winter season, when extreme air temperature events are more common. In summary, the final choice about the best model of residential electricity use is the one which maximises adjusted R^2, has the smallest AIC and BIC statistic and generates the lowest MAPE levels.

4.2.3 Projecting residential electricity use in the south U.S. climatic region (2046-55)

Coefficients retrieved from the favoured model specification are combined with input data comprising scenario values during the 2046-55 period to devise mid-21st century projections of residential electricity use in the south U.S. climatic region. Future weather data are sourced from the statistically-downscaled output of 20 global climate models (GCMs), conforming to assumptions about a high-end climate change trajectory in the mid-21st century. Electricity use projections in this chapter adhere to an extreme instead of a moderate climate change scenario, as this allows studying the implications for long-term projections of electricity use of following a climatic trajectory which is characterised by rapidly growing climate extremes. Future *HDDs* and *CDDs* are calculated at the county level and aggregated at the state level according to the output of the multi-model ensemble. A new array of extreme heat and cold temperature indicators is also constructed applying the same qualification criteria as in 4.2.2. With respect to non-climatic impacts, the average annual growth of personal income and electricity price in 2018-50 is calculated based on reference macro-economic and fuel price projections conducted by the U.S. EIA.

Scenarios of residential electricity use in the south U.S. climatic region, generated by multiplying the historical model's parameter coefficients and future climatic and non-climatic values, are then benchmarked against data observed in 2000-15. Focus is placed on annual differences of residential electricity use between the 2046-55 and 2000-15 periods for different south U.S. climatic sub-regions, as well as on seasonal consumption patterns. Finally, in order to evaluate the sensitivity of results to the selected model structure, projections from the extended specifications are compared with those generated in 2046-55 through the $Base_1$ and $Base_{opt}$ model.

4.2.4 Case of application

4.2.4.1 Choice of geographic region

In this study, monthly information was utilised concerning electricity consumption in the residential sector of states belonging to the south climatic regions of United States (split to the Southwest, South, and Southeast sub-region as in in Figure 4-3, as defined by Karl and Koss (1984)). The focus of this investigation is placed on southern states for which past assessments showed that they have historically experienced the strongest annual increases in heat wave days (especially the Southeast), over the largest portion of land area (Smith et al., 2013). As a result of this exposure, it is likely that local populations have developed adaptation mechanisms suitable for alleviating the adverse effects of extreme heat events; one of which is adaptation through mechanical air-conditioning. About 87% of total U.S. households used air-conditioning equipment in 2015, as reported in the EIA's RECs datasets (U.S. EIA, 2017b), while diffusion rates approach full saturation in areas with hot and humid climate (~94%). Seasonal residential electricity use in southern states is therefore expected to exhibit a clearer signal, created by the more intense use of air-conditioning during heat wave events.

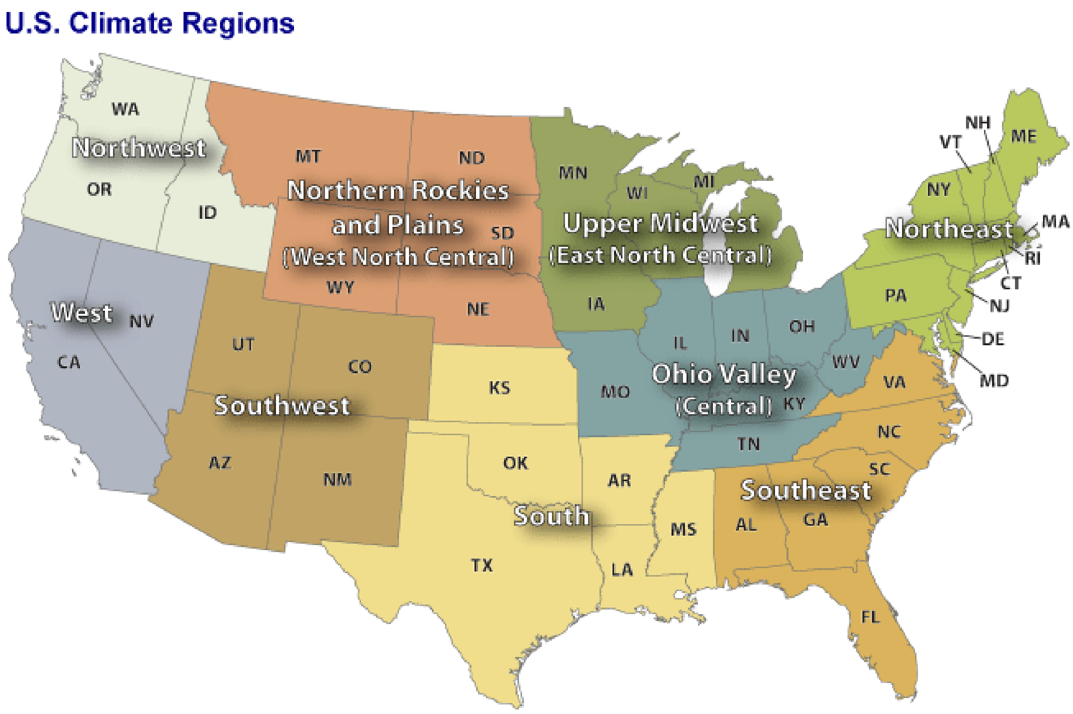


Figure 4-3 Classification of contiguous U.S. states according to climatic conditions Source: NOAA (2020)

4.2.4.2 Data requirements

Various sources were accessed to collect data for the 16 states comprising the south U.S. climatic region during the historical modelling training (2000-15) and validation (2016-18) period. Monthly data regarding the amount of electricity consumed in the residential sector (*EL*) and mean retail prices of electricity (*EP*) were sourced from the 861M form, maintained by the EIA (U.S. EIA, 2020b). Annual, state-level, population statistics (*POP*) were collected from the U.S. Census Bureau and then transformed into monthly estimates using cubic spline interpolation (U.S. Census Bureau, 2019). Quarterly personal income statistics (*INC*) were obtained for each state from the U.S. Bureau of Economic Analysis (U.S. BEA, 2019) and converted into monthly values using the same interpolation technique. Consumer price indices (CPIs) developed for research purposes by the U.S. Bureau of Labour Statistics (U.S. BLS, 2019) using current methods (CPI-U-RS) (Stewart and Reed, 1999) were also collected. These were used to express nominal state-level personal income and electricity prices in 2018's (January) constant terms.

With respect to past meteorological data, time series of daily average near-surface temperature were calculated at the county level from the gridded output of the North American Regional Reanalysis (NARR) project, which is coordinated by the NCEP (NCEP, 2016). These data were analysed to develop heating and cooling degree day metrics with varying temperature thresholds in 2000-18. On the other hand, readily available sets of historical monthly degree days for south U.S. states were obtained from the NOAA's website (NOAA, 2019). A summary of climatic and non-climatic variables included in the base model of residential electricity use for the south U.S. climatic region is provided in Table 4-3. Climatic data necessary for the construction of extreme temperature indices (i.e., daily maximum and minimum temperature, and monthly average humidity for every county) were also sourced from NARR datasets.

Devising future trajectories of socio-economic and electricity price data, required the collection of reference-case scenario data from EIA's 2019 annual energy outlook (U.S. EIA, 2019a). EIA's scenarios of the U.S.-aggregate real GDP combined with future population between 2018 and 2050 were used to calculate the long-term average annual growth rate of personal income (*INC*). This annual growth rate is converted to a monthly growth rate, which is applied uniformly to all states comprising the sample to project *INC* levels in the 2046-55 period. Since the collected historical income data are seasonally-adjusted, it is not possible to correct future *INC* projections for specific month-to-month differences.

Reference-case data on future U.S.-average fuel prices (2018-50) in the residential sector were sourced to estimate monthly electricity price growth rates

Table 4-3 Descriptive statistics of state-level variables for the south U.S. climatic region (2000-18)

Variable	Sym.	Mean	Std. Dev.	Max	Min
Electricity use (TWh/mo)	EL	3.25	3.10	18.62	0.33
Per capita electricity use (kWh/pop•mo)	EL_PC	447.38	140.79	869.69	183.19
Population	POP	7,005,774	6,128,947	28,786,816	1,815,902
Personal income (000’ 2018 $/pop)	INC	42.01	5.33	58.68	31.27
Electricity price (2018 Cents/kWh)	EP	11.33	1.24	16.42	7.75
Cooling degree days	CDD[a]	157	190	804	0
Heating degree days	HDD[a]	274	320	1444	0

[a] Degree day statistics correspond to NOAA’s published values for a fixed threshold of 18.3^{0}C.

for the south U.S. climatic region. For the projections in 2046-55, historical electricity price records were first seasonally-adjusted using centred moving averages. State-specific seasonal indices computed based on historical *EP* data (2000-18) were subsequently re-applied on electricity price projections in 2046-55 to re-introduce the seasonal component. As this study focuses on future climate-based effects on residential electricity use, no data were sourced for high and low-end trajectories of socio-economic and fuel price indicators.

Quantifying the impacts of climate change on residential electricity use in the mid-21st century involved collecting data concerning the long-term evolution of local outdoor temperature and specific humidity. Monthly, state-level, degree days (2046-55) were estimated from daily mean grid temperatures, extracted from 20 global climate model projections of the Coupled Model Intercomparison Project-Phase 5 (CMIP5). The obtained datasets contained statistically-downscaled climate products based on the Multivariate Adaptive Constructed Analogs (MACA) method (Abatzoglou and Brown, 2012) and trained with observation data from Livneh et al. (2013). Due to the finer resolution of obtained meteorological data (1/16 degrees vs. 1/3 degrees for NARR), spatial interpolation to the county population centres is based on the 10 nearest grid points instead.

Extreme heat and cold variables were constructed utilising MACA datasets of daily maximum and minimum temperature during the same projection period. Finally, the same source was accessed to retrieve projections of monthly-mean specific humidity in 2046-55 for each south U.S. state. Since this study focuses on the effects of extreme weather on the climate-sensitivity of future residential electricity use, all constructed climate variables adhere to assumptions of the Representative concentration pathway (RCP) 8.5 scenario. This emissions pathway follows the extreme end of climate change, whereby future greenhouse gas emissions remain unmitigated, increasing radiative forcing up to 8.5 Wm^{-2} by 2100. (Riahi et al., 2011). Table 4-4 summarises the set of climatic and non-climatic assumptions governing residential electricity use projections in 2046-55.

Table 4-4 Mean growth rate (2018-50) of variables used in the scenario analysis for the south U.S. region

Category	Variable	Annual growth rate (%)
Socio-economic	POP	0.53
	INC	1.35
Fuel Price	EP	0.17
Climatic	CDD, HDD, NHW, FHW, IHW, NCW, FCW, ICW, HUM	n/a (RCP8.5)

4.3 Results

4.3.1 Extreme temperature indices (2000-18)

This section presents a summary of the extreme temperature metrics which were calculated for the south U.S. climatic region according to the qualification criteria outlined in section 4.2.2. Figure 4-4 and Figure 4-5 display the spatial distribution of the mean duration (top panel), frequency (middle panel) and intensity (bottom panel) metrics, for extreme heat and cold events, respectively. Long-term (2000-18) statistics are also averaged for each sub-region in Table 4-5. Heat and cold wave indices show significant variability over the south U.S. climatic region; their spatial profile depends both on the type of observed extreme (i.e., heat or cold-related one) and on the choice of extreme weather attribute (i.e., duration, frequency or intensity). In general, households in the south U.S. climatic region faced a higher number of heat wave days and episodes than cold wave ones.

Table 4-5 Annual extreme temperature statistics (2000-18) divided by sub-region for the 16 states in the south U.S. climatic region

Climatic sub-region	NHW (days)	FHW (episodes)	IHW (℃)	NCW (days)	FCW (episodes)	ICW (℃)
Southeast	12.33	1.73	13.31	6.45	1.19	16.54
South	16.28	1.80	23.90	5.99	1.14	16.98
Southwest	14.58	1.97	14.84	8.41	1.51	20.35

Studying the regional distribution of extreme heat events shows that states in the south climatic sub-region have experienced the largest number of heat wave days, while southeast states have encountered the fewest ones (Table 4-5). Annual number of *HWDs* range from 16.8 days in Texas to just about 11.2 days in Florida. An interesting observation is that while Florida exhibits the fewest *HWDs* amongst all southern states, at the same time it has the second highest number of long-term (2000-18) annual *CDDs* based on Figure 4-2, meaning that residents are accustomed to a relatively *stable* warm weather. A residential electricity use model solely based on traditional degree day metrics would not be able to simulate this complex temperature effect.

Statistics for the frequency of heat wave events show greater spatial dispersion. Heat wave episodes are on average more common in the southwest climatic sub-region. The cumulative exceedance of daily maximum temperature from t_1 and t_2 thresholds is largest for the south climatic sub-region, with Kansas experiencing the most intense events. It is again interesting to note that Kansas has the lowest number of long-term annual *CDDs* in the south climatic sub-region (and 6th lowest cooling requirements across the whole south climatic region from Figure 4-2). This implies that relatively cool weather in the summer is interspersed by high temperature extremes, whose effect on AC residential electricity consumption is not captured in a straightforward way by traditional *CDD* metrics.

With regards to results about the duration, frequency and intensity of cold waves in south U.S. states, a simpler picture emerges as the southwest sub-region has the highest score in all categories (Table 4-5). New Mexico experienced the highest average number of cold wave days (9.8 days/year) during the time period 2000-18, while Texas - the state with highest annual count of *HWDs* - experience the lowest level of cold wave days (5.1 days/year). Arizona, which has the 3rd highest annual count of *CWDs* across the south climatic region, is also the state with the 2nd lowest long-term (2000-18) annual *HDDs* from inspection of Figure 4-2. Furthermore, the impact of prolonged extreme cold events on residential electricity use may not be sufficiently described through the use of traditional *HDD* metrics. *CWDs* are more common in New Mexico and Arizona (1.7 and 1.6 events/year). Lastly, Utah, which is the coldest state in the south U.S. climatic region based on the annual count of *HDDs*, also experiences the most intense cold waves.

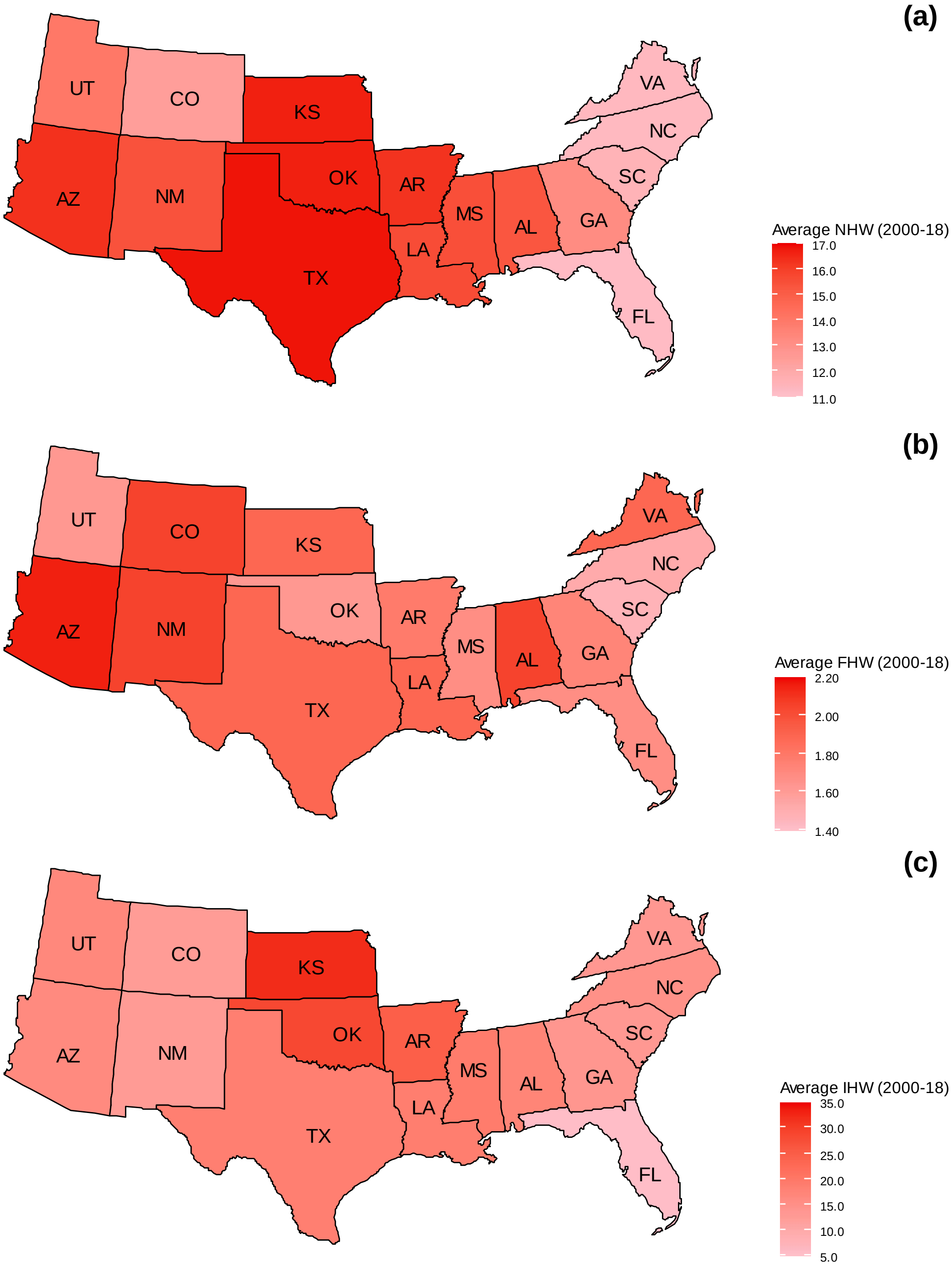


Figure 4-4 Extreme heat statistics (2000-18) for the 16 states in the south U.S. region regarding (a) heat wave days per year, (b) heat wave episodes per year and (c) annual cumulative departure of daily t_{max} from relative HW thresholds

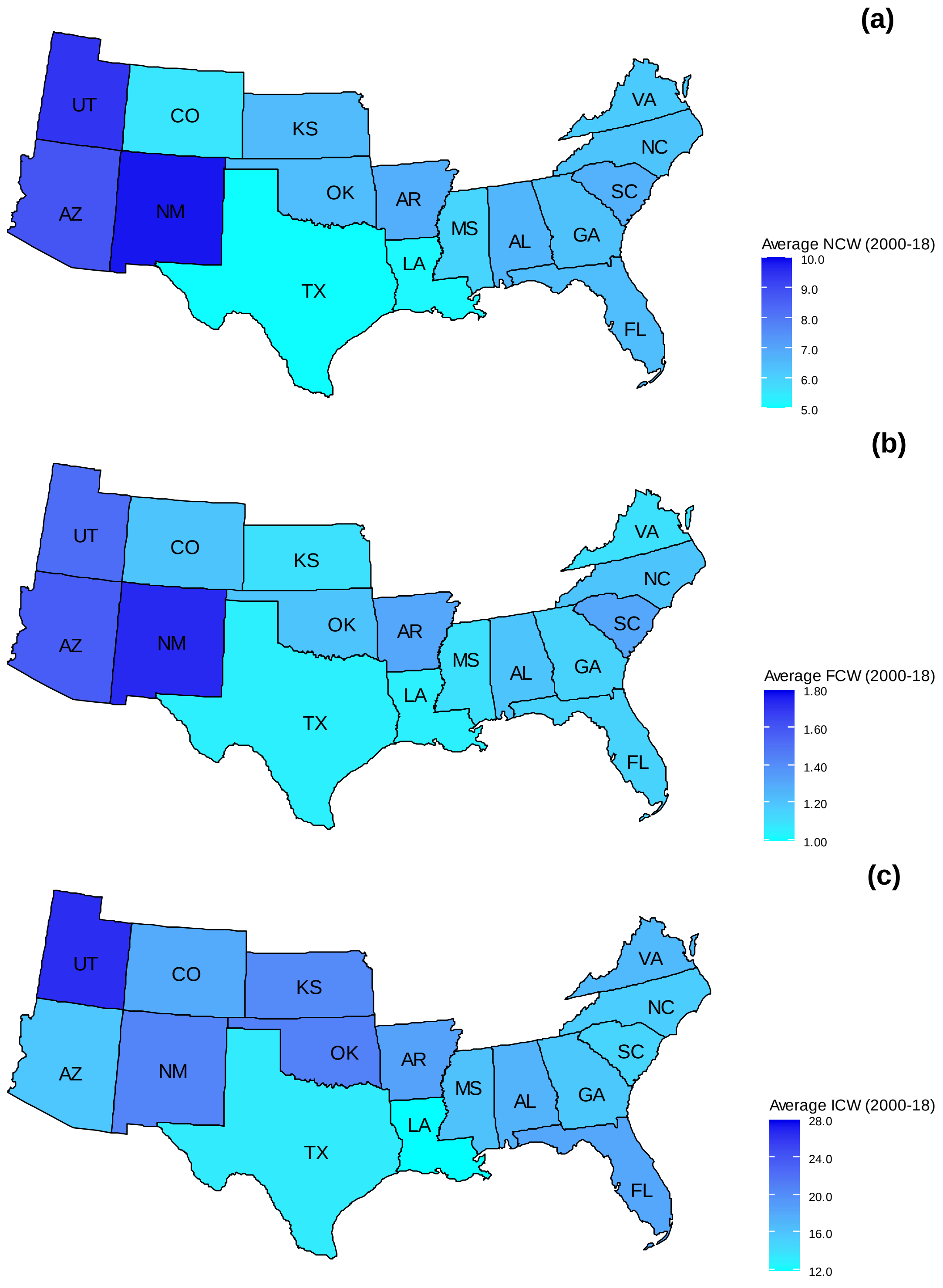


Figure 4-5 Extreme cold statistics (2000-18) for the 16 states in the south U.S. region regarding (a) cold wave days per year, (b) cold wave episodes per year and (c) annual cumulative departure of daily t_{min} from relative CW thresholds

4.3.2 Reference residential electricity use model (2000-15)

After the model of per capita residential electricity use is set up according to the reference specification $Base_0$, its coefficients are estimated via the FE approach and using data for the historical period 2000-15. Econometric estimation results for the reference, as well as the best performing *Base*, *Ext* and *Hum* specification are summarised in Table 4-6, based on the R^2/AIC/BIC criterion. Table 4-6 also reports specification tests conducted (F-test, Hausman) to confirm the superiority of the FE over the pooling and RE estimator, respectively. The former test provides concrete evidence about the presence of state-specific unobserved effects (significant at 1%), thus deeming the pooling estimator as inappropriate. The null hypothesis asserting that no correlation exists between unit-specific intercepts and the explanatory variables is rejected at the 1% significance level through the Hausman test, which signifies the suitability of the FE over the RE method. The overall model fit is deemed as very good, since the reference $Base_0$ model explains about 84% of the variation in *EL_PC* data (2000-15) for the states in the south U.S. climatic region.

Investigating the output of the FE estimator for the reference $Base_0$ model confirms that all explanatory parameters have a highly statistically-significant effect on per capita residential electricity use in the hypothesised direction. Increasing electricity prices (*EP*) have a decreasing effect on residential electricity use, with each unit price increase (Cents/kWh) reducing per capita consumption by 6.06 kWh/pop (standard error (se) 1.27) as per the reference specification. Estimating the marginal effect of personal income requires estimating the partial differential of *EL_PC* with respect to both the linear and quadratic *INC* term, as shown by eqn. (4-6):

$$\frac{\partial\ EL\_PC}{\partial\ INC} = \beta_{INC} + 2 \times \beta_{INCSQ} \times INC \tag{4-6}$$

Using parameter coefficients (β_{INC} and β_{INCSQ}) generated under the $Base_0$ model and the sample's mean value of monthly *INC* for the 2000-15 period (US$ 41,280), the within-group effect of income on *EL_PC* is estimated to be +2.54 kWh/pop (se 0.88). The standard error is calculated by aggregating the uncertainty in estimation accuracy of β_{INC} and β_{INCSQ}, using the variance sum law. Since the coefficient of *INCSQ* has a negative sign (significant at 1%), the impact of an additional *INC* unit (000' $/pop) on per capita electricity use becomes smaller at higher income levels, showing diminishing marginal effects of income and pointing to potential saturation. The marginal effect of personal income reaches full saturation ($\frac{\partial\ EL_PC}{\partial\ INC} \approx 0$) at US$ (constant 2018) 50,956 per person, above which a further increase of *INC* is thought to reduce per capita residential electricity use. It should be noted that this personal income level is exceeded by only two states in the sample during the 2000-15 period.

Table 4-6 FE estimation results of EL_PC (kWh/pop•mo) model for the south U.S. climatic region (2000-15)

	$Base_0$	$Base_{opt}$	Ext_{avdur}	Hum_{avdur}
INC (000' $/pop)	13.371***	12.947***	12.612***	12.254***
	(4.535)	(4.569)	(4.553)	(4.370)
INCSQ	-0.131***	-0.125***	-0.122**	-0.119**
	(0.050)	(0.048)	(0.048)	(0.046)
EP (cents/kWh)	-6.056***	-6.634***	-6.790***	-7.315***
	(1.274)	(1.254)	(1.255)	(1.318)
CDD	0.410***	0.827***	0.872***	0.961***
	(0.027)	(0.035)	(0.035)	(0.031)
HDD	0.113***	0.167***	0.130***	0.092***
	(0.013)	(0.022)	(0.020)	(0.018)
NHW_{av}			-0.078	-6.865***
			(0.403)	(1.185)
NCW_{av}			4.798***	4.850***
			(0.986)	(0.903)
HUM (g/kg)				-5.615***
				(1.366)
NHW_{av} × HUM				0.453***
				(0.081)
Observations	3072	3072	3072	3072
$\overline{\beta_s}$	142.303	68.782	178.589*	235.235**
	(105.069)	(108.176)	(106.632)	(102.030)
F-test	619.86***	784.06***	787.10***	479.6***
Hausman test	53.68***	123.74***	386.57***	1621.4***
R^2 (adj.)	0.844	0.852	0.856	0.861

Statistically significant *** at 1%, ** at 5%, * at 10%, and confidence level. Note: Standard errors in parenthesis are computed via *a la Driscoll and Kraay* estimator which is robust to serial and cross-sectional correlation (Hoechle, 2007).

With respect to the climate-sensitive part of electricity use, both the heating and cooling degree day metric were found to have a positive and statistically-significant impact on residential electricity use. On marginal terms, the *CDD* coefficient is about 4 times as large as the *HDD* one, with each 100 extra cooling degree days (ceteris paribus) contributing to a 41.0 kWh/pop (se 2.7) increase of per capita electricity use. The larger coefficient for *CDDs* possibly reflects the larger market share of electric air-conditioning in the residential sector of south

U.S. states relative to electric heating (e.g. AC and electric heating penetration in the south census region which contains the majority of states of the south U.S. climatic region was respectively at 95% and 56% for 2015 (U.S. EIA, 2017c; U.S. EIA, 2017b)) , and (b) the lower efficiency of space cooling compared to heating (Hadley et al., 2006). Space heating is also delivered through technologies using heating fuels other than electricity, such as natural gas, oil and wood.

In order to detect the presence of an aggregate time trend in residential electricity consumption data, the coefficients of estimated year-specific dummies (*Year*) are extracted under the $Base_0$ model. The annual effects are jointly significant ($\chi^2(15)$ =74.18***), implying that collectively their size is different from the reference year's (2000) level. An increase in annual effects in the 2002-06 period (relative to year 2000) is followed by a slightly decreasing trend until 2009 (Figure 4-6), which is due to macro-economic trends not captured by the model's explanatory parameters. The sharp peak observed in 2010's effect, requires further explanation; 2010 was the coldest year during the historical (2000-15) analysis period, having the highest number of regional-average annual *HDDs*. While the FE model captures the effect of cold weather on space heating electricity use, the *HDD* coefficient represents the change in *EL_PC* for an additional degree day, averaged across the states in the sample. In other words, an extra *HDD* is assumed to cause the same marginal increase of residential electricity use for all states in the south U.S. climatic region. While this is preferable when studying the average "behaviour" of a system, outliers in electricity use data may not be adequately captured.

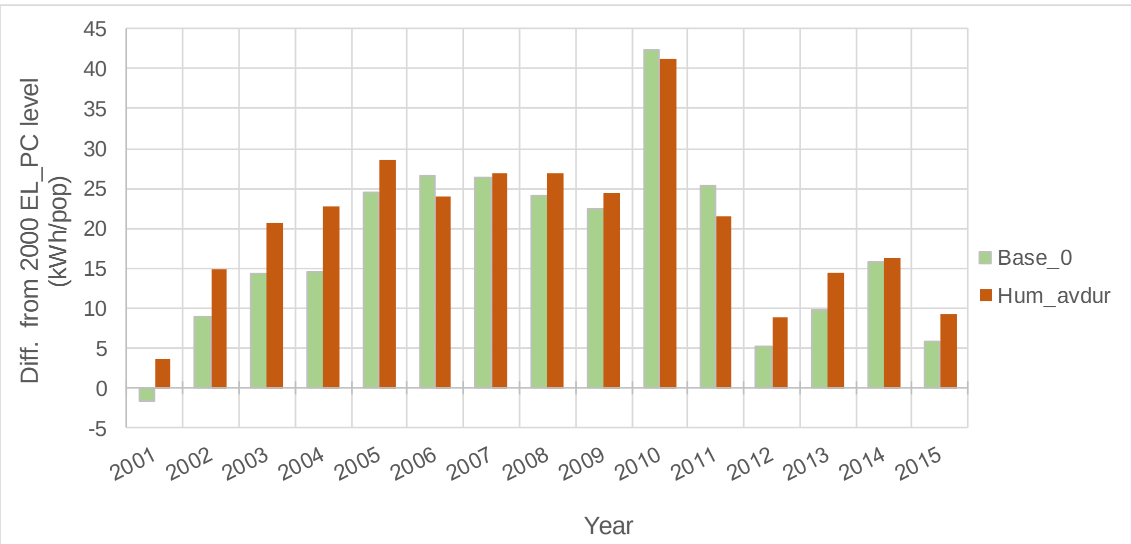


Figure 4-6 Variation of annual-specific effects under the reference and humidity-based model for the 16 states in the south U.S. region

A potential reason for the presence of outliers is significant between-state differences in the percentage of households using electricity as their main heating fuel. For example, about 80% of residences in Florida chose electricity as their primary heating fuel in 2009, while only 50% of households made that choice in Alabama and Texas (U.S. EIA, 2013). Differences in penetration rates of electric heating could therefore lead to a variation in the sensitivity of electricity use to *HDDs*. This can partly explain the weaker response of per capita electricity use to cold stress in 2010 as simulated by the base model (which is compensated by the positive annual dummy).

After 2010, a reduction in the size of annual dummies is observed until 2015 when it levels-off at 2000's levels[9]. The declining time trend is possibly a reflection of energy savings achieved in the residential sector through the implementation of stricter efficiency standards. As Davis (2017) proposes, the replacement of old lighting with energy-efficient light-emitting diodes (LEDs) in U.S. households has contributed to important decreases of per-capita electricity consumption in the post-2010 period. The same qualitative findings are obtained when assessing the variation in the size of annual-specific effects generated under the humidity-based Hum_{avdur} specification for the same time period.

Lastly, the relative magnitude of monthly dummies is compared, whose role is to depict the seasonal component of per capita residential electricity use which is not explained by the set of socio-economic, fuel price and climate variables included in the base model. Figure 4-7 displays the fixed seasonality of per capital electricity use with respect to January's levels under the $Base_0$ model. The null hypothesis of month-specific effects being identical and equal to the January's level is firmly rejected ($\chi^2(11)$ =1271***). Average residential electricity use during the spring and autumn season is 75 and 187 kWh/pop lower than winter season's consumption levels. The relative difference in monthly effects is notably smaller for July, August and September; the three months associated with the highest level of per capita electricity use in the south U.S. climatic region (2000-15). Moreover, the fact that estimated fixed effects for these 3 months turn out to be statistically insignificant underlines the good performance of the reference model during most of the cooling season. On the other hand, the larger deviation of modelled consumption data from real values during spring and autumn (which is compensated by monthly dummies) may be attributed to the weaker sensitivity of *EL_PC* to degree days in these seasons. This could be the result of residents seeking to restore thermal comfort in households using less energy-intensive technologies (e.g., fans or portable electric heaters).

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[9] The dummies for years 2012-15 are also statistically insignificant.

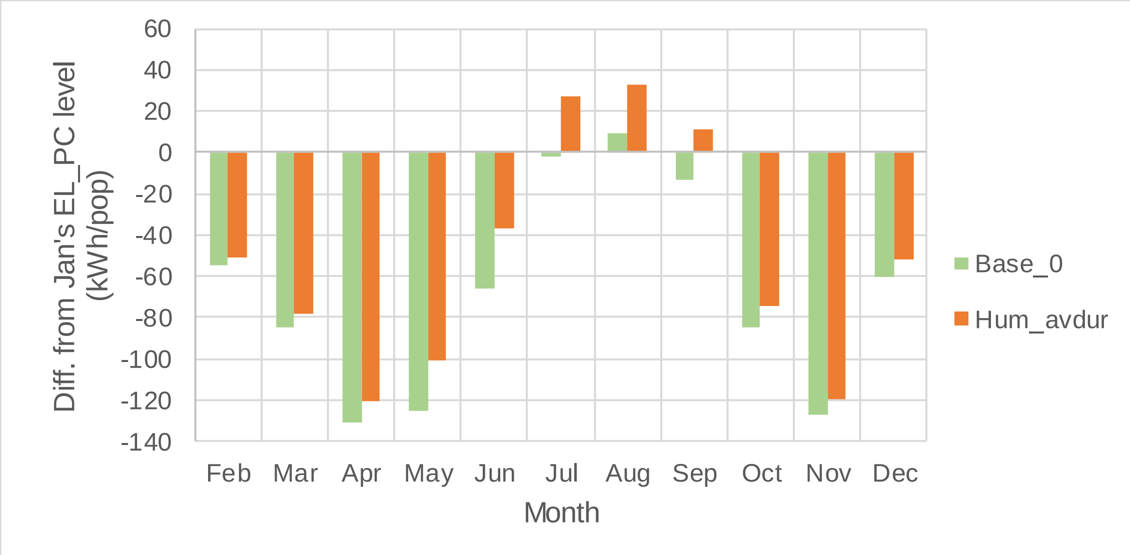

Figure 4-7 Variation of month-specific effects under the reference and humidity-based model for the 16 states in the south U.S. region

Extending the base specification to incorporate the new modelling features (under Hum_{avdur}) reduces the size of month-specific effects in spring, autumn and winter, as also shown in Figure 4-7. This implies that during those months more data variation can be explained through the climatic metrics and less through the fixed monthly dummies relative to the reference model. The same applies for model predictions in June. On the other hand, climatic metrics through the Hum_{avdur} model tend to slightly underestimate residential electricity use in July and August, which is compensated by the positive month-specific effects.

4.3.3 Comparing the performance of different climate metrics

The performance of the per capita residential electricity use model for the south U.S. climatic region is subsequently compared for all candidate specifications employing alternative metrics of climate-sensitive energy use. The proposed amendments to the reference specification involve first computing degree days from interpolated reanalysis temperature data and allowing the regionally-uniform set point temperatures for heat and cold stress to vary. The optimised degree day model is then extended to capture the complex effects of heat and cold waves on residential electricity use. Finally, a specific humidity variable is incorporated to the extended specifications. Statistical criteria employed in the selection process for the "best" *EL_PC* model, comprise adjusted R^2, AIC and BIC concerning model fit, and annual and seasonal MAPE regarding their forecasting accuracy.

4.3.3.1 Testing different degree day temperature thresholds

First, the analysis identifies the set of set-point temperatures, which when applied to *CDD* and *HDD* calculations uniformly across the south climatic region, yield the best fit for the historical electricity use model. The iterative process involving varying individual set points for *CDDs* and *HDDs* in the range of 15.3-22.3 ℃ (with a step of 1 ℃) results in 64 *EL_PC* model estimations, each associated with a unique code name; for example, CDD18-HDD18 refers to model **$Base_1$** in which both cooling and heating degree day variables were calculated based on the 18.3 ℃ temperature threshold. Following each model run, the adj. R^2 statistic is extracted, as graphically presented through the heat map in Figure 4-8. The adopted colour scaling scheme depicts a transition from low through medium to high adj. R^2 values as a change from green through yellow to red colour.

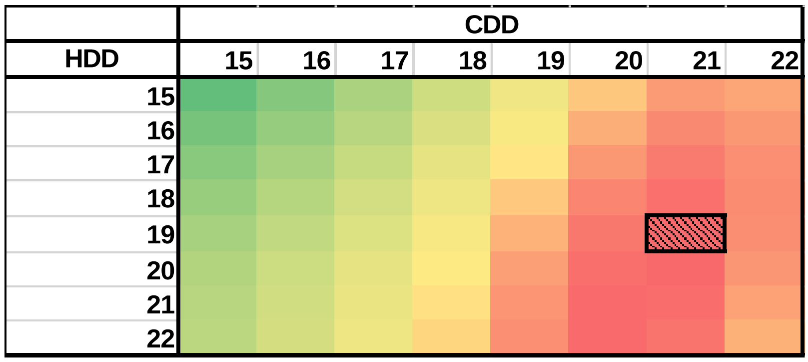

Figure 4-8 Heat map of R^2 (adj.) for all combinations of HDD and CDD set points for the 16 states in the south U.S. region

[the colour scaling scheme dictates that low (0.820-0.830), medium (0.840-0.850) and high (0.850-0.853) R^2 values are displayed in green, yellow, red colour, respectively.]

According to the heat map in Figure 4-8, $Base_1$ using degree days built from reanalysis data can explain the same amount of variance (84%) in *EL_PC* data as $Base_0$ using NOAA's external degree days. The model's goodness-of-fit improves (cells have redder colour) for cooling-specific thresholds ranging from 20.3 to 21.3 ℃ and heating-related thresholds above 17.3 ℃, which reduces the number of possible combinations to 10 (2x5). Amongst remaining candidate specifications, highest adj. R^2 (0.852) arises for the CDD21-HDD19, CDD21-HDD20, CDD20-HDD21 and CDD20-HDD22. Finally, the first model specification is favoured for two reasons: (a) the difference in adj. R^2 values for these 4 specifications is in the order of 10^{-5} thus it is of negligible magnitude, and (b) the third and second candidate specification violates the assumptions of the "comfort zone" model, which asserts that cooling and heating temperature set-points are separated by a climate-insensitive zone, which designates the range of baseload residential consumption. Moreover, the first specification is preferred (hereby named as **Base$_{opt}$**), in order to allow for a sufficiently wide comfort zone and prevent the instantaneous switch from space heating to cooling equipment in the 20-21 ℃ interval assumed by the second candidate model. This result supports the hypothesis that people residing in warmer south U.S. states tend to switch on their space heating and cooling devices at air temperatures higher than the traditional 18.3 ℃ threshold.

The FE estimation results for the optimised Base$_{opt}$ model are also reported in Table 4-6. Adjusting the reference temperature based on which state-level *CDDs* and *HDDs* are computed has a small impact on the size of socio-economic and fuel price effects, which preserve the expected coefficient sign. Raising the set-point temperature of *CDDs* to 21.3 ^{0}C, leads to filtering out variation of electricity use at temperatures in the range of 18.3-21.3 ^{0}C which is attributed to increased AC electricity consumption via the CDD18-HDD18 specification. This in effect has increased the sensitivity of *EL_PC* to the *CDD* metric under the Base$_{opt}$ specification (larger coefficient compared to the Base$_1$ model run). On the other hand, using a higher than 18.3 ^{0}C cut-off point for heating demand calculations (19.3 ℃), has a smaller effect on the size of the *HDD* coefficient.

4.3.3.2 Testing different heat and cold wave day metrics

At a second stage, the performance of the residential electricity use model is improved by complementing the optimised Base$_{opt}$ degree day specification with variables controlling for the duration, frequency and intensity of extreme heat and cold events, as defined in Table 4-2. Evaluating the model fit of extended specifications, relative to base ones, requires factoring in the degree of overfitting which results from the addition of new explanatory variables. Besides the adj. R^2 statistic, preference towards a specific specification is therefore established through the AIC and BIC criterion, as formulated in eqn. (4-2) and (4-3). Figure 4-9 presents the outcome of these statistical tests (adj. R^2, AIC and BIC score) for all the base and extended specifications. Description of extreme temperature effects has a relatively small but positive impact on model performance, as the variation in *EL_PC* explained by the 6 extended specifications is respectively 1.1% and 0.3-0.4% higher relative to the Base$_0$ and Base$_{opt}$ model. However, there is no clear indication about which specific extended specification produces the best model fit based on this test, as the value of adj. R^2 is maximised (0.856) for Ext$_{dum}$, Ext$_{dur}$, Ext$_{frq}$ and Ext$_{avdur}$.

Results on the AIC and BIC criteria reaffirm the previous finding: models based on the extended specifications outperform their simplified counterparts (i.e., models with less parameters). The lowest AIC and BIC score is obtained for the

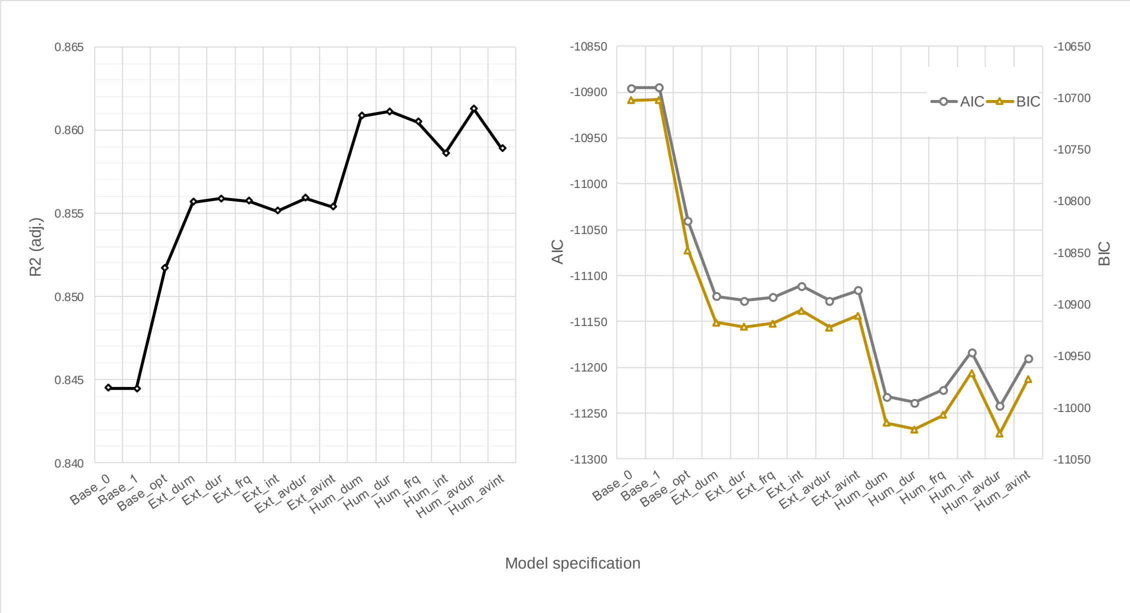

Figure 4-9 Indicators of model fit for the 16 states in the south U.S. climatic region

[left panel for adj. R^2 and right panel for AIC, BIC]

two models respectively controlling for the total duration (Ext$_{dur}$) and average duration (Ext$_{avdur}$) of extreme heat and cold events within a month. Absolute AIC and BIC scores in Figure 4-9 are converted into Akaike and Schwarz weights through eqn. (4-4), accordingly. Amongst the 9 developed specifications (3 base and 6 extended ones), the probability of Ext$_{avdur}$ and Ext$_{dur}$ constituting the best *EL_PC* model is about 50% and 40%, accordingly.

Given the higher possibility for Ext$_{avdur}$ being the optimal model, Table 4-6 also reports FE estimation results for the independent variables included in this specification. The coefficient estimates for the socio-economic and fuel price predictor variables adjust slightly after the addition of extreme temperature metrics. The NCW_{av} variable, which measures the mean number of *CWDs* (per episode) is found to have a highly statistically-significant effect on monthly per capita electricity use. Longer cold wave events in winter therefore exacerbate the use of electric heaters in households. Addition of the NCW_{av} metric also has an impact on the size of estimated effects for *HDDs*. The *HDD* coefficient becomes substantially smaller, as some of the monthly variation of space heating electricity use is now explained by the extreme cold metric instead. The NHW_{av} variable, which accounts for the average duration of heat waves, falls short of reaching statistical significance and has a negative sign. The poor performance of the NHW_{av} metric could be attributed to omitted humidity which may confound the impact of *HWDs* on AC electricity consumption across the south U.S. climatic region; a topic which is investigated next. Nevertheless, the marginal impact of

CDDs on space cooling electricity use increases slightly under Ext_{avdur}, as it compensates for the negative effect of the NHW_{av} metric during summer.

4.3.3.3 Testing the addition of specific humidity statistics

Using the same set of quantitative criteria as previously, overall model fit is evaluated for specifications specifically accommodating an interaction between extreme heat and specific humidity metrics. The share of variation in *EL_PC* explained by the humidity-based extended models is overall higher compared to base ones, as demonstrated by the improved adj. R^2 statistics (Figure 4-9). The 3 specifications associated with the best model fit is Hum_{dum}, Hum_{dur} and Hum_{avdur}, with an adj. R^2 level reaching 0.861. This constitutes a 1.7% and 1.0% improvement in adj. R^2 relative to the reference Base_0 and optimised Base_{opt} degree day model, respectively. In order to check the robustness of this finding, AIC and BIC statistics are compared for all 15 candidate specifications (3 Base + 6 Extended +6 Humidity) in Figure 4-9. In this case, the Hum_{avdur} model, with an interaction for humidity and mean duration of heat wave events, is shown to significantly outperform all others, having both the lowest AIC and BIC statistic. In terms of Akaike and Schwarz weights, the Hum_{avdur} model has an 86% probability of being the optimal model, compared to a 13% probability for Hum_{dur}.

The FE estimation output for the Hum_{avdur} model is reported in the last column of Table 4-6. Inclusion of the interaction term ($HUM \times NHW_{av}$) causes the marginal effect of personal income (*INC*) on per capita electricity use to reduce down to 2.41 kWh/pop (se 0.91) at mean regional income level. Conversely, the marginal effect of electricity price (*EP*) becomes more negative at -7.32 kWh/pop (se 1.32). The coefficient pertaining to the effect of *HDDs* decreases further, while the sensitivity of monthly electricity use to the mean duration of cold waves (NCW_{av}) increases. The coefficient for *HUM*, interpreted as specific humidity's marginal effect on *EL_PC* when NHW_{av} is equal to zero - a condition that is always satisfied during the winter season – is negative. This indicates that air humidity puts a downward pressure on residential space heating electricity consumption. This comes to strong agreement with results from Wang and Bielicki (2018), in which humidity was found to have a negative impact on hourly electric load in different U.S. geographical zones at low temperatures.

Identification of a highly statistically-significant positive interaction term suggests that the effect of average heat wave duration (NHW_{av}) on per capita electricity use increases with the monthly average level of specific humidity (*HUM*). This agrees with the hypothesis made earlier in this chapter that extreme heat affects AC electricity consumption in households more under conditions of high air humidity. As a result of the significant interaction, the negative coefficient sign for

NHW_{av} represents the main effect of the extreme heat variable at HUM=0 level. The total marginal effect of mean heat wave duration is calculated via eqn. (4-7) as the partial derivative of *EL_PC* with respect to NHW_{av}:

$$\frac{\partial\ EL\_PC}{\partial\ NHWav} = \alpha_{NHWav} + \alpha_{NHWav*HUM} \times HUM \tag{4-7}$$

As extreme heat episodes rarely occur during non-summer months, the impact of an additional *HWD* (per episode) on *EL_PC* is evaluated using the median value[10] of JJA specific humidity, recorded over the south U.S. climatic region in the 2000-15 period (14.86 g/kg). This yields a negative marginal effect on *EL_PC* equal to -0.12 kWh/pop (se 0.44). While a negatively signed relationship between heat wave mean duration and per capita electricity use is counterintuitive, the obtained effect is characterised by a very large estimation error. The important uncertainty suggests that the size of NHW_{av}-based effects varies significantly over the states in the south U.S. climatic region.

In order to demonstrate the spatial variation of humidity-heat wave duration effects, marginal NHW_{av} impacts on residential electricity use are re-estimated for individual south U.S. climatic sub-regions. At median JJA *HUM* levels, this effect is estimated to be +0.32 kWh/pop (s.e. 0.47) for the southeast, +0.17 kWh/pop (s.e. 0.46) for the south and -3.7 kWh/pop (s.e. 0.69) for the southwest sub-region. While the impact of an additional *HWD* (per episode) on residential electricity use has a positive sign for the southeast and south climatic-sub region at median summer humidity level, the respective effect for the southwest territory has a perversely *negative* sign. Results for the southwest U.S. sub-region disagree with the original hypothesis asserting that increased air humidity levels compound the impact of hot weather on AC electricity use. It is interesting to note that the marginal effect calculated in eqn. (4-7) turns positive at *HUM* values higher than 15.12 g/kg; which is above the maximum specific humidity level recorded for southwest states in the period 2000-15 (11.23 g/kg). This could imply that households in southwest U.S. states have developed other adaptive mechanisms to counteract heat stress during a heat wave event.

4.3.3.4 Forecasting accuracy of different candidate model specifications

While sections 4.3.3.1, 4.3.3.2 and 4.3.3.3 focus on modelling aspects linked to the achieved model fit through various specifications, this section discusses the extent to which each candidate model can be employed for forecasting purposes. Figure 4-10 compares the prediction accuracy of the 15 candidate specifications

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[10] I choose the median instead of mean regional value of monthly HUM, since the probability distribution of humidity data is highly (negatively) skewed.

for the model's in-sample (2000-15) and out-of-sample (2016-18) data, based on annual and seasonal MAPE statistics. With regards to the training period 2000-15, predictions generated through humidity-based extended *EL_PC* models are generally characterised by a smaller annual error, compared to those produced via the degree day models. Optimising the choice of set point temperatures in degree day calculations ($Base_{opt}$) results in a 0.2% and 0.3% reduction of annual MAPE relative to the $Base_0$ and $Base_1$ model, respectively. Incorporating extreme heat and cold metrics, while also controlling for air humidity, achieves a further 0.2-0.3% reduction in annual prediction error. Hum_{avdur}, which was previously identified as the model fitting historical electricity use data best, has the second lowest annual MAPE (7.4%), still with a less than 0.1% difference from the best-performing model (Hum_{dum}).

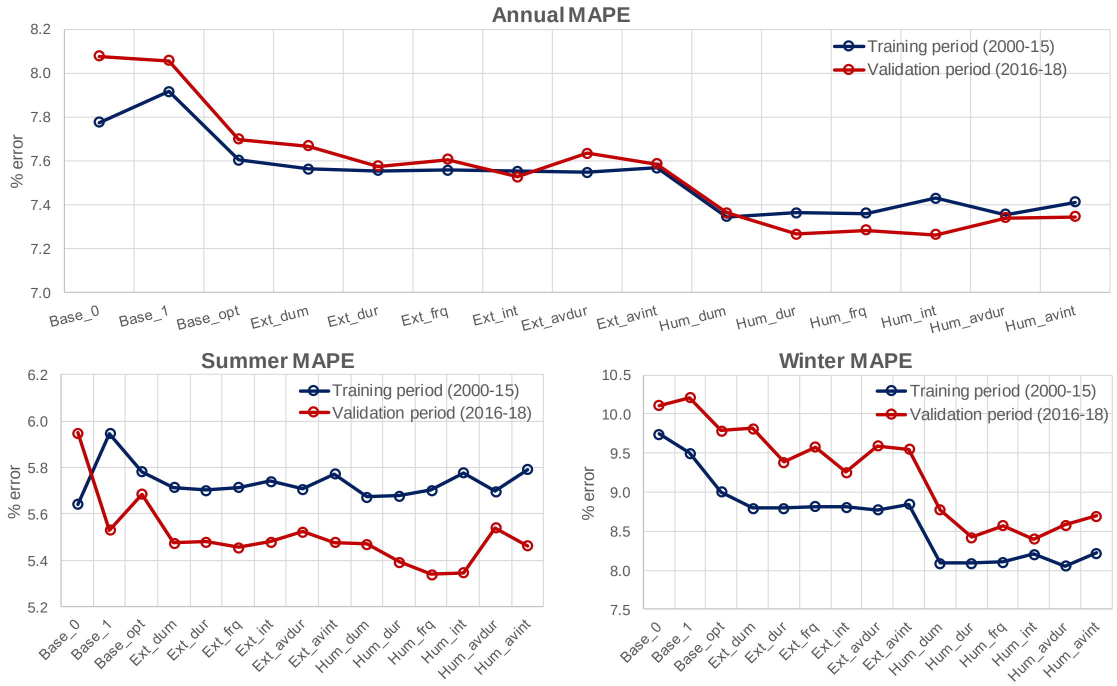


Figure 4-10 Prediction accuracy indicators during the training and validation period for the 16 states in the south U.S. region

[top panel: annual MAPE, bottom left: summer MAPE, bottom right: winter MAPE]

Decomposing annual percentage errors to seasonal MAPE statistics helps identify the improvements in the prediction accuracy of space cooling and heating electricity loads from applying alternative climate metrics. From inspection of Figure 4-10, it is evident that while including extreme temperature metrics and a humidity interaction decreases the forecasting error during winter months, adding these modelling features has a negligible impact on the MAPE value for summer. In other words, controlling for humidity and extreme temperature events is shown to result in better predictions for space heating electricity demand during the historical period 2000-15. As a result, while the reduction in seasonal MAPE between the reference degree day model ($Base_0$) and humidity-based extended models ranges at 1.5-1.7% during winter, a very small increase is observed for summer months (0-0.2%). It is not possible to identify the single-best performing humidity-based specification from these results, as between-model differences in seasonal MAPE statistics are not significant (< 0.1%).

The forecasting accuracy of different models of residential electricity use for the south U.S. climatic region is also assessed for data recorded during the historical period 2016-18. The results for annual and seasonal MAPE statistics are also summarised in Figure 4-10. Similar to the training period's findings, humidity-based extended specifications are associated with a smaller prediction error, as demonstrated by the declining annual MAPE value. A 0.4% decrease in annual MAPE is realised through the optimised degree day model, which is accompanied by a further 0.3-0.4% reduction through humidity-based extended specifications, respectively. Once again, it is difficult to determine the single-best performing model based on annual errors, as 5 individual specifications, including Hum_{avdur}, reduce annual MAPE statistic down to 7.3%.

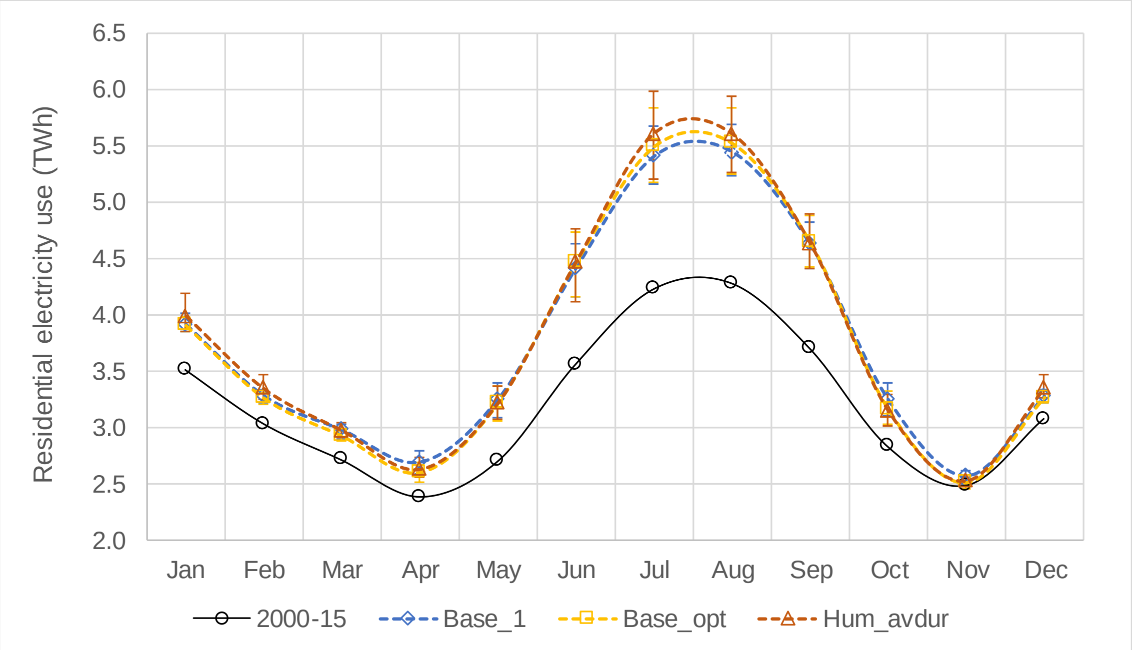
Seasonal MAPE statistics computed for the out-of-sample datasets (2016-18) present a clearer picture regarding the superiority of humidity-based extended models as forecasting tools. As with the training period's results, the reduction in seasonal MAPE statistics achieved via the extended specifications is more robust during the winter season: while a modest reduction (0.3-0.4%) in the winter's prediction error is achieved by fine-tuning degree day set-point temperatures, addition of extreme temperature metrics and a humidity interaction term further decreases seasonal MAPE by 1.0-1.4%. The best-performing *EL_PC* models during winter months is Hum_{dur} and Hum_{int} with a seasonal MAPE at 8.4%, while Hum_{avdur} – the model achieving optimal model fit – follows closely at 8.6%. The evidence about the superiority of extended specifications in the summer season is once again weaker. Still, the best-performing humidity-based specifications (HUM_{frq} and Hum_{int}) manage to improve the prediction of summertime residential electricity use by 0.6% and 0.3%, compared to $Base_0$ and $Base_{opt}$, respectively. Adopting the Hum_{avdur} specification instead, decreases summer's forecasting error respectively by 0.4% and 0.1%.

4.3.4 Projections of residential electricity use (2046-55)

In the previous section, the idea of an improved model of monthly residential electricity use for the states of the south U.S. climatic region was put forward; one which in addition to socio-economic and fuel price controls, includes more comprehensive metrics of climate-sensitive electricity demand. Adjusting the temperature set-points of degree day metrics according to the historical variation of regional electricity use resulted in better modelling properties, relative to the customary approach of using a uniform 18.3 ℃ threshold. Moreover, incorporating more complex temperature effects to explain the variation of space heating and cooling electricity use led to even larger improvements in terms of the model's fit and prediction accuracy. While the modelling benefits from utilising variables that account for the impacts of extreme temperature episodes and air humidity have been demonstrated in the previous sections, what remains to be answered is the practical usefulness of incorporating these features in long-term projections of residential electricity use. Potential large deviations of projections from the fully-extended model, from those generated though the more simplified degree day specification, would signal the need for more sophisticated energy demand forecasting tools. These tools could then form the basis for revising electricity generation capacity expansion plans for the south U.S. region, in accordance with the evolution of mean and extreme weather variables under different climate change scenarios.

The practical value of developing more complex models is evaluated by comparing projections of south U.S. residential electricity use in the 2046-55 period, devised according to coefficient estimates for the $Base_1$, $Base_{opt}$ and Hum_{avdur} model (Table 4-6). Since NOAA does not publish long-term projections of degree days for U.S. states, $Base_1$ is employed instead as the reference model for future projections since it also uses *CDDs*/*HDDs* calculated with a fixed 18.3 ℃ set point and has the same explanatory power like $Base_0$. Comparability of projections is established by using the same set of assumptions relating to the long-term evolution of state-level socio-economic (*POP*, *INC*), fuel price (*EP*) and multiple climatic variables (Table 4-4). The monthly temporal resolution of the *EL_PC* model, allows projecting annual and seasonal differences of residential electricity use between the future (2046-55) and current (2000-15) period.

The resulting model projections of average residential electricity use in the south U.S. climatic region under the three specifications are presented with dotted lines in Figure 4-11. It should be noted that the variability in projections (indicated by the error bars) represents the range of potential *EL_PC* model outcomes, as a result of the uncertainty in future climate-based data, which were obtained from the multi-model ensemble (Table A-1). Based on mid-range projections, regional average residential electricity use grows by 17.1% (12.8-21.4%) and 16.8% (12.2-21.6%) in 2046-55 relative to the 2000-15 period for the $Base_1$ and $Base_{opt}$ model, respectively. Mean regional residential electricity use increases by 18.1% (12.6-23.9%) under the humidity-based extended specification, Hum_{avdur}. While the mid-range estimate of annual electricity use in 2046-55 for Hum_{avdur} is only 1% higher than the respective value for the degree day specifications, the deviation is larger at the upper limit of models uncertainty (~2%).



Note: Error bars represent data input uncertainty from the 20 climatic model simulations.

Figure 4-11 Projections (2046-55) of mean residential electricity use for the 16 states in the south U.S. climatic region

While the difference in future estimates of residential electricity use between the base and humidity-based specifications is small on an annual basis, the divergence of projections is more notable on a monthly basis as shown in Figure 4-11. More specifically, mid-range summertime residential electricity use across the south U.S. climatic region is projected to be 26.5% (20.6-32.6%) and 28.4% (20.9-35.9%) higher in 2046-55 relative to 2000-15 levels for $Base_1$ and $Base_{opt}$, while the relative growth is higher at 29.9% (20.8-38.2%) for Hum_{avdur}. It is therefore evident that under the warming pattern predicted by the RCP8.5 scenario increased mean temperatures and humidity, together with longer extreme heat episodes, will place extra pressure on regional power infrastructures; an additional electricity demand for residential air-conditioning which is not captured entirely by the *CDD* variable in the two base models.

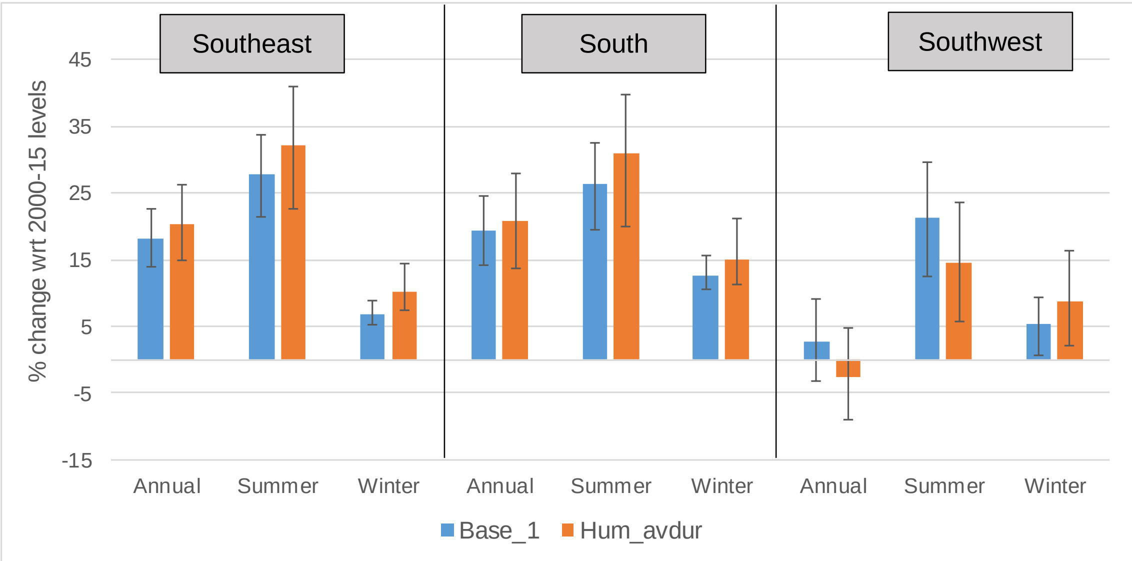
As with the results for summer months, a discrepancy is found in future projections of wintertime residential electricity use between the degree day and extended models. In the mid-range case, average seasonal electricity use across south U.S. states increases respectively by 8.8% (7.0-11.1%) and 8.4% (6.8-10.4%) in 2046-55 for the $Base_1$ and $Base_{opt}$ specification. The lower estimate for

Base_{opt} is justified by the smaller size of the marginal *HDD* effect estimated under this specification. Under the humidity-based model, $\text{Hum}_{\text{avdur}}$, regional residential electricity use during winter increases by 11.0% (7.7-15.7%) in 2046-55, relative to 2000-15 levels. This result appears to be counterintuitive at first sight, as the response coefficient for *HDDs* decreases further under the $\text{Hum}_{\text{avdur}}$ model. Intuitively, an equal decrease in the number of regional *HDDs* in line with RCP8.5 scenario specifications should have yielded a lower heating electricity demand estimate under the full model. However, analysis of climatic simulations obtained for 2046-55 shows that a reduction in future *HDD* levels is accompanied by an increase in *CWDs*. That more extreme cold weather raises future residential electricity demand during the winter season, despite the upward shift of mean outdoor temperature across the south U.S. climatic region.

The anticipated impacts of climate change on residential electricity use in the 2046-55 period, as determined through the RCP8.5 simulations, are expected to significantly vary across the south U.S. climatic region. The spatial heterogeneity of annual and seasonal climatic impacts is not directly observed in Figure 4-11, which presents the average behaviour of future residential electricity use for the whole of the region. Figure 4-12 disaggregates the projections of residential electricity use (2046-55) to individual sub-regions (southwest, south, southeast) for the reference base (Base_1) and the fully fledged ($\text{Hum}_{\text{avdur}}$) specification.

Among the 3 climatic sub-regions, south is projected to have the largest increase of annual residential electricity use relative to 2000-15 levels (19.4% and 20.7% in the mid-range case under the Base_1 and $\text{Hum}_{\text{avdur}}$, respectively). The annual trend is dominated by growing electricity loads in the summer period, which are shown to increase by 26.4% and 31.0% under mid-range scenarios respectively for Base_1 and $\text{Hum}_{\text{avdur}}$. On the other hand, the southwest sub-region records the smallest relative increase in annual electricity use levels under the Base_1 model (2.8%), which turns negative (-2.7%) under the full model. While mid-range electricity use in southwest U.S. states shows increases during both summer and winter months, these are counterbalanced by electricity demand reductions in autumn and spring, possibly due to lower seasonal space heating requirements.

Projections for 2046-55 devised for the southeast and south sub-region support the previous finding that a model with description of extreme temperature-humidity events projects a stronger increase in residential electricity use compared to the degree day model. Moreover, differences in predictions between the two models become larger at the upper limit of projections' uncertainty. For example, the projection of summertime residential electricity use in southeast states is 4.5% higher for the humidity-based model in the mid-range case, while the corresponding deviation from Base_1 is 7.1% at the upper limit of uncertainty.



Note: Error bars represent data input uncertainty from the 20 climatic model simulations.

Figure 4-12 Projections of residential electricity use in 2046-55 for the southeast (6 states), south (6 states) and southwest (4 states) sub-region versus current levels

The only exception is scenario analysis results for the southwest sub-region. With respect to mid-range projections in 2046-55, the reference degree day model predicts a larger positive change of residential electricity use. This is more pronounced for summertime electricity consumption since the upward pressure added by the heat wave-humidity interaction through the Hum_{avdur} specification is non-existent. This is due to the low level of air specific humidity in the southwest sub-region (JJA average *HUM* increases from 7.09 to 9.48 g/kg), which does not exceed the HUM threshold (shown to be 15.12 g/kg via eqn. (4-7)), above of which the marginal effect of heat waves on *EL_PC* becomes positive. The larger estimate of wintertime residential electricity use in 2046-55 for the humidity-based specification is due to the upward pressure added by the cold wave metric.

4.4 Discussion

4.4.1 Evaluating the performance of alternative climate metrics

Section 4.3.3 quantified the benefits harnessed in optimising and extending historical models of residential (per capita) electricity use, considering both the degree of model fit and forecasting accuracy properties. Results from different statistical tests led to the general conclusion that humidity-based extended specifications fit the historical data better and produce more accurate predictions, as they outperform degree day models in the vast majority of tested categories. However, no humidity-based specification could be distinguished as the single best-performing model of residential electricity use for the south U.S. climatic region under every category, when comparing the selection criteria summarised in Table 4-7. Nevertheless, the Hum_{avdur} model, which incorporates metrics for the average duration of heat and cold wave episodes and a specific humidity variable, achieved the highest score in 5 out of 9 tested categories and was therefore adopted as the optimal *EL_PC* model for the south U.S. climatic region.

Table 4-7 Summary of best-performing models according to different statistical criteria

				MAPE (2000-15)			MAPE (2016-18)		
Model	R^2	AIC	BIC	Annual	Summer	Winter.	Annual	Summer	Winter
$Base_0$					✓				
Hum_{dum}	✓			✓		✓			
Hum_{dur}	✓					✓	✓		✓
Hum_{frq}						✓	✓	✓	
Hum_{int}							✓	✓	✓
Hum_{avdur}	✓	✓	✓			✓	✓		
Hum_{avint}							✓		

The preferred specification (Hum_{avdur}) could explain the largest variation in historical residential electricity use data (highest R^2 adj.), which is 2% higher than the one explained via the reference degree day model. It was also the most parsimonious one having the lowest AIC and BIC statistics. Moreover, Hum_{avdur} was amongst the specifications with the smallest prediction error; it decreased the annual forecasting error by 0.4% and 0.7% in the training and validation period, respectively, relative to the reference degree day model $Base_0$. It also resulted in a 1.7% and 1.5% lower prediction error (relative to $Base_0$) for winter months in the 2000-15 and 2016-18 period, respectively. While its prediction error in summer was slightly higher than that for $Base_0$ in the 2000-15 estimation period (~0.1%), it still achieved a 0.4% reduction of summertime MAPE in the 2016-18 forecasting period.

Furthermore, the implications for long-term projections of residential electricity use in the south U.S. climatic region were demonstrated from incorporating the additional weather effects. The model which explains climate-sensitive electricity demand based on a set of empirically-determined degree days, cold and heat wave days and humidity metrics (Hum_{avdur}) was shown to project slightly higher (~1%) electricity use levels in 2046-55, compared to the reference one. The difference in model projections was however more pronounced during the cooling and heating season. Furthermore, capturing the more complex effects of climate change and the resulting use of HVAC equipment, through the extended specifications, may have significant implications for seasonal electricity use and peak demand forecasts, rather than for all-year-round baseload consumption.

4.4.2 Implications for the south U.S. power sector

While the previous discussion evolved around the implications of accounting for reviewed climatic metrics on projections of residential electricity use, it is also important to assess the potential implications for future electricity generating capacity expansion. As the forecasted level of monthly electricity demand in 2046-55 increases under the Hum_{avdur} specification, so is the need for future generation capacity across the south U.S. power sector. While the *EL_PC* model cannot explain future changes in the intra-monthly or intra-daily variation of residential electricity demand due to climate change, the plots in Figure 4-11 indicate that the "peakiness" of heating and cooling loads in 2046-55 becomes more pronounced under the fully-fledged model. For power sectors designed to sustain maximum electricity loads during summer (see for example the profile of hourly electricity demand for the Texas region in Figure 4-13), increased demand "peakiness" implies that more capital needs to be invested towards expanding peak capacity and safeguarding the reliability of power supply and distribution.

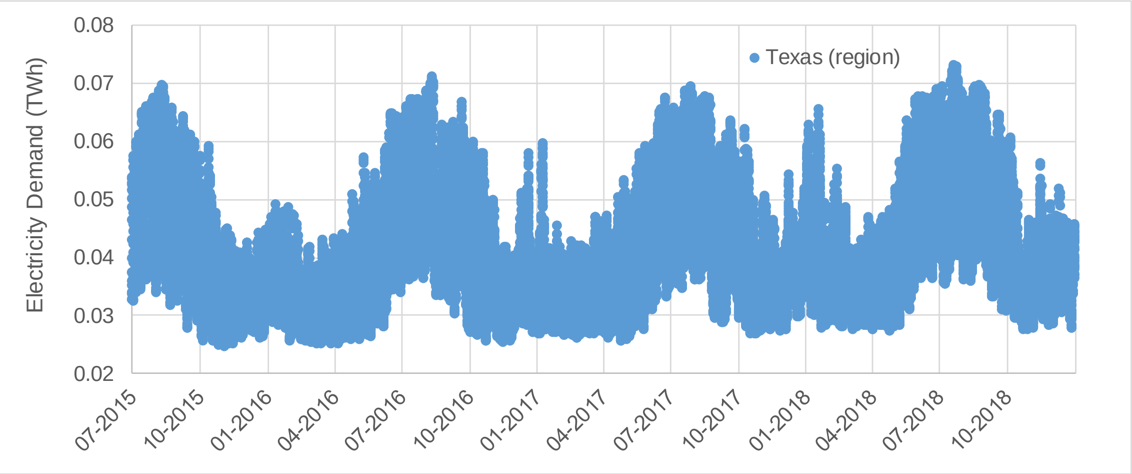


Figure 4-13 Hourly profile of electricity demand for the Texas region in 2015-18 Source: (U.S. EIA, 2020c)

To put this into a wider context, the projected increases of regional residential electricity use in 2046-55 are translated as direct summertime impacts on the south U.S. power infrastructure, in terms of the capacity required to meet additional cooling loads under the full model (Hum_{avdur}). Aggregate electricity use estimates during summer (measured in TWh) are converted into instantaneous load (measured in GW), by dividing them with the total number of hours in each month. In doing so, the crude still necessary assumption is made, given the absence of future modelled data with finer temporal resolution, that demand for electricity is evenly distributed over the hours in a month. Finally, seasonal differences in the level of instantaneous load, as projected through the $Base_1$ and Hum_{avdur} model in 2046-55, are compared with the net summer capacity size of power plants, as estimated by the EIA for different energy sources in 2018 (U.S. EIA, 2019b). Statistics about the generating capacity of power plants are collected and averaged over the 16 states belonging to the south U.S. climatic region. Results of this comparative analysis are summarised in Table 4-8.

Table 4-8 Power plants required to meet additional summertime electricity load in the 16 states of the south U.S. region under the full model

			Additional number of power plants		
Energy source	Total number of power plants	Net summer capacity per plant (GW)	Min	Mean	Max
Coal	108	0.908	0	3	5
Natural Gas	662	0.377	1	8	13
Solar thermal and Photovoltaic (PV)	992	0.014	16	214	357

In the mid-range case, the projected level (2046-55) of total residential electricity use during summer months across the south U.S. climatic region is 6.5 TWh higher under the Hum_{avdur}, relative to the $Base_1$ model. This quantity when converted to instantaneous load difference (2.9 GW) amounts to the size of 3 coal power plants, or alternatively to the capacity of 8 natural gas generators. Political commitment to decarbonise power grids, would require a sizeable investment in renewable solar-based capacity in the south U.S. region as demonstrated under the full model in 2046-55, which represents a 20% growth in the number of solar power plants relative to 2018's level. It should be noted that the difference between the two model outputs becomes much smaller at the lower limit of projections uncertainty. In the winter, the difference in mid-range projections of south U.S. electricity use projected for the base and full model is lower at 3.4 TWh, which translates to an instantaneous load change of 1.6 GW.

4.5 Conclusions

This chapter aimed at improving our understanding of the relationship between residential electricity use and weather, based on a number of omitted features in current degree day methods, using the case study of the south U.S. climatic region. The starting point for this assessment was a historical residential electricity use model (2000-15) which uses external degree days and also controls for the effect of personal income and electricity price. A more accurate description of historical climate-sensitive electricity demand was pursued through multiple measures, initially involving the use of degree day metrics constructed from high-resolution reanalysis temperature data with empirically determined temperature thresholds. The second and third step of analysis explored the magnitude of additional benefits achieved by complementing the residential electricity use model with climatic metrics parameterising attributes of extreme temperature episodes and air humidity, respectively. Finally, this study evaluated the sensitivity of long-term projections (2046-55) of residential electricity use on an annual and seasonal basis to the choice between the base and extended model, incorporating the more complex effects of predicted climate change.

First, results relating to the historical analysis period highlight the benefits for model fit and prediction ability of rising the temperature set-points of *CDDs* and *HDDs* from the traditional 18.3 ℃ threshold to 21.3 ℃ and 19.3 ℃, respectively. The optimised degree day model, which explains 1% more variation of per capita electricity use in the south U.S. region compared to the reference model, reduces the annual prediction error by 0.2% and 0.4% for the estimation (2000-15) and forecasting (2016-18) period, respectively. Results for the forecasting error over the summer and winter season also suggest the superiority of the comfort zone over the single base temperature model (except from 2000-15 results considering the summer’s prediction error).

Second, extending the optimised degree day specification to accommodate the effects of heat and cold waves, as well as those of specific humidity, had an equally-sized positive impact on the electricity use model’s overall performance to that from the previous step. Statistical tests indicate a preference towards a model accounting for the impact of average heat and cold wave duration and the amplifying effect of humidity during periods of extreme heat. The preferred specification increases the amount of explained data variance by a further 1% and has a 90% probability of being the optimal model according to the AIC and BIC criterion. In terms of its forecasting ability, the humidity-based model reduces the annual prediction error by 0.2% and 0.4% relative to the optimised degree day model during 2000-15 and 2016-18, respectively. While controlling for air humidity turns the effect of heat waves on electricity use statistically significant, this leads to a more significant decrease in the model's prediction error during winter months (in the range of 0.9-1.2%). Evidence about a small reduction (~0.1%) in prediction error during the summer season is only obtained for the validation period's analysis.

Third, results showed that besides improving model fit and forecasting ability, incorporating the more complex temperature effects has implications for long-term forecasting of seasonal space heating and cooling electricity loads. Under an extreme climate change case and reference assumptions about personal income and electricity price growth, average annual electricity use in the south U.S. region increases by 12-22% and 13-24% in 2046-55 relative to 2000-15, under the optimised degree day and humidity-based model. While between-model differences are small on an annual basis, the divergence of projections is more pronounced on a sub-annual basis. Regional residential electricity consumption as projected under the full model in 2046-55 is 0-2% and 1-5% higher during the summer and winter season, respectively, compared to the optimised base model. Sub-regional results demonstrated that impacts on projections of AC electricity use are larger across southeast and south states, with increased humidity levels. Furthermore, this stresses the need for regional utility planning to consider the expected growth of heat and cold wave episodes, as well as the role of humidity, in estimating future capacity requirements.

In summary, this case study demonstrated the positive (but moderate) value added for modelling fit and forecasting quality through optimising traditional degree day metrics and incorporating complex temperature-humidity effects. However, the conclusions of this assessment relate only to residential electricity use behaviours observed in the south U.S. climatic region, thus more evidence is required for generalising them to a larger geographic region. Moreover, this chapter has only considered the uncertainty from climate model simulations in projections of future residential electricity use, under a single climatic, socio-economic and fuel price trajectory. The next chapter will seek to generalise the conclusions obtained from this regional study in an effort to construct a more comprehensive model of electricity use for the whole of U.S. residential sector. This model will form the basis for devising projections of national-level residential electricity use in 2050, which embody the input uncertainty from a range of socio-economic, fuel price and climatic scenario trajectories.

Chapter 5

A model of residential electricity use for the contiguous United States to 2050

5.1 Introduction

5.1.1 Lessons from Chapter 4

The main finding from the historical analysis in Chapter 4 is that modelling of residential space heating and cooling electricity use for the south U.S. region is sequentially improved through application of:

a) Degree day metrics calculated based on interpolated temperature grid data and on optimised region-specific temperature set points.
b) Novel climate metrics encapsulating the more complex impacts of extreme heat and cold events.
c) A specific humidity variable that is interacted with the extreme heat metric.

The results obtained in Chapter 4 regarding the applicability of different climatic metrics are applicable to the geographic scope of that particular study, as inference for climatic and non-climatic effects is conditional on the panel of 16 states belonging to the warm south U.S. climatic region. In order to generalise conclusions about the explanatory power of reviewed climatic metrics for other climate types, the previous assessment is replicated in the cold north U.S. climatic region. Potential agreement between Chapter 4 and Chapter 5 about the practical usefulness of adopting various climate metrics to explain the variation of historical residential electricity use would further challenge the validity of traditional degree day metrics as a comprehensive measure of climate-sensitive energy demand.

Moreover, the previous chapter has only considered the uncertainty in climate model simulations under a single emissions pathway for devising projections of future residential electricity use for the south U.S. climatic region. As climate is not the only source of uncertainty for future projections, this chapter also explores interactions with uncertainties relating to the future evolution of non-climatic drivers, including personal income and fuel prices. Development of multiple scenarios allows quantifying the impact of climatic and non-climatic factors on mid-21st century residential electricity demand in the contiguous U.S. region, on an annual and monthly basis.

Studies specifically concerned with the long-term impact of climate change in the United States - the country with the largest building final energy consumption (IEA, 2019f) - find that heating demand will decrease and cooling demand will decrease as a result of higher temperatures. These studies do not always agree about the sign of the net effect of climate change on delivered energy use in buildings, namely as to whether decreased heating fuel usage will outweigh cooling-based increases due to warmer weather (Wilbanks et al., 2008). Nevertheless, there is compelling evidence that, apart from some northern states, higher temperatures will cause an increase of total and peak electricity consumption in the buildings sector, as space cooling demand becomes more important (Brown et al., 2016). Electricity is also the largest source of energy for the U.S. residential sector, accounting for almost half of total sectoral final consumption in 2017 (IEA, 2019f). Moreover, the contribution of space cooling to final electricity consumption is estimated to be 17% in the same year (IEA, 2019b). On the other hand, the relative contribution of space heating to electricity consumption is substantially lower (less than 2% in 2015), as it is mostly provided through natural gas.

5.1.2 Specific research objectives

Chapter 5 re-addresses RQ1 by evaluating the performance of the alternative climate metrics developed in Chapter 4 in an econometric model of residential electricity use this time covering north U.S. states. This is done to generalise conclusions about the need of using more complex climate metrics in models quantifying climate-sensitive electricity demand for countries with distinct climate types and thus a different balance between heating and cooling demand. Chapter 5 also tackles RQ2 which seeks to model and project the effect of both climatic and non-climatic factors on electricity consumption in the mid-21st century, using the case study of contiguous U.S. residential sector. This chapter utilises results regarding the suitability of different climate metrics in the historical model analysis to project the impact of climate change on future residential electricity use. Since socio-economic and energy price factors are also drivers of electricity use in households, their future impact on electricity demand is compared with that of climate change on an annual and seasonal basis.

This chapter constitutes of a first attempt to estimate aggregate residential electricity consumption for 49 U.S. states (this includes all contiguous U.S. states plus the District of Columbia, minus the state of Alaska and Hawaii) via panel data regression and to quantify its annual and intra-annual variation in the mid-21st century. While panel data models have been extensively used to study determinants of past building electricity consumption (Paul et al., 2009; Alberini and Filippini, 2011; Salari and Javid, 2016), only a handful of them have been used as impact assessment tools (Deschênes and Greenstone, 2011; De Cian et al., 2013) and even fewer have tested various metrics for the climate-sensitive component of electricity demand. The specific research objectives of this chapter are outlined below:

(a) First, replicate the steps of the assessment conducted in Chapter 4 which involves testing different metrics of climate-sensitive residential electricity use for 21 states in the north (Northeast, East North Central, West North Central) U.S. climatic region. Based on the outcome of this replication exercise, a suitable model of monthly residential electricity is estimated for the contiguous United States using state-level data for the historical time period 2000-18.

(b) Second, explore the size and uncertainty of climate change impacts on future residential electricity use (2046-55) and compare them with those of evolving personal income and electricity prices, on an annual and sub-annual basis. The objective of this second part is to integrate a low and high RCP emissions trajectory with socio-economic and energy price projections in the mid-21st century and perform a sensitivity analysis of national residential electricity consumption. The temporal resolution achieved by this study permits a distinction to be made between impacts on annual aggregate and monthly peak electricity consumption.

(c) Finally, compare the set of scenarios of national residential electricity use in the mid-2^{1st} century constructed here with those generated through the NEMS modelling tool. This final part evaluates the differences in projected increases of annual residential electricity consumption in 2046-55, relative to 2018 levels, between my FE econometric model and the modelling tool developed by the U.S. EIA.

5.1.3 Chapter structure

The replication exercise is tackled in section 5.2.1, while the final state-level model of contiguous U.S. residential electricity use is formulated in section 5.2.2 and estimated in section 5.3.2.2. Potential sources of simulated climate data which aid in constructing future climatic metrics are identified in section 5.2.4. Projections of per capita and total residential electricity use for the contiguous U.S. region in the mid-21st century are executed in section 5.3.3. The chapter also provides a wider discussion of findings from Chapter 4 and Chapter 5 about the relative performance of reviewed climatic metrics in the south, north and contiguous U.S. region. More specifically, sections 5.4.1 and 5.4.2 respectively compare regional and national results concerning the explanatory power and estimated effects for the reviewed climatic metrics. Finally, section 5.5 summarises the conclusions of this chapter.

5.2 Data and Methodology

5.2.1 Modelling framework

As with the south U.S. region, the north and contiguous U.S.-level analysis is based on the general modelling framework which was developed in section 3.3.1 to study the impacts of space cooling electricity demand for a nearly-saturated residential AC market. Chapter 5 extends this general framework by repeating the same steps as outlined in Chapter 4 (Figure 4-1), in optimising the statistical performance of the state-level model of historical residential electricity use. The same mathematical model of monthly state-level residential electricity use which was previously constructed for the south U.S. climatic region is first estimated for north U.S. states in 2000-15, and subsequently for the contiguous U.S. region in the period 2000-18. In its basic form, the climate-sensitive component of electricity demand is depicted through external heating and cooling degree day variables (*HDD*s/*CDD*s), while the climate-insensitive part is modelled through a set of personal income (*INC*) and electricity price (*EP*) variables.

Similar to Chapter 4, alternative metrics of climate-sensitive residential electricity use are sequentially added to the base model specification, including heating and cooling degree days measured against varying temperature set points, extreme heat and cold indicators and a specific humidity variable. Each time a new metric is incorporated to the model specification its performance is tested against historical electricity use data. The preferred specification is used together with state-level monthly input data for the time period 2000-18 to estimate a FE panel data model of contiguous U.S. residential electricity consumption. Combinations of future scenario values are subsequently fed into the estimated model to construct projections of residential electricity use in the mid-21st century and measure the relative contribution of climate, socio-economic and fuel price trajectories.

5.2.2 Modelling historical residential electricity use for the contiguous U.S. region (2000-18)

This study uses panel data comprising a time series of monthly observations made on selected variables and across different federal units (states). The first level of analysis involves estimating a FE panel data model of state-level per capita electricity use (*EL_PC*) for the north U.S. climatic region based on a linear combination of socio-economic (*INC, INCSQ*), fuel price (*EP*) and climate-based (*CDD* and *HDD*) variables, which matches the one adopted for the south U.S. case study. Month and year-specific effects are also added to the econometric estimation to control for the unobserved variation in data, as demonstrated through eqn. (3-10). The climate metrics used in this investigation are presented in section 4.2.2.1.

Three base specifications are first employed to assess the statistical performance of degree day metrics constructed alternatively by means of weather station and gridded reanalysis data and based on different assumptions about heating and cooling-related base temperatures: the first one utilises degree days made available through the NOAA's website and acts as a reference point against which the performance of alternative specifications is subsequently compared ($Base_0$). The second method utilises degree days calculated using the gridded data interpolation method described in section 4.2.2.1 and a uniform temperature threshold for heat and cold demand at 18.3 ℃ across the U.S. ($Base_1$). The last approach involves the implementation of heating and cooling degree day metrics whose temperature set points are separately altered until they provide the best fit to historical electricity use data ($Base_{opt}$). Similar to previous analysis, *CDDs* and *HDDs* are calculated simultaneously for all states based on cut-off points which are allowed to vary from 15.3 to 22.3 ℃, with a 1 ℃ step each time.

Moreover, the optimal base specification ($Base_{opt}$) identified in the first level of analysis is extended to accommodate the reviewed metrics parameterising attributes of extreme temperature events. Extended specifications alternatively control for the duration (Ext_{dum}), frequency (Ext_{frq}), and intensity of extreme heat/cold events (Ext_{int}), as well as mean duration per episode (Ext_{avdur}), daily mean intensity (Ex_{avint}) and single heat/ cold way occurrence (Ext_{dum}). The final level of analysis complements the aforementioned extended model specifications with a specific humidity variable which is interacted with the corresponding extreme heat component. This is performed to account for the potential interdependence between heat wave and humidity impacts on AC-based residential electricity use. This yields the final group of humidity-based extended specifications, namely Hum_{dur}, Hum_{frq}, Hum_{int}, Hum_{avdur}, Hum_{avint} and Hum_{dum}. In the same fashion as in Chapter 4, the coefficients of the *EL_PC* model under all candidate specifications are estimated using data for the time period 2000-15, while all models are validated for the time period 2016-18. The statistical criteria listed in section 4.2.2.2 are applied to rank different model specifications according to how well they fit past observations (adjusted R^2, AIC and BIC score) and their forecasting ability (annual and seasonal MAPE statistics).

Based on the correspondence of results about the statistical performance of different climatic metrics between the south and north U.S. region, a suitable specification is chosen to model historical (per capita) residential electricity use in the whole of contiguous United States (49 states). The U.S. model of residential electricity use is estimated using the full range of historical input data (2000-18) under both the various base and extended specifications, as in the case of the regional models. Since there is no validation period this time, the final decision about the optimal *EL_PC* model specification is guided through regression accuracy tests only (adjusted R^2, AIC and BIC score). The appropriateness of the FE panel data estimator to identify the size of climatic and non-climatic effects on *EL_PC* is verified on the basis of formal statistical tests. The first hypothesis that needs to be tested is whether state-specific effects are present in the panel or a 'pooled' OLS model would suffice. Following this, a Hausman specification test is employed to choose between a FE and RE model, whose main difference lies with the potential correlation/ non-correlation of unit-specific effects with the model's explanatory variables (Baltagi, 2008).

5.2.3 Projecting residential electricity use in the contiguous U.S. region (2046-55)

Projections in 2050 (2046-55) are constructed according to the mathematical model describing per capita residential electricity use for the contiguous United States in the historical period 2000-18, as explained in section 5.2.2. The empirical model's parameter coefficients, which represent the size of climatic and non-climatic temporal effects on *EL_PC*, are multiplied with multiple scenario data from the time period 2046-55 to devise projections of per-capita and total U.S. residential electricity consumption in the mid-21st century. New sets of state-level climate metrics (*CDD* and *HDD*) are calculated for a high-end and low-end climate change trajectory. Future values for the non-climatic explanatory variables (*INC* and *EP*) are also estimated by applying uniform growth rates across the contiguous U.S. region obtained under the EIA's reference, high and low economic development scenario. In order to compare the size of individual effects, the contribution of each explanatory variable to the increase in per capita residential electricity use between current (2000-18) and future (2046-55) levels is quantified. The effect – on average across the 49 states – of *CDD*, *HDD*, *INC* and *EP* on future annual and monthly *EL_PC* levels is calculated under all scenario combinations, through respectively utilising eqns. (5-1)-(5-4):

$$\Delta(EL\_PC^{CDD}) = \beta_{CDD}\Delta(CDD) \tag{5-1}$$

$$\Delta(EL\_PC^{HDD}) = \beta_{CDD}\Delta(HDD) \tag{5-2}$$

$$\Delta(EL\_PC^{INC}) = \beta_{INC}\Delta(INC) + \sum_{reg=1}^{9} \beta_{INCSQ}\Delta(INCSQ) \tag{5-3}$$

$$\Delta(EL\_PC^{EP}) = \beta_{EP}\Delta(EP) \tag{5-4}$$

where Δ calculates respective differences in the mean value of investigated variables between 2046-55 and 2000-18. Please note that since no information is available about the change in seasonality of residential electricity prices and personal income in 2046-55, their partial effect on future per capita electricity use is uniformly distributed throughout the year. Moreover, projections of U.S.-average monthly residential electricity use are presented for the reference case, combined with the two RCP scenarios. Finally, the sensitivity of these projections is tested to differing assumptions about the annual growth of socio-economic and fuel price parameters by the mid-21st century.

5.2.4 Data Requirements

5.2.4.1 Historical model of U.S. residential electricity use

The sources identified in Chapter 4 (section 4.2.4.2) were accessed to repeat the data collection process for the remaining states in the contiguous U.S. region (of which the north climatic region is a sub-set) during the historical modelling period (2000-18). The variable of per capita electricity use (*EL_PC*) was derived based on monthly data about the amount of state-level domestic electricity sales (*EL*), divided by population (*POP*), which was first transformed from annual into monthly estimates using cubic spline interpolation. Based on the same interpolation method, quarterly state-level personal income estimates (*INC*) were converted into monthly values. Average monthly retail prices of electricity (*EP*) were also collected for all states in the sample. In order to account for inflation, nominal *INC* and *EP* values were adjusted to 2018's (January) constant terms using the CPI-U-RS dataset.

Past climatic information for the rest of the states comprising the contiguous U.S. region was compiled by repeating the same data collection and transformation process described in Chapter 4. For the $Base_0$ specification, monthly state-level *CDDs* and *HDDs* were sourced from the NOAA's website. For the remaining base and extended specifications, time series of meteorological variables (i.e., daily average, daily maximum and daily minimum temperature, and monthly average specific humidity) were initially calculated at the county level from the gridded reanalysis data files created as part of the NARR project. County-level values were computed after matching each county's centre of population for 2010 to the 4 nearest NARR grid points. Air temperature and humidity at the population centre of all counties was then estimated using the inverse distance weighting method, given by eqn. (4-1).

Records of monthly, county-level, heating and cooling degree days (*HDD*/*CDD*), and specific humidity (*Hum*), were then constructed for the time period 2000-18 and averaged across each state, using county populations for 2010 as weightings (Figure 4-2). Finally, the quantitative criteria defined in section 4.2.2.1 were used together with computed daily max/min air temperatures from the NARR data files to construct past extreme heat and cold temperature metrics (i.e., *NHW*, *FHW*, *IHW*, *NCW*, *FCW*, *ICW*) for the remaining contiguous U.S. states. A summary of climatic and non-climatic variables included in the $Base_0$ model of U.S. residential electricity use is provided in Table 5-1.

Table 5-1 Definition of state-level variables and descriptive statistics for the contiguous United States (2000-18)

Variable	Symbol	Mean	Std. Dev.	Max	Min
Electricity use (TWh/mo)	EL	2.30	2.34	18.62	0.07
Per capita electricity use (kWh/pop•mo)	EL_PC	391.51	134.18	933.78	130.08
Population	POP	6,196,755	6,779,975	39,487,794	493,457
Personal income (000’ 2018 $/pop)	INC	46.63	8.49	81.83	31.27
Electricity price (2018 Cents/kWh)	EP	12.49	3.12	25.25	6.80
Heating degree days	HDD[a]	422	422	1941	0
Cooling degree days	CDD[a]	96	148	804	0

[a] Degree day statistics correspond to NOAA’s published values for a fixed threshold of 18.3^{0}C.

5.2.4.2 Projections of future U.S. residential electricity use

Scenarios (2046-55) of future U.S.-wide residential electricity use were built by collating information regarding the long-term evolution of climatic and non-climatic input data. Devising future trajectories of socio-economic and fuel price variables, required the collection of scenario data from EIA’s 2019 annual energy outlook, this time not only for the reference but also for the high and low economic development case (U.S. EIA, 2019a). The long-term (2018-50) average annual growth rate of personal income (*INC*) was calculated based on EIA's scenario data for future national real GDP and population. This annual growth rate was converted into monthly percentage increases and applied uniformly to all 49 states in the sample to project seasonally-adjusted *INC* levels in the 2046-55 period. Data on future (2018-50) U.S.-average fuel prices in the residential sector were sourced for the reference, high and low economic development case to estimate electricity price growth rates for the contiguous United States. For the projections in 2046-55, historical electricity prices were initially seasonally-adjusted using the centred moving averages method, as explained in section 4.2.4.2. State-specific seasonal indices computed based on historical *EP* data (2000-18) were then re-applied on electricity price projections in 2046-55 to re-introduce their seasonal component.

Quantifying the impacts of climate change on national residential electricity use in the mid-21st century involved identifying suitable sources for future climatic data covering the full contiguous U.S. domain. The analysis performed in Chapter 4 for the south U.S. region required the collection of MACA climate data products with daily (i.e., max and min temperature) and monthly (i.e., specific humidity) temporal resolution in the 2046-55 period, under the assumptions of the RCP8.5 emissions scenario. The files containing the gridded output from multiple GCMs required a combined disk memory space of more than 100 GB. Storing the same set of variables for the contiguous U.S. region would prove to be extremely computationally-inefficient. As a result, I refrain from calculating future values of the extreme heat/cold metrics and humidity variables for the whole contiguous U.S. domain.

Nevertheless, the historical model of U.S. residential electricity use (2000-18) still controls for these variables since this helps mitigate the potential issue of omitted variable bias which could arise for example from the correlation between air temperature and specific humidity. In case these two variables are correlated, omission of the humidity metric would mean that the estimated *CDD* and *HDD* coefficient would combine the effect of temperature and humidity on per capita electricity use (Auffhammer et al., 2013). Including both variables ensures that an unbiased *CDD* and *HDD* coefficient is used when estimating the future impact of climate change on annual and seasonal U.S. residential electricity consumption.

For future sets of (2046-55) degree days, daily records of maximum and minimum temperature over the contiguous U.S. domain were extracted from the projections of 16 GCMs belonging to the CMIP5 project (Table A-2), as facilitated by the World Climate Research Programme (WCRP) (WCRP, 2013). These climate model projections have been statistically-downscaled based on the Bias-Correction Constructed Analogues (BCCA) method (Brekke et al., 2013) and are available at a spatial resolution of 1/8 degrees. In order to describe the two opposite ends of projected climate change, RCPs 8.5 and 2.6 were chosen for inclusion, with the former one (i.e. 'unmitigated greenhouse gas emissions' case) boosting radiative forcing up to 8.5 Wm^{-2} in 2100 and the latter one (i.e. 'strongly reduced greenhouse gas emissions' case) reducing it down to 2.6 Wm^{-2} in 2100 (van Vuuren et al., 2011; Riahi et al., 2011).

Finally, monthly *HDDs* and *CDD*s were calculated at the county level for the time period 2046-55, taking mean values from the output of the 16 climate models run in accordance with RCP8.5 and RCP2.6 descriptions. County-level degree days are then averaged across each state, using again county populations for 2010 as weightings. Table 5-2 lists the assumptions underlying the evolution of climatic and non-climatic variables used for the scenario analysis period.

Table 5-2 Mean growth rate (2018-50) of variables used in the scenario analysis for the contiguous United States (2018-50)

		Annual growth rate (%)		
Category	Variable	Low	Reference	High
Socio-economic	POP	0.42	0.53	0.66
	INC	0.97	1.35	1.69
Fuel Price	EP	0.06	0.17	0.27
Climatic	CDD, HDD		n/a (RCP2.6/RCP8.5)	

5.3 Results

The results section is organised as follows: section 5.3.1 attempts to replicate conclusions about the model fit (2000-15) and forecasting ability (2016-18) of different metrics of climate-sensitive electricity use in the north U.S. region. Section 5.3.2 then identifies the preferred specification which is used together with the full range of available historical data (2000-18) to estimate a model of contiguous U.S. (per capita) residential electricity use. Finally, section 5.3.3 presents scenario analysis results regarding the impact of climate change, economic growth and growing fuel prices on future (2046-50) per capita and total U.S. residential electricity use.

5.3.1 Replication of the south U.S. analysis in the north U.S. climatic region

In order to identify the combination of degree day variables producing the best fit for historical residential electricity use data (2000-15) in the north U.S. region under the $Base_{opt}$ model, a heat map of adjusted R^2 is constructed, which is presented in Figure 5-1. Result for north U.S. states show that amongst possible degree day groupings, the model's goodness-of-fit is maximised (adj. R^2=0.705) when the threshold for cooling demand is set at temperatures equal or less than 18.3 ℃, while that for heating has less influence on the model's performance. As the performance of the remaining specifications is indistinguishable on the ground of adj. R^2 differences (<0.001), the CDD18-HDD15 model is finally selected which allows for the wider theoretical comfort zone between space heating and cooling demand. Optimised *CDD* and *HDD* set point temperatures for the north U.S. region are lower than the ones selected for states in the south U.S. region (CDD21-HDD19), which agrees with the hypothesis that occupants in colder U.S. states have lower (higher) tolerance towards heat (cold).

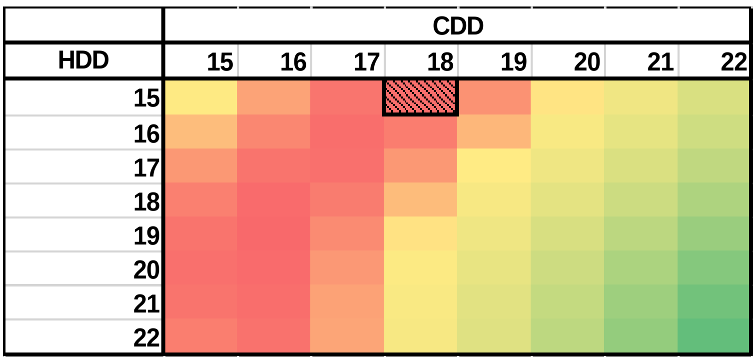


Figure 5-1 Heat map of R² (adj.) for all combinations of HDD and CDD set points for the north U.S. region (21 states)

[the colour scaling scheme dictates that low (0.68-0.69), medium (0.69-0.70) and high (0.700-0.705) R^2 values are displayed in green, yellow and red colour, respectively]

Following the optimisation process, econometric estimation diagnostics for the 2000-15 period are generated for the three base *EL_PC* specifications (i.e., $Base_0$, $Base_1$ and $Base_{opt}$). These are plotted on the same graphs in Figure 5-2. Contrary to results in Chapter 4 concerning the south U.S. region (Figure 4-9), the $Base_0$ specification, which employs NOAA's published degree days with a uniform threshold temperature of 18.3 ℃, outperforms the $Base_1$, still only by a slight margin. In addition to yielding a lower AIC and BIC score than $Base_1$, $Base_0$ is associated with a higher adj. R^2, being capable of explaining 70.4% of variation in the dependent variable. On the other hand, the FE panel data model using the empirically-derived degree days ($Base_1$) explains 70.3% of variation in historical *EL_PC* data, which increases slightly to 70.5% for the model with optimised heating and cooling base temperatures ($Base_{opt}$).

Second, unrestricted model specifications, involving those being extended to account for the effects of unusually hot and cold temperatures on north U.S. residential electricity use are estimated using data for the 2000-15 period. The degree of model fit under the 6 extended specification is then assessed on the basis of their adjusted R^2, AIC and BIC scores, who are also reported in Figure 5-2. Unlike the south U.S. climatic region, modelling per capita electricity use for north U.S. states does not improve when adding the extreme temperature metrics. While all extended specifications tend to have a lower AIC statistic relative to the $Base_{opt}$ one, the amount of additional variance they can explain is less than 0.1% and they are still outperformed by the optimised degree day model in terms of the BIC criterion.

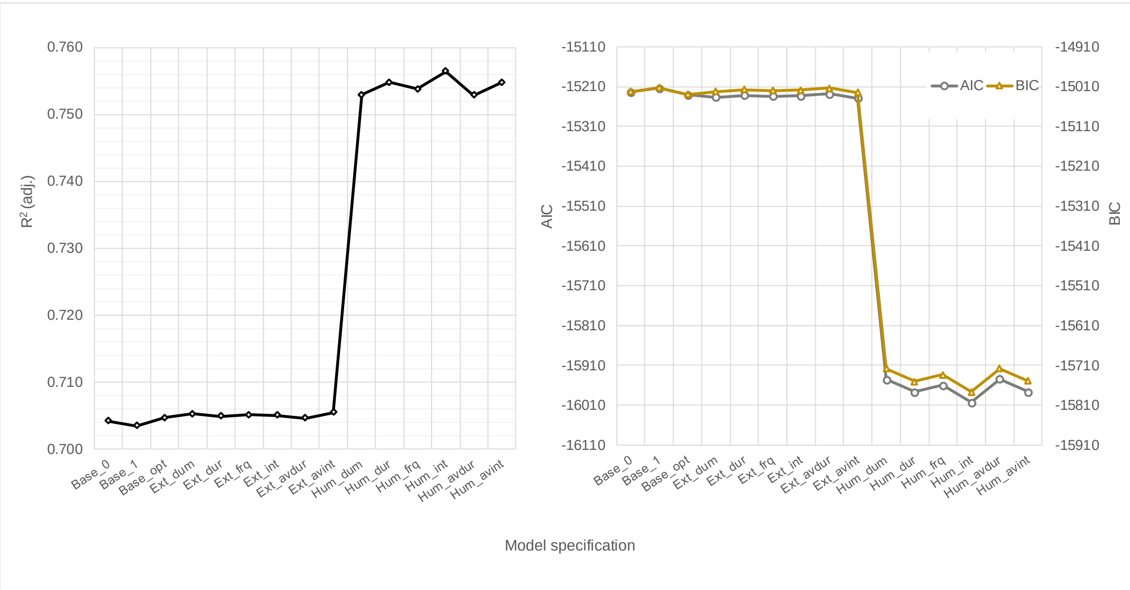


Figure 5-2 Indicators of model fit for the 21 states in the north U.S. climatic region

[Left panel: adj. R^2, Right panel: AIC, BIC)]

The benefits for the statistical properties of the north U.S. residential electricity use model become far more discernible when the air humidity variable is incorporated in the extended specifications. All humidity-based extended specifications explain about 5% additional variation of historical residential electricity use for north U.S. states compared to the $Base_{opt}$ model (Figure 5-2), with the best-performing one (Hum_{int}) having an adj. R^2 value equal to 0.756. In addition to achieving the highest adj. R^2 statistic, the fully-fledged Hum_{int} specification (which includes metrics for the intensity of extreme heat and cold events, the former one also interacted with a specific humidity variable) attains the lowest AIC and BIC statistic. According to both Akaike and Schwarz weights, this model has a 100% probability of being the best-performing electricity use model for north U.S. states amongst candidate specifications.

Finally, all candidate specifications for the north U.S. residential electricity use model are ranked according to their prediction capability over the estimation (2000-15) and validation (2016-18) period. The annual and seasonal MAPE statistics for all per capita electricity use models are plotted in Figure 5-3. On an annual basis, results for the forecasting accuracy of *EL_PC* models strongly agree with those concerning model fit as humidity-based extended specifications outperform all base ones. More specifically, the annual prediction error (averaged across all states) is respectively 0.6-0.7% and 0.8-0.9% lower under the humidity-based specifications compared to the best-performing degree day model in the 2000-15 and 2016-18 period, respectively. Although Hum$_{int}$ is the model which was previously found to fit historical data best, all humidity-based specifications yield the same annual MAPE statistic for the 2000-15 period (~7.5%). For the forecasting period 2016-18, Hum$_{dum}$ and Hum$_{avint}$ obtain the smallest annual forecasting error at 7.3%, while Hum$_{int}$ follows very closely with an annual MAPE level of 7.4%.

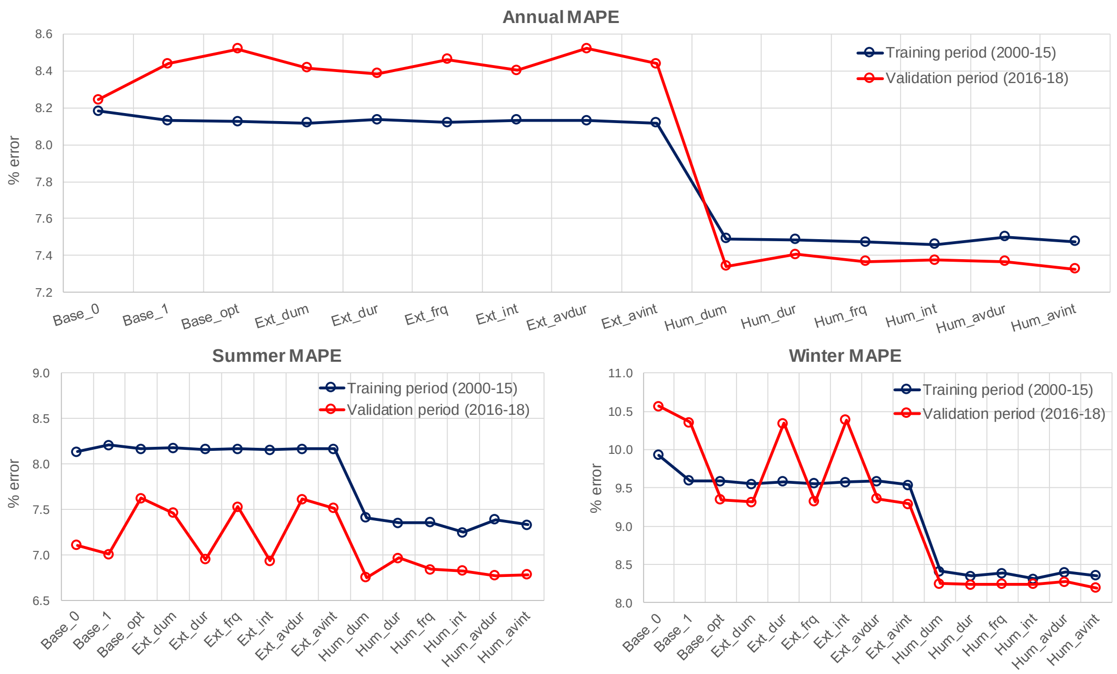


Figure 5-3 Prediction accuracy indicators during the training and validation period for the 21 states in the north U.S. region

[top panel: annual MAPE, bottom left: summer MAPE, bottom right: winter MAPE]

The main finding from the analysis of annual MAPE statistics that humidity-based specifications have the competitive advantage over other candidates is also reflected through the seasonal error analysis. With respect to 2000-15's summer and wintertime residential electricity use across north U.S. states, humidity-based specifications have respectively MAPE values of 7.2-7.4% and 8.3-8.4%, while the corresponding values for the best performing base model are 8.1% and 9.6%. Similarly, the forecasting error of humidity-based *EL_PC* models in 2016-18 is 6.7-7.0% and 8.2-8.3% during summer and winter months, which is lower than MAPE values generated under the best-performing base model (7.0% and 9.3% in summer and winter). Similar to the south U.S. case study (Figure 4-10), adding air humidity in the north U.S. *EL_PC* model as an interaction variable has an effect in improving overall prediction ability, which is more evident for winter months. On the other hand, inclusion of the newly-developed extreme heat and cold metrics alone has no impact on the mode's forecasting ability, which was not the case with the analysis of residential electricity use for the south U.S. region.

In summary, there is adequate evidence to claim that humidity-based specifications outperform traditional degree day ones and thus are more appropriate for analysing past and future trends of north U.S. residential electricity use, as it was also the case in the south U.S. case study. Table 5-3 demonstrates that Hum_{int} was found to be the best-performing model under 7 out of the 9 examined categories, followed by Hum_{dum} (4 out of 9 categories). Detailed econometric estimation results concerning residential electricity use in the 21 north U.S. states under the Hum_{int} specification (2000-15) are provided in the Appendix B (Table B-2). A detailed comparison of econometric estimation results between the north, south and contiguous U.S. region is provided in section 5.4.2.

Table 5-3 Summary of best-performing models according to different statistical criteria for the north U.S. region

				MAPE (2000-15)			MAPE (2016-18)		
Model	R^2	AIC	BIC	Annual	Summer	Winter	Annual	Summer	Winter
Hum_{dum}				✓			✓	✓	✓
Hum_{dur}				✓		✓			✓
Hum_{frq}				✓					✓
Hum_{int}	✓	✓	✓	✓	✓	✓			✓
Hum_{avdur}				✓					
Hum_{avint}				✓			✓		✓

5.3.2 Historical model of contiguous U.S. residential electricity use (2000-18)

Presented evidence for the south and north climatic regions in Chapter 4 and section 5.3.1 does therefore allow generalising conclusions about the overall superiority of humidity-based extended specifications over traditional degree day models. In comparison with the analysis performed for the south U.S. climatic region, evidence about the benefits for historic modelling of residential electricity use from the addition of extreme weather metrics is much weaker for north USA. Still, the specific humidity variable seems to be a better explanatory factor of residential electricity use for the north U.S. climatic region, despite the lower all-year-round regional levels of air humidity. Since the next objective of this chapter is to devise projections of U.S. residential electricity use in the mid-21st century under various climatic and non-climatic trajectories, humidity-based models are selected over degree day-based ones as a more reliable forecasting tool.

5.3.2.1 Selecting an optimal model specification for the contiguous U.S. region

Preliminary estimation results for the 2000-18 period showed that the coefficient of the squared income variable (*INCSQ*), intended to capture potential non-linear wealth effects on domestic electricity demand, does not turn to be statistical significant under most of the candidate specifications. This could suggest that the rate by which income effects saturate varies between regions, which cannot be captured by a single coefficient. Evidence about the saturation of income effects in the south U.S. climatic region has already been provided in Table 4-6. In order to accommodate the potential regional heterogeneity of saturation effects, the base model in eqn. (3-10), is modified through eqn. (5-5) to interact *INCSQ* with all 9 climatic sub-regions (*Cl_Reg*) comprising the contiguous U.S. domain:

$$EL\_PC_{s,mo} = \beta_s + \underbrace{\beta_1}_{(+)} INC_{s,mo} + \sum_{reg=1}^{9} \underbrace{\beta_{2,reg}}_{(-)} INCSQ_{s,mo} \times Cl\_Reg_s + \underbrace{\beta_3}_{(-)} EP_{s,mo} + \underbrace{\beta_4}_{+} CDD_{s,mo} + \underbrace{\beta_5}_{(+)} HDD_{s,mo} + \sum_{k=2}^{19} \beta_{7,k} Year_{k,y} + \sum_{l=2}^{12} \beta_{6,l} Month_{l,mo} + \varepsilon_{s,mo} \tag{5-5}$$

Moreover, since the preferred humidity-based specification for the north U.S. climatic region does not coincide with that found for the south region, the best-performing specification for the national model is chosen based on regression diagnostics (i.e., adj. R^2, AIC, BIC) generated using the full range of historical data (2000-18). First, similar to section 5.3.1, the optimal degree day specification is selected by independently varying the heating and cooling-related base temperatures for the contiguous U.S. region in the range from 15.3 ℃ to 21.3 ℃, with a step of 1 ℃ each time, and obtaining the adj. R^2 statistic. The result of this exercise is presented in a heat map format in Figure 5-4. Among potential combinations of national-level degree day set points, the specification which fits the historical electricity use data best (adj. R^2= 0.748) and at the same time accommodates the widest comfort zone is CDD20-HDD17. As expected, optimal threshold temperatures for the whole of contiguous U.S. region range higher (lower) than those found for the north (south) U.S. climatic regions.

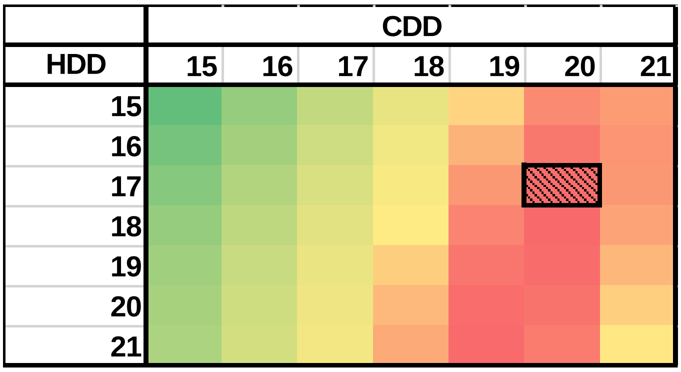


Figure 5-4 Heat map of R^2 (adj.) for all combinations of HDD and CDD set points for the contiguous U.S. region (49 states)

[the colour scaling scheme dictates that low (0.71-0.72), medium (0.73-0.74) and high (0.74-0.75) R^2 values are displayed in green, yellow and red colour, respectively]

Indicators of model fit during the time period 2000-18 under different candidate specifications are then plotted in Figure 5-5. The obtained statistical tests produce patterns which generally differ from those observed in Figure 5-2 and Figure 4-9, respectively for the north and south U.S. climatic regions. Unlike the south and north U.S. region, the superiority of the humidity-based specifications over traditional degree day models is not directly visible for the contiguous U.S. analysis. While all Hum specifications are associated with the highest adj. R^2 statistic (adj. R^2=0.754), this equals the degree of fitting achieved through the more simplified $Base_0$ model, which employs external NOAA's degree day metrics. Nevertheless, there is not enough evidence to support that $Base_0$ is the most parsimonious model, as two humidity-based extended models (i.e., Hum_{dur} and Hum_{frq}) have the lowest AIC score.

According to Akaike weights, the Hum_{dur} model (i.e., with a description of heat and cold wave duration and a humidity interaction) has a 95% probability of being the best possible model for the 2000-18 period. The larger penalty imposed by the BIC criterion for information loss through the addition of new explanatory

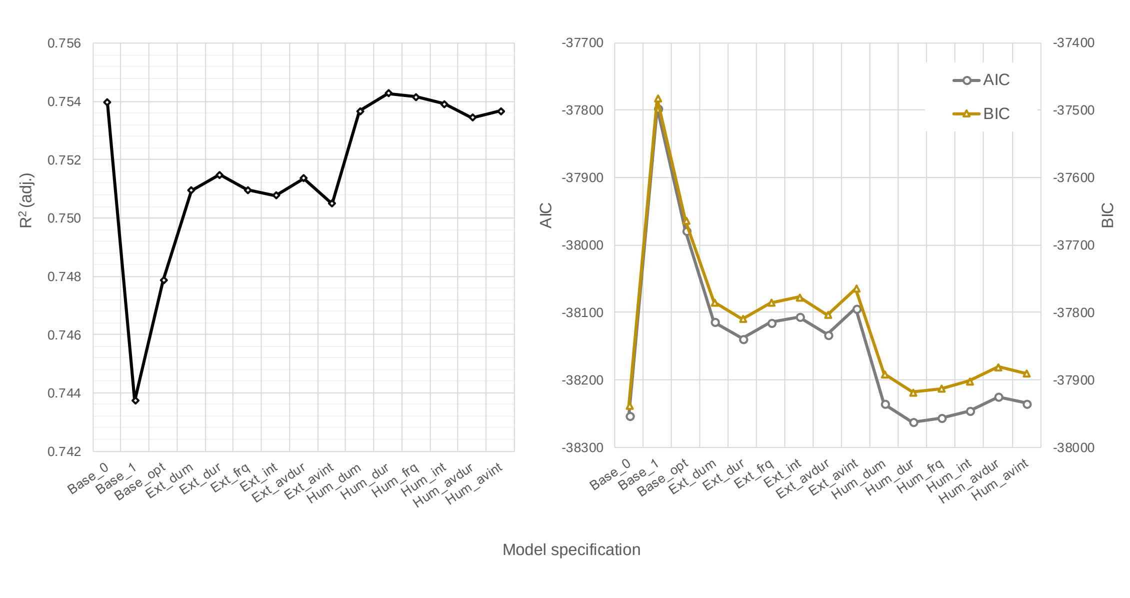


Figure 5-5 Indicators of model fit for the 49 states in the contiguous U.S. region

[Left panel: adj. R^2, Right panel: AIC, BIC]

variables, makes the simplified $Base_0$ model being the preferred model. Nevertheless, Hum_{dur} has the lowest BIC score amongst the humidity-based specifications and is the one selected next for estimating a U.S.-wide model of residential electricity use for the historical period 2000-18.

5.3.2.2 Econometric estimation results (2000-18)

Table 5-4 presents a summary output of the FE estimator for the preferred model (Hum_{dur}) of per capita electricity use in the contiguous U.S. residential sector, containing generated regression coefficients along with their robust standard errors. As a point of comparison, results are also presented for the reference $Base_0$ model estimated for the same time period (2000-18), as well as the best-performing base ($Base_{opt}$) and extended specification (Ext_{dur}), based on the R^2, AIC and BIC criterion. In all cases, the conducted F-test rejects the null hypothesis that intercepts are homogeneous between the 49 states and signifies the presence of state-level fixed effects and thus the inappropriateness of a pooled OLS estimator. Moreover, the outcome of the Hausman test is demonstrably in favour of the FE over the RE estimator under the preferred $Base_{opt}$, Ext_{dur} and Hum_{dur} specification (while the test statistic for the $Base_0$ one is only marginally insignificant). The FE panel data estimator is therefore adopted to estimate the "within" effect of climatic and non-climatic factors on per capita residential electricity use for the contiguous U.S. region.

Table 5-4 Estimation results of EL_PC (kWh/pop•mo) model under different specifications for the contiguous USA (2000-18)

	$Base_0$	$Base_{opt}$	Ext_{dur}	Hum_{dur}
INC (000' $/pop)	5.429***	4.925***	5.093***	5.192***
	(1.148)	(1.251)	(1.274)	(1.315)
INCSQ	- 0.037***	- 0.030**	- 0.030**	-0.032***
	(0.011)	(0.012)	(0.012)	(0.012)
INCSQ x NW	-0.043***	-0.043**	-0.043**	-0.041**
	(0.017)	(0.020)	(0.019)	(0.017)
INCSQ x SE	-0.051***	-0.047***	-0.047***	-0.046***
	(0.010)	(0.010)	(0.010)	(0.009)
INCSQ x WNC	0.024***	0.022**	0.021**	0.022***
	(0.007)	(0.009)	(0.009)	(0.008)
EP (c/kWh)	-6.635***	-7.020***	-7.103***	-7.009***
	(0.725)	(0.849)	(0.853)	(0.841)
CDD	0.543***	0.967***	1.018***	1.001***
	(0.016)	(0.025)	(0.025)	(0.019)
HDD	0.088***	0.181***	0.158***	0.157***
	(0.008)	(0.014)	(0.012)	(0.013)
NHW			-0.862***	-5.116***
			(0.221)	(0.782)
NCW			2.573***	2.592***
			(0.737)	(0.737)
HUM (g/kg)				0.581
				(0.940)
NHW × HUM				0.343***
				(0.060)
Observations	11172	11172	11172	11172
$\overline{\beta_s}$	282.63***	288.66***	285.93***	281.18***
	(36.25)	(37.55)	(37.96)	(39.63)
F-test	185.03***	170.40***	170.06***	170.68***
Hausman test	53.534	74.144***	84.872***	75.712***
R^2 (adj.)	0.754	0.748	0.751	0.754

Statistically significant *** at 1%, ** at 5%, * at 10%, and confidence level. Note: Standard errors in parenthesis are computed via *a la Driscoll and Kraay* estimator which is robust to serial and cross-sectional correlation. This tables presents the values of the *INCSQxCl_Reg* interactions with a statistically-significant effect. NW stands for Northwest, SE for Southeast and WNC for West North Central.

Examining the output of the FE estimator under each specification confirms that all explanatory parameters have an effect on per capita electricity use (*EL_PC*) in the hypothesised direction. For the humidity-based model, a unit (c/kWh) increase in electricity price (*EP*) decreases per capita residential electricity consumption by 7.01 kWh/pop (se 0.84). The magnitude of this effect does not change significantly under different model specifications. Estimating the marginal effect of personal income on *EL_PC* requires taking into account both the linear and quadratic *INC* term, through eqn. (4-6) as well as the relative differences in the size of the *INCSQ* coefficient between different climatic regions. In particular, results reported in Table 5-4 show that the marginal effect of the *INCSQ* term in northwest, southeast and west north central states is different from that in other U.S. regions given the statistically-significant interaction.

Using parameter coefficients (β_{INC} and β_{INCSQ}) generated under the Hum_{dur} and regional mean values of monthly *INC* for the 2000-18 period, the main effect of income is found to be +2.49 kWh/pop (se 0.86) for all but the 14 states in the northwest, southeast and west north central sub-region. Adding the interaction for northwest, southeast and west north central states yields a marginal *INC* effect of -1.28 kWh/pop (se 1.52), -1.57 kWh/pop (se 1.22) and +4.20 kWh/pop (se 0.86) when calculated at mean (2000-18) income values, respectively. Since *INCSQ* effects (main + interaction) are negative, the impact of an additional *INC* unit (000 $/pop) on per capita electricity use becomes smaller at higher income levels. Personal income effects become fully saturated ($\frac{\partial\ EL_PC}{\partial\ INC} \approx 0$) as expected at rates which vary between the climatic regions in the contiguous U.S. region.

For the 35 states not belonging to the 3 aforementioned sub-regions, the impact of personal income on residential electricity use reaches saturation at US$ (constant 2018) 80, 908 per person. That is almost twice (~1.7) as high as the current mean income level (2000-18) in these states. The corresponding demand saturation level for southeast and northwest states is much lower at US$ (constant 2018) 33.066 and 35,693 per person, respectively. This level was already exceeded during the historical analysis period 2000-18, which justifies the negative sign of the marginal *INC* effect obtained earlier for these regions.

The low saturation point for income effects in the southeast sub-region can be justified from the fact that penetration of AC equipment has virtually reached a full saturation level. Diffusion of air-conditioners in the South Atlantic census division, which contains most of the southeast states, was 95% in 2015 (U.S. EIA, 2017b). Although cooling requirements are extremely high in the sub-region (2^{nd} highest annual *CDD*s across the U.S. in 200-18), further *CDD* increases do not spur greater adoption of space cooling. Southeast is also the climatic sub-region with the lowest heating requirements based on the annual number of *HDDs* in

2000-18. Overall low need for space heating, in combination with the already high diffusion rates for electric heaters in the sub-region, justify the lower demand saturation levels.

On the other hand, northwest states have traditionally the lowest penetration rates for AC equipment across the contiguous U.S. area, which can be due to the cold and marine-type of climates which residents experience in this area. The low demand saturation level (US$ 35,693) may therefore indicate the small fraction of household expenditures which is allocated to electricity-driven AC equipment, due to the mild summer seasons (northwest states had the lowest number of annual *CDDs* in the 2000-18 period amongst all sub-regions). Finally, the impact of personal income on *EL_PC* is far from reaching its saturation point in west north central states, as this occurs only after *INC* level reaches US$ (constant 2018) 246,629 per person. Although this is an extreme outlier, it can indicate the ongoing diffusion of electric space heaters in cold U.S. areas, as these become more efficient under low temperature conditions (U.S. EIA, 2017d). West north central has the highest demand for space heating amongst all U.S. climatic regions according to the annual mean level of *HDDs* in the 2000-18 period. The high saturation level for income effects could therefore show the high penetration potential for electric heaters. The same qualitative findings are obtained by examining econometric estimation results from other model specifications.

Climatic variables appearing to have a positive effect on residential electricity use under all specifications are, as expected, *CDDs* and *HDDs*. As with results for the south and north U.S. region (Table 4-6 and Table B-2), the response of U.S.-wide electricity consumption to outdoor air temperature is found to be asymmetrical with respect to space heating and cooling use. In this case, the effect of an additional *CDD* on *EL_PC* being about 5 times as large as the marginal effect of *HDD* under the optimal degree day Base_{opt} model (the corresponding ratio for *CDD-HDD* effects in the south and north U.S. region was 5:1 and 2:1). The weaker response to changing *HDDs* is reflective of the fact that space cooling is more widely adopted in the U.S. than electric heating, as it is provided by other fuels, including natural gas, fuel oil and wood[11]. Still, the absolute level of *HDDs* in the contiguous U.S. region and thus total heating requirements far exceed space cooling requirements (the ratio of *HDDs* to *CDDs* is 4:1 during the 2000-18 period according to Table 5-1).

Apart from the traditional degree days, extreme temperature metrics incorporated in the Ext_{dur} and Hum_{dur} specification are associated with a statistically significant

[11] About 35%, 49%, 5%, 4% and 3% of U.S. households had respectively electricity, natural gas, fuel oil, propane and wood as their main heating fuel in 2015 (U.S. EIA, 2017c). The corresponding saturation level for space cooling is at 87%.

effect. More specifically, duration of extreme cold episodes (*NCW*) has a positive impact on monthly *EL_PC*, with an extra *CWD* increasing per capita electricity use by 2.6 kWh/pop (se 0.7). Similar to Chapter 4 (Table 4-6), the effect of the duration of extreme heat events (*NHW*) on residential electricity use is found to strongly depend on mean specific humidity levels. The positive interaction term suggests that high humidity levels in a heat wave event amplify the need for comfort cooling services in the U.S. residential sector. Calculating the total marginal effect of heat wave duration on *EL_PC* therefore requires taking into account both the main *NHW* effect, which is negative, and the interaction term as in eqn. (4-7).

The marginal effect of heat wave duration on *EL_PC* is calculated using the median value of JJA specific humidity, recorded over the contiguous U.S. domain for the 2000-18 period (12.83 g/kg). This yields a negative marginal effect on *EL_PC* equal to -0.71 kWh/pop (se 0.18). The negatively signed effect suggests that heat waves have an increasing effect on AC electricity use only when it is very humid outside. Under low humidity conditions, extremely high temperatures may encourage people to spend more time outdoors and in commercial buildings, resulting in overall reduced residential electricity use. The marginal effect of *NHW* becomes positive for *HUM* values higher than 14.90 g/kg. The only climatic sub-regions with recorded average JJA specific humidity levels (2000-18) over this threshold is south and southeast, which is in close agreement with findings from Chapter 4. The coefficient for the *HUM* variable, interpreted as specific humidity's base effect on *EL_PC*, when *NHW* is equal to zero, is positive in contrast to estimation results in Table 4-6, still it is not statistically significant.

In order to detect the presence of an aggregate time trend in U.S. residential electricity use data, the change in the size of year-specific dummies (*Year*) is assessed. For the Hum_{dur} model, the annual effects are jointly significant ($\chi 2(18)$ =269.3***), implying that collectively their size is different from the reference year's (2000) level. The size of individual annual effects displays similar patterns between the two specifications as shown in Figure 5-6. A general increasing trend in annual dummies is observed between 2000 and 2010 (except from a small decline from 2008 and 2009) which can be attributed to macro-economic trends not captured by the FE model's explanatory variables. Also, 2010 was the year with the most extreme heating season for contiguous U.S. households according to average DJF *HDDs*. This may partly explain the peak in annual dummies observed for 2010. Annual dummy variables decrease after 2010, similar to the pattern observed in Chapter 4 for the south U.S. region[12]. As discussed in the previous chapter, the declining time trend in the post-2010 period may reflect

[12] The dummies for years 2015-18 are also statistically insignificant under Hum_{dur}.

energy savings achieved in the U.S. residential sector through stricter efficiency standards, including the mass adoption of energy-efficient LEDs (Davis, 2017).

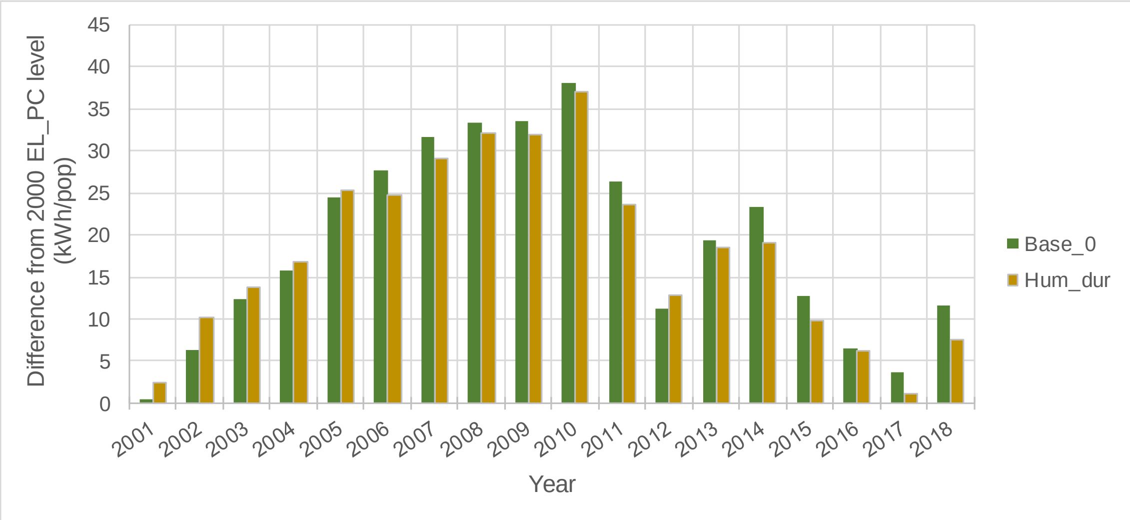


Figure 5-6 Variation of annual-specific effects under the reference and humidity-based model for the 49 states in the contiguous U.S. region

Estimation results for the *EL_PC* model uncovered month-specific effects shaping the annual profile of residential electricity use, as monthly dummy variables, $Month_{2\text{-}12}$, are jointly significant ($\chi 2(11)$ =1023.9*** under the Hum_{dur} specification). The fluctuating size of their coefficients, as shown in Figure 5-7, implies that after correcting for the impact of climatic and non-climatic factors in Hum_{dur}, average per capita electricity use during spring and autumn is 65 kWh/pop and 55 kWh/pop lower compared to that during winter. Similar to Chapter 4, this result could indicate that degree day metrics tend to overestimate the influence of outdoor temperature over periods of relatively mild weather, when

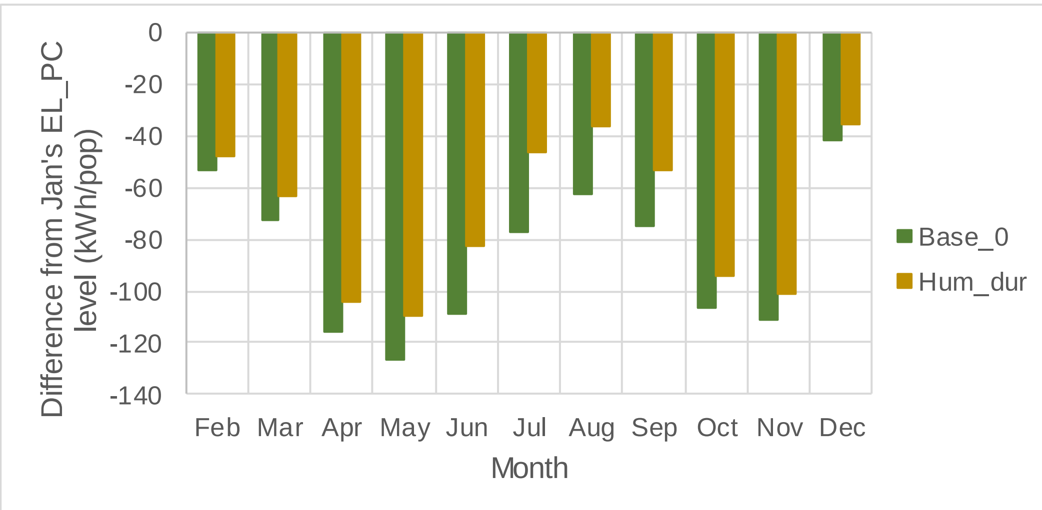


Figure 5-7 Variation of month-specific effects under the reference and humidity-based model for the 49 states in the contiguous U.S. region

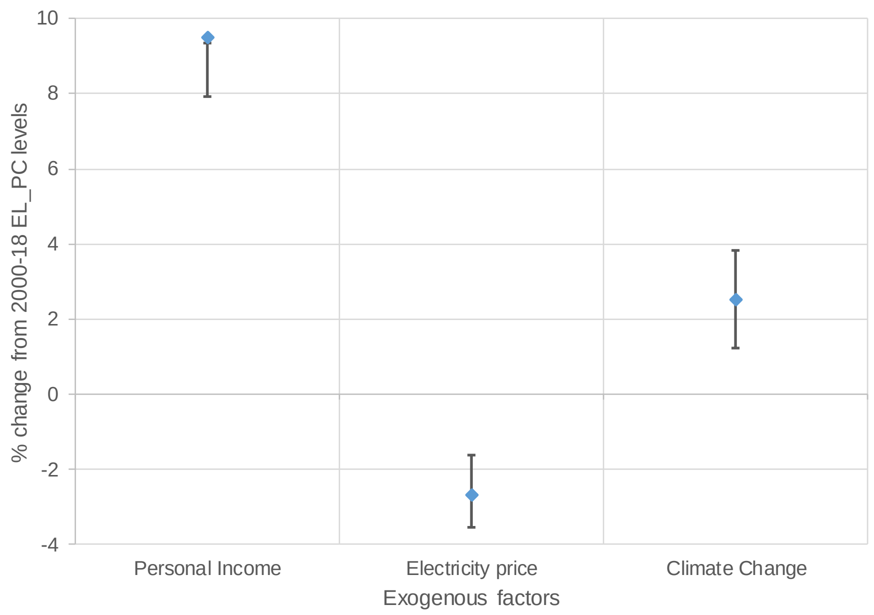
in reality a small deviation from the set point temperature would not signal a significant increase in residential electricity use. On the other hand, selection of a higher temperature set point for *CDDs* under Hum_{dur} has shrunk the size of summer-specific effects relative to $Base_0$. This in effect has improved the combined contribution of *CDDs*, the *HWDs* metric and specific humidity variable in explaining the variation of per capita electricity consumption in the summer.

5.3.3 Projections of residential electricity use (2046-55)

In section 5.3.2, monthly, state-level, per capita residential electricity use in the contiguous U.S. region was modelled during the period 2000-18 based on a set of climatic and non-climatic variables. Section 5.3.2.1 evaluated the performance of the historical electricity use model after testing different combinations of metrics of climate-sensitive energy use, including degree days with customised temperature thresholds, extreme heat and cold metrics and a specific humidity variable. The outcome of this analysis was that the humidity-based specification (Hum_{dur}) with empirically-derived degree days and a description about the duration of heat and cold wave events produced the best model fit. As a result, residential electricity use projections in the mid-21st century conducted in this section are based on parameter estimation results obtained for the Hum_{dur} model in Table 5-4.

New sets of *HDD* and *CDD* variables are calculated for the 2046-55 period using the same 20.3 ℃ cooling and 17.3 ℃ heating-related thresholds adopted during the historical modelling phase. According to RCP8.5-based climate model simulations, annual *CDDs* (2046-55 average) averaged over the states in contiguous U.S. region grow by 55% (21-82%), while *HDDs* decline by 20% (9-32%), relative to the time period 2000-18. The country-average increase in annual *CDDs* is smaller at 24% (0-59%) under the RCP2.6-based trajectories, yet *HDDs* are still forecasted to decrease by 13% (5-22%). The main estimate presents the relative difference from the mean value of the multi-model ensemble for 2046-55, while numbers in the parentheses denote respective minimum and maximum values. The effect of individual RCP storylines on per capita electricity use is estimated by isolating the residential cooling (EL_PC_{cool}) and heating (EL_PC_{heat}) components of electricity use, which are in turn affected by changes in *CDDs* and *HDDs* between the time periods 2046-55 and 2000-18. Due to data limitations pertaining to the use of future humidity statistics, state-level values of extreme temperature metrics (*NHW* and *NCW*) and specific humidity (*HUMD*) are kept constant at 2000-18 levels for the scenario modelling phase (2046-55).

Since degree days are not the sole determinant of future residential electricity demand, the effect of all non-climatic (*INC*, *EP*) explanatory factors is evaluated, through eqns. (5-1)-(5-4), on country-wide, per capita, residential electricity consumption. As the true value of explanatory parameters is fairly uncertain in the long term, a sensitivity analysis is performed which establishes error ranges for the changes in *EL_PC* from present (2000-18) to future (2046-55) levels attributed to each exogenous factor. These ranges are calculated by combining input uncertainty of climatic and non-climatic scenario data and the associated effect on electricity consumption, obtained from econometric estimation results in Table 5-4. It is important to note that the uncertainty in temperature projections from different GCMs under a single climatic trajectory is not taken into account, thus only the mean values of the multi-model ensemble are adopted for the sensitivity analysis. On an annual basis (Figure 5-8), the most significant explanatory parameter is personal income (*INC*) whose country-average effect on *EL_PC* ranges from a 7.9% to a 9.5% increase (9.5% under the reference case).



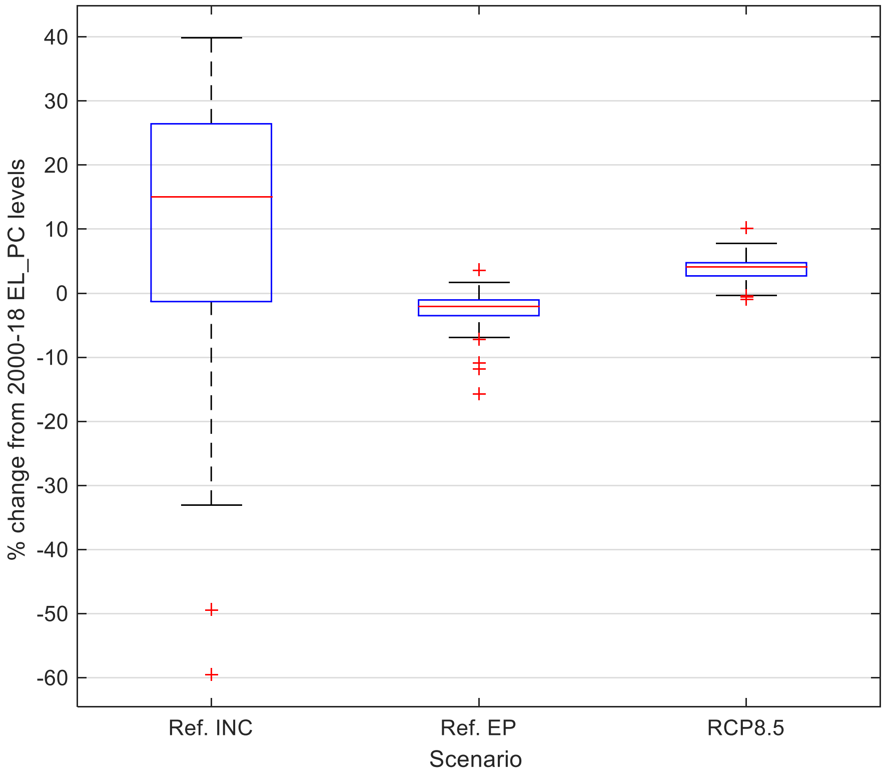
Note: For climate change, the diamond marker represents the mean impact between the RCP8.5 and RCP2.6 climatic trajectories.

Figure 5-8 Impact of exogenous factors on annual-average U.S. per capita residential electricity use between the 2000-18 and 2046-55 period

Surprisingly enough, the impact of growing personal income on (per capita) residential electricity use is not projected in 2046-55 to be higher under the EIA's high economic development case (relative to the reference and low economic development case). While a higher income trajectory in the future will spur the greater use and adoption of space cooling and heating equipment across the contiguous U.S. region (which has an increasing effect on electricity use), it also causes more households replacing their electric equipment with a less energy intensive one (which has a decreasing effect on electricity use). Since the residential AC market has almost saturated across most of U.S. regions, the latter effect is expected to be more pronounced leading to smaller increases in overall electricity use in the future when income grows faster. For, example the mean impact of personal income on future annual *EL_PC* levels in California (west climatic region) is a net increase (+10.7 kWh/pop) for the reference case, while it becomes a net decrease (-8.0 kWh/pop) in the high economic development case due to state-level income exceeding the established saturation level by a greater amount. On the other hand, the corresponding income effects for Kentucky (central climatic region) is +50.6 kWh/pop and +56.1 kWh/pop in the reference and high-income cases, as state-level *INC* does not reach a saturation point by 2046-55. When averaged across all contiguous U.S. states, the increase in personal income effects on future *EL_PC* between the reference and high economic development case are completely offset by negative impact changes.

On the other hand, the net effect of climate change on annual U.S.-average per capita electricity use in the 2046-55 period (relative to 2000-18) is lower yet less certain than that of economic growth. Due to the opposing direction of *CDD* and *HDD*-related impacts, the overall impact of climate change on country-average *EL_PC* levels is merely a 1.2% and 3.8% increase under the RCP2.6 and RCP8.5 case, respectively. The effect of growing electricity prices is comparable with that of climate change on an annual basis, as it is responsible for a 1.6-3.6% reduction of per capita residential electricity use between 2046-55 and 2000-18 levels (-2.7% in the Ref. case). The impact of high and low climate change and electricity price trajectories on U.S.-wide *EL_PC* levels is therefore more uncertain relative to that of economic growth as shown by the shorter error bars. However, one should note that Figure 5-8 masks the spatial variability of personal income impacts, which are much more unevenly distributed across the U.S. region relative to other factors. This is demonstrated by the boxplot in Figure 5-9, which shows the wider spatial dispersion of positive and negative income-related impacts on per capita electricity use for the reference economic development case, when compared to the effect of climatic and fuel price factors.

Combinations of alternative climatic, socio-economic and fuel price assumptions give rise to 18 per capita electricity use scenarios in 2046-55, all of which are illustrated in Figure 5-10. All presented cases result in annual U.S.-average *EL_PC* levels that are above current ones (2000-18). Using reference case assumptions, an 8.1% (+22 kWh/pop) and 10.6% (+32 kWh/pop) increase in annual per capita residential electricity use is calculated under the RCP2.6 and RCP8.5-based trajectory, respectively. Due to demand saturation with respect to personal income changes, the largest absolute positive impact on *EL_PC* (+38



Note: The red horizontal value represents the median value, the blue box length the interquartile range, the top (bottom) whisker the maximum (minimum) value and the red crosses the outliers of the distribution.

Figure 5-9 Spatial variation of impacts on future annual EL_PC

kWh/pop or +11.5% or) is projected via the RCP8.5 scenario when enacted with assumptions about low economic and low electricity price growth. On the other hand, the smallest positive impact on *EL_PC* (+11 kWh/pop or +5.6%) is achieved through the RCP2.6 storyline, with faster economic development and escalating fuel prices.

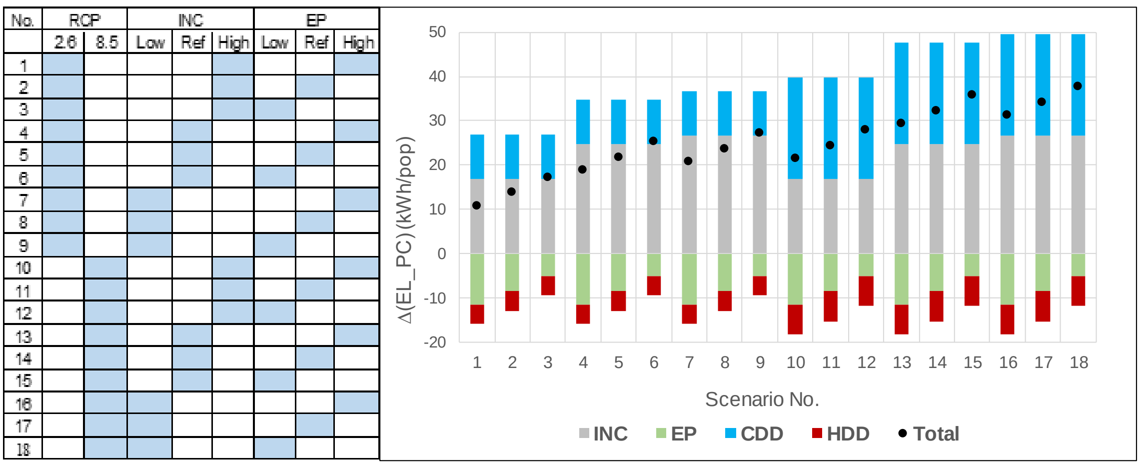
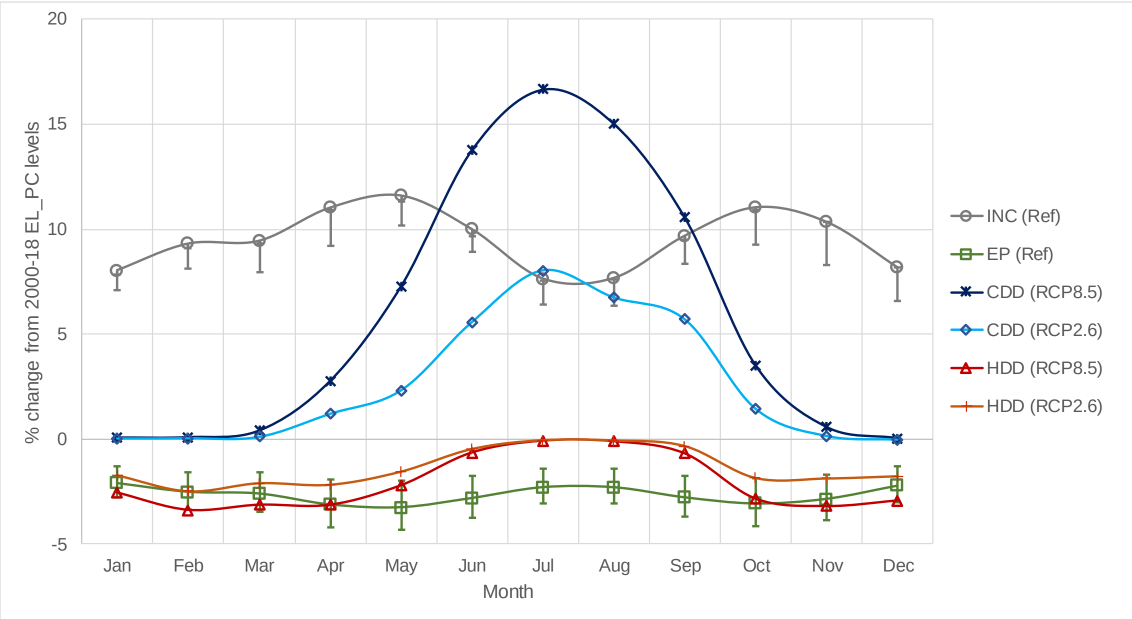


Figure 5-10 Average change in annual U.S. per capita electricity use level between the 2046-55 and 2000-18 period under all scenario combinations, broken down to the contribution of exogenous factors

It is important to note that potential efficiency improvements in the U.S. residential sector, which could offset to some degree future personal income and cooling-related *EL_PC* increases, are not considered in the scenario analysis, as their effect cannot be explicitly simulated within an econometric setting. One way around this would be to extrapolate the future level of year-specific (*Year*) effects based on the post-2010 observed negative trend in historical annual dummies (Figure 5-6), which would implicitly parameterise residential electricity use reductions due to efficiency gains. While annual effects decrease after 2010 (possibly as a result of stricter efficiency standards in households), they become statistically insignificant after 2014, which prohibits deriving a long-term trend based on historical data. Residential electricity use projections therefore adopt an annual dummy value set to zero.

Examining sub-annual climatic impacts on future *EL_PC* components reveals a more complex picture, as demonstrated by Figure 5-11. The strongest effect of *CDDs* on EL_PC_{cool} is obtained during the summer season, when electric AC is expected to increase by 7% for the moderate (RCP2.6) and 15% for the extreme (RCP8.5) climate change scenario. In the latter case, the impact of climate change far exceeds the seasonal effect of growing electricity prices on *EL_PC* (-1% to -4%), while it also exceeds that of evolving personal income (+6% to +10%). In both absolute and relative terms, space cooling increases the most in July under both climate change scenarios. On the other hand, *HDD* impacts on

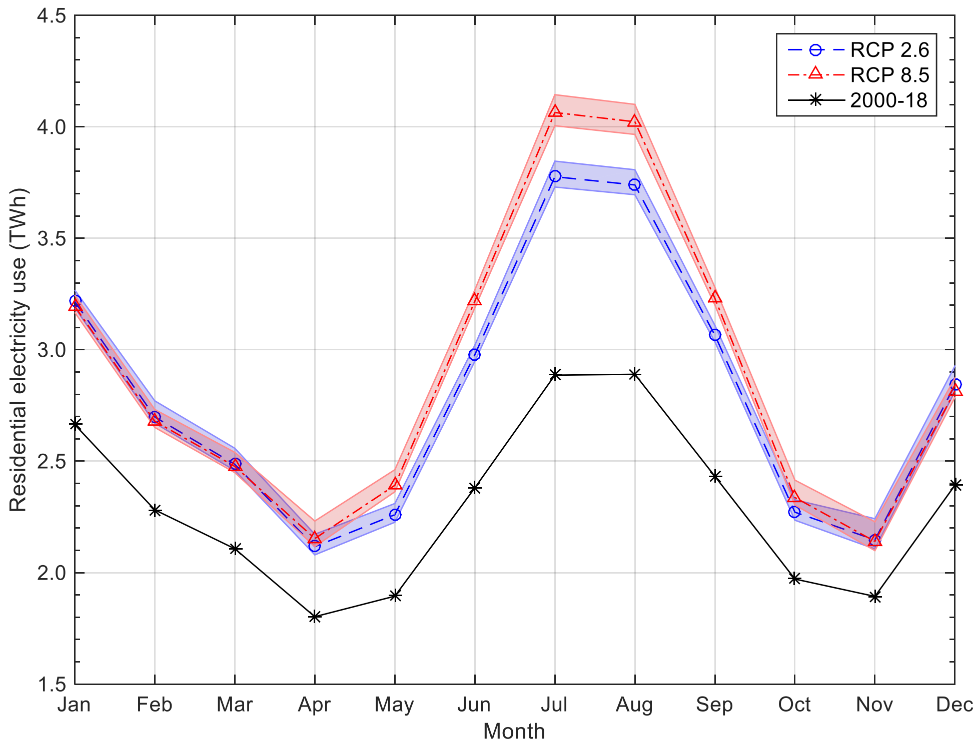


Note: The dashed red and blue lines delineate respective reference cases, while shaded regions represent the range of uncertainty in socio-economic and fuel price scenarios.

Figure 5-11 Monthly variation of exogenous impacts on future (2046-55) U.S.-average per capita electricity use levels

EL_PC_{heat} are larger in winter, with per capita space heating electricity use decreasing by 2% and 3% for RCP2.6 and RCP8.5, respectively. February is the month during which per capita electricity use records the largest proportional and absolute reduction from 2000-18 levels under both climatic trajectories.

In order to convert mid-21st-century *EL_PC* scenarios into absolute residential electricity use estimates, the output of the scenario modelling in 2046-55 is adjusted to population growth rates corresponding to the three socio-economic cases (reference, high and low economic development), as listed in Table 5-2. These projections are presented below in Figure 5-12.



Note: The dashed red and blue lines delineate respective reference cases, while shaded regions represent the range of uncertainty in socio-economic and fuel price scenarios.

Figure 5-12 Mid-21st-century projections of U.S.-average residential electricity use according to the RCP8.5 and RCP2.6 scenarios

In Figure 5-12, projections of U.S.-average residential electricity use are plotted with monthly resolution and compared to equivalent 2000-18 levels. According to the reference case, annual-average electricity consumption in U.S. residential sector is expected to increase by 22% under the RCP2.6 and 26% under the RCP8.5 storyline. Projected growth of residential electricity use varies between +19% for the most moderate (bottom line of blue area) and +27% for the most extreme scenario (top line of red area), underlining the additional uncertainty added by population scenario data. When compared to 2018 instead of 2000-18 levels, reference mid-21st century U.S. residential electricity use increases by 12% (10% to14%) and 16% (14%-18%) under the high and low-end climate change trajectory, respectively.

Important insights are derived when the seasonal variation of U.S. residential electricity use in the mid-21st century is compared to that in 2000-18 (Figure 5-12). Residential electricity use during an average summer in 2046-55 increases by 29% (26% to 30%) under the RCP2.6 and by 39% (36% to 40%) under the RCP8.5-based scenario (relative to 2000-18), thereby showing stronger growth than the previous annual-average estimation. On the other hand, the increase in residential electricity use during an average winter is substantially smaller than the annual change and is less sensitive to climatic trajectories, since it ranges from 19% (RCP2.6) to 18% (RCP8.5) for the reference case. Hence, it becomes apparent that the summer profile of U.S. residential electricity consumption is going to be increasingly vulnerable to climate change, with peak electric demand showing strong increases regardless of the assumed RCP scenario.

5.4 Discussion

Results for the benefits of econometrically modelling climate-sensitive residential electricity use based on alternative climate metrics differ for the south, north and contiguous U.S. case study. This discussion section below provides a synthesis of findings from Chapter 4 and 5 regarding the performance of different climatic indicators in the historical modelling phase for the south, north and contiguous region of the United States. This comparison, which is presented in section 5.4.1, is based primarily on the relative size of statistical improvements achieved from the successive addition of individual indicators of climate-sensitive electricity use. Moreover, section 5.4.2, analyses the main differences in the estimated size of climatic and non-climatic effects for the three case studies.

5.4.1 Relative performance of climatic indicators in the south, north and contiguous U.S. region

Differences in the performance of climatic metrics between the three case studies are evaluated specifically on the basis of improvements to the achieved fit and forecasting ability of the historical residential electricity use model. The first category of improvements relates to the additional variation (if any) each model can explain following the addition of a new set of climatic metrics, quantified through increases in the adj. R^2 statistic. The second category involves advances to the overall forecasting capability of each model specification for the forecasting period (2016-18), evaluated in terms of the reductions in annual and seasonal MAPE statistics. Improvements in the aforementioned statistical criteria are always quantified relative to the reference $Base_0$ model, which utilises readily-available heating and cooling degree day metrics produced by NOAA according to a uniform 18.3 ℃ temperature set point. The result of this analysis for the south, north and contiguous U.S. region is summarised in Table 5-5.

Table 5-5 shows that the performance of the south and north U.S. residential electricity use model generally improves with the modification of current and addition of new climatic metrics, while that for the contiguous United States remained indifferent. Amongst the two regional assessments, impacts on goodness-of-fit were more substantial for the one focusing on past residential electricity use in the cold region of north United States, as adj. R^2 increased by up to 5%. Introduction of humidity was solely responsible for that increase which can be also confirmed from inspection of reductions in annual MAPE statistics. As of 2015, more than a quarter of households in the northeast census region (which is a sub-set of the northeast climatic sub-region) had a dehumidifier , in contrast to the south census region (which includes the majority of states in the south climatic sub-region) where less than 10% of households owned one (U.S. EIA, 2017b). This signifies the role specific humidity has in explaining latent electricity loads in places where dehumidifiers are more widely adopted.

While the change in model's goodness-of-fit is lower at +2% for the south U.S. region, findings show a more consistent pattern since unlike the north U.S. case study adj. R^2 statistic, as well as annual and seasonal forecasting errors, improve for every step. Amongst the applied metrics, optimising the choice of temperature threshold in degree day calculations and controlling for specific humidity had the strongest impact on the model's explanatory power, with each increasing adj. R^2 by 1%. On the other hand, *HWD* and *CWD* metrics had a smaller influence on the historical model's fit and forecasting ability. While the extra amount of electricity load which can be explained by these metrics is limited, Chapter 4 showed that their interaction with humidity is important for seasonal projections of south U.S. residential electricity in the mid-21st century.

It should be noted that according to seasonal MAPE statistics for the south and north U.S. case study, employing the humidity-based specification reduces the electricity use model's forecasting error the most during winter months. In the south U.S. climatic region this could be attributed to the current low penetration rates for dehumidifiers in households. The small impact on seasonal prediction error for northern U.S. states could be because use of dehumidifiers is more spread out over a year and not concentrated during summer months. According to U.S. EIA (2017a) close to 60% of dehumidifier users in northeast U.S. households uses their equipment for more than 4 months in a year.

Table 5-5 Change in model fit (adj. R^2) and forecasting capability (MAPE) for each combination of climate metrics relative to the reference model

		South U.S. climatic region				North U.S. climatic region				Contiguous U.S.
No.	Description of specification	Adj. R^2	MAPE (2016-18)			Adj. R^2	MAPE (2016-18)			Adj. R^2
			Annual	Summer	Winter		Annual	Summer	Winter	
1	Empirical degree days with uniform 18.3 ℃ set point	0%	0%	+0.4%	-0.1%	-0.1%	-0.2%	+0.1%	+0.2%	-1.0%
2	No. (1) + optimised heating and cooling-related thresholds	+0.7%	+0.4%	+0.3%	+0.3%	+0.1%	-0.3%	-0.5%	+1.2%	-0.6%
3	No. (2) + extreme heat and cold wave day metrics	+1.1%	+0.5%	+0.5%	+0.9%	+ 0.1%	-0.2%	+0.2%	+1.3%	-0.3 %
4	No. (3) + specific humidity interaction	+1.7%	+0.8%	+0.6%	+1.7%	+5.2%	+0.9%	+0.4%	+2.4%	0%

Note: Positive (negative) changes to statistical criteria are marked with blue (orange) colour, while no change is shown with grey colour.

Finally, it is important to note that addition of reviewed climatic metrics, including the specific humidity interaction variable has a small effect on model performance for the contiguous U.S. residential electricity use model. This can be explained by the opposing direction of humidity effects in the south and north U.S. region: As explained by Auffhammer et al. (2013), increased evaporation in warm areas, such as the south U.S. region, leads to a “cooling” effect, which is translated into reduced demand for space cooling. As a result, humidity (disregarding the interaction with the extreme heat metric) was associated with a negative main effect on residential electricity use for the south U.S. case study. On the other hand, increased evaporation in cold areas leads to a “heating” effect as warm air arrives from the tropics. This justifies the positive sign of the main humidity effect in north U.S. states. These two opposing effects may cancel out each other which can explain their small explanatory power in the national-level model.

5.4.2 Differences in estimation results for the south, north and contiguous U.S. region

This section compares estimation results generated under the optimal humidity-based specification for the south (Hum_{avdur}), north (Hum_{int}) and contiguous (Hum_{dur}) U.S. region, listed in Table 4-6, Table B-2 and Table 5-4, respectively. First, the marginal effect of personal income on *EL_PC*, calculated at average (2000-15) *INC* levels in the north U.S. region, amounts to 3.12 kWh/pop, versus 2.41 kWh/pop estimated for the south U.S. region. Despite the stronger marginal impact of income, saturation of *INC* effects in the north U.S. region is attained at much higher income levels (US$ (constant 2018) 92,262), which is almost twice as high as the saturation point found for south U.S. states (US$ (constant 2018) 51,374). This could be attributed to the generally higher absolute per capita income levels in the north U.S. region, especially for northeast states where average monthly personal income exceeds US$ (constant 2018) 50,000 during the model’s estimation period 2000-15.

The higher saturation level for income effects across northern U.S. states could also suggest that growing affluence levels results in increased diffusion of electric equipment in households, including HVAC technologies. For example, 85% of states belonging to the northeast census region, which is a sub-set of the northeast climatic sub-region, had an air-conditioner installed in 2015 (U.S. EIA, 2017b), with that percentage being lower at 71% in 2001 (U.S. EIA, 2001). On the other hand, penetration in the West South Central Division, which is a subset of the south U.S. climatic sub-region, did not increase between 20001 and 2015, but remained close to 95%, which can justify the lower demand saturation level. Econometric estimation results for the contiguous U.S. *EL_PC* model in section

5.4.2 agreed with the identified North-South disparity of income saturation effects, with the exception of Northwest states.

In contrast to the south U.S. region, an additional *HDD* in the north U.S. climatic region has a twice as large impact on per capita electricity use (0.34 kWh/pop) compared to an extra *CDD*, under the Hum_{int} specification. In the case of the south U.S. region, the marginal impact of *CDDs* was more than ten times as large as that for *HDDs* under Hum_{avdur}, which suggests that residential AC demand is more relevant for these states. It is important to note that the significant reduction in the size of the *CDD* parameter coefficient for the north U.S. region is attributed to the addition of the specific humidity metric, which has also an increasing effect on *EL_PC*. The important sensitivity of the estimated *CDD* parameter to addition of the specific humidity metric can be justified by the large fraction of households in the north U.S. region which own a dehumidifier, as explained in the previous section. This highlights the need for explicitly controlling for specific humidity in models of residential electricity use as they confound the impact of temperature metrics (dry-bulb degree days) on space cooling demand. The opposing direction of humidity effects between north and south states (remember that humidity has a negative effect on electricity use in the southern states) can also explain why the parameter for humidity in the U.S.-wide model is not statistically significant.

Extreme heat and cold metrics have negligible influence on the performance of the per capita residential electricity use model for the north U.S. climatic region. This is also demonstrated through parameter significance testing, since both the estimated parameter for the intensity of heat wave and cold wave events in the north U.S. Hum_{int} model turn out to be insignificant. On the other hand, the heat and cold wave day metrics were found to have a statistically-significant effect on residential electricity use in the south (Hum_{avdur}) and contiguous (Hum_{dur}) U.S. model. Nevertheless, the interaction between air humidity and the corresponding heat wave metric is statistically significant in both the regional and national model. The positive interaction term suggests that the impact of heat waves on north U.S. per capita electricity use becomes greater in more humid environments. Since the main (negative) *IHW* effect is insignificant in the humidity-based model, the effect of heat wave intensity cannot be evaluated when humidity is zero. This slightly differs from results for the south and contiguous U.S. region which found that the impact of the *HWD* metrics (NHW_{av} and *NHW*, respectively) switches from negative to positive after mean specific humidity reaches 15 g/kg.

5.5 Conclusions

Chapter 5 has built on previous chapter's findings concerning the practical usefulness of using different climatic metrics to model historical residential electricity use for the south U.S. climatic region (16 states), by replicating the same assessment in the north U.S. climatic region (21 states). Following the generalisability of results about the explanatory power of different climatic indicators, this chapter developed a panel data model for analysing historical trends of residential electricity use for the 49 states comprising the contiguous U.S. region (2000-18). The historical model was then used together with scenario data to evaluate the future impacts (2046-55) of climatic, socio-economic and fuel price trajectories on U.S.-wide residential electricity use. From this study, four key conclusions are drawn:

First, in agreement with results from Chapter 4, incorporating the new climatic metrics has improved the quality of the state-level residential electricity use model for the north U.S. region relative to base degree day specifications. The preferred humidity-based specification explains about 5% more variation of past residential electricity use in north U.S. states relative to specifications which only employ externally or empirically-derived degree day metrics, attributed to the addition of the specific humidity metric. Moreover, the optimal humidity-based model for the north U.S. region has a 1% smaller annual forecasting error in the estimation (2000-15) and forecasting (20016-18) period compared to degree day-based ones, with most of the improvement in prediction accuracy originating in winter months. Despite the general agreement in results between the south and north U.S. region, application of the new climatic metrics in the U.S.-wide analysis had a smaller impact on the goodness-of-fit of the residential electricity use model. This may suggest that the developed metrics are better in explaining electricity use patterns in regions with homogeneous climatic characteristics. Nevertheless, the adopted extended model for the full historical period, Hum_{dur}[13], was the most parsimonious according to the AIC criterion and reduced reliance of predictions on monthly dummies during summer, when most electric space cooling occurs.

Second, is that, amongst modelled explanatory variables, personal income has the largest impact on annual, population-corrected, U.S. residential electricity use in the mid-21st century. Its effect ranges from a 7.9% to 9.5% relative increase of *EL_PC* for the high and reference economic growth case, respectively. Saturation of the effect of income for some states by 2046-55 implies that further increases in household affluence levels lead to a decrease, instead of an increase, of U.S.-average per capita electricity use. As a result, scenarios whose narrative involves assumptions about a slowly evolving economy generally project slightly higher absolute *EL_PC* levels by the mid-21st century. Climate change ranks second,

[13] Hum_{dur} adopts a 17.3 ℃ and 20.3 ℃ cut-off point for HDD and CDD calculations, controls for the effect of the duration of extreme heat and cold episodes and the interaction between air humidity and heat wave duration.

having an annual positive effect on per capita electricity consumption in the range of 1.2% to 3.8%. The positive impact of climate change on annual *EL_PC* is counterbalanced by the negative effect of growing electricity prices in 2046-55, which ranges from -1.6% to -3.6%. Plans about the expansion of baseload generating capacity for the U.S. residential sector should not only be evaluated in terms of national and regional socio-economic (i.e., income and population) trends, but should also consider the stress on power supply added by changing climatic patterns.

Third, the impacts of climate change are much more significant when examining the peak residential electricity demand in the summer. Under the high-end climate change scenario, electricity use (per capita) was shown to grow by 15% during summer months relative to 2000-18 levels; an effect that is almost five and two times as large as the equivalent for high electricity prices and reference-case income, respectively. Electricity consumed per capita for space cooling purposes still increases by 7% during summer relative to the baseline 2000-18, even for the low-end climate change case. A shift of electricity demand towards warmer months, after the disproportionate increase of summer peak in 2046-55 (~34%), will reshape annual load curves; an effect which is not described in the electricity market module of NEMS.

These findings have important implications for long-term electricity systems planning in the U.S. region, as more generating capacity will be required to meet increased seasonal electricity demand. Intensified need for residential AC services during periods of hot weather can increase both total generation requirements and peak system's demand, which would inevitably challenge the stable operation of electrical grids, as a result of lowering load factors. Declining technology costs and improved efficiency will increase the amount of low-carbon electrical capacity to be installed by 2050 in meeting future AC-driven peak demand. Energy storage technologies, often in the form of batteries, can increase the degree of utilisation of renewable energy production in the power grid, by flexibly storing and moving it to periods with high electricity demand, although current storage costs are not nontrivial (Denholm et al., 2010). Energy storage when combined with high deployment rates of solar PV capacity has also the potential of meeting large portions of U.S. peak electricity demand and replacing the existing, high-pollutant, peaking power plants (Denholm et al., 2019). A necessary step for accomplishing this goal is that modelling of climate change impacts at the regional spatial scale is better integrated to capacity expansion models. That would also guarantee that public policy efforts made towards reducing residential energy consumption and power sector's maximum output would not disregard the demand for extra reserve capacity to be deployed during the summer.

Fourth, U.S. reference case residential electricity consumption is projected to be ~14% higher in 2046-55 than 2018, which is comparable with the increase forecasted by NEMS for the 2018-50 period (~12%) (U.S. EIA, 2019a). Although the two results are generated via energy models characterised by fundamental differences in the adopted methodology, the agreement in future projections could be attributed to my modelling assumptions about diminishing personal income effects. My approach helps establish a demand saturation level after certain income levels have been exceeded, but it also allows accounting for the possibility that wealthier households invest in less energy-intensive appliances in the long-run, curbing projected increases of future electricity use. My assumptions about a non-constant relationship between residential electricity use and economic growth (i.e., variable $\frac{\partial EL\_PC}{\partial INC}$) can be similarly adopted in other assessments of future trends of electricity use in saturated AC markets. However, it is uncertain whether the introduction of energy-efficient equipment will lower long-term electricity use in households as residents may still choose to make inefficient use of the new appliances (Emodi et al., 2018).

This chapter has demonstrated the implications of different climatic and non-climatic trajectories for future electricity use levels in the economically-matured U.S. residential sector. As penetration rates for different electric appliances (including that for space cooling) are approaching towards a saturation point, further personal income growth leads to gradually a smaller increase of residential electricity use, which turns into a decrease for some U.S. states by 2050. Moreover, the role of climate becomes more important in the future as thermal discomfort encourages households to increase the use of their existing AC equipment (i.e. the intensive margin). Conversely, the next chapter (Chapter 6) analyses past (2000-15) and future (2016-50) trends of AC residential electricity consumption for the EU-28 region, where there is a large penetration potential for space cooling devices. It will ultimately seek to understand the climatic and non-climatic factors which drive future EU-28 space cooling electricity consumption, through growing AC adoption (i.e. the extensive margin).

Chapter 6

A model of residential space cooling electricity use for the EU-28 region to 2050

6.1 Introduction

6.1.1 Background: EU space cooling

In the EU-28 region, while residential space cooling currently forms a minor share of sectoral final energy use (0.6% in 2015) it was the fastest growing household end-use during the time period 2000-15, recording an average consumption growth rate of 6.3% per year (Figure 6-1) (JRC, 2017). Residential air-conditioning also has an enormous future growth potential in the EU-28 as less than 10% of household floor area is currently cooled (RESCUE, 2014). Since space cooling in EU-28 households is usually supplied through electric RAC units (Pezzutto et al., 2017), the expected growth of residential AC markets across Europe (Pezzutto et al., 2016) will intensify pressure on national electricity sectors. This translates into a need for additional generating capacity and more effective management of summer time peak loads; issues which are already evident in Mediterranean EU-28 countries (Izquierdo et al., 2011).

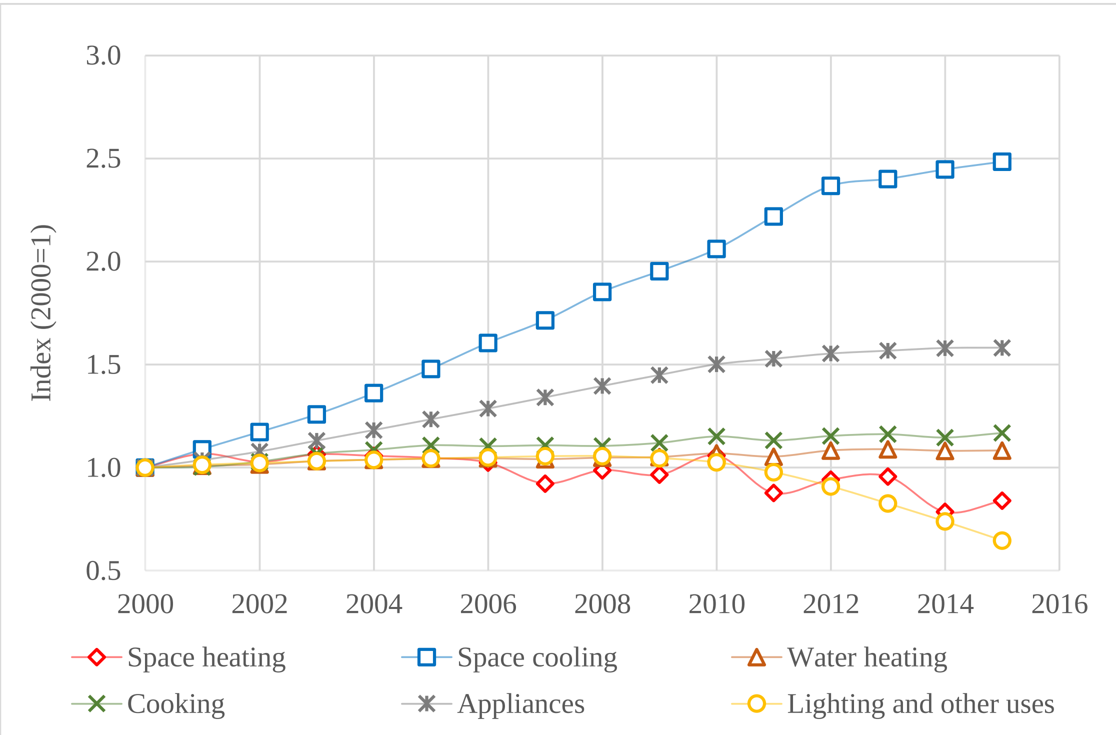


Figure 6-1 Indexed evolution of EU-28 residential final energy use by end-use service (2000-15) Source: JRC (2017)

Institutions of the European Union have long recognised the significant contribution of both space heating and cooling in meeting the mid- (2020/30) and long-term (2050) energy reduction and decarbonisation goals. This has motivated the development and endorsement of a strategy which introduces a multidimensional toolbox for sustainable and efficient heating and cooling systems (European Commission, 2016a). However, this strategy also acknowledges the lack of comprehensive knowledge about the current state of cooling sectors across the EU-28 region and calls for Member States to further assess the evolution of AC demand through scenarios. A comprehensive assessment of national cooling demand potentials was also required by Article 14 (and accompanying Annex VIII) of the Energy Efficiency Directive 2012/27/EU (European Parliament, 2012), which had to be accompanied by a cost-benefit analysis on the economic viability of different solutions for efficient cooling systems. However, due to scarcity of statistical data, only 8 EU-28 countries, most of them with warm summer weather (e.g., Spain and Italy), have delivered estimates for current and future residential space cooling demand (Jakubcionis and Carlsson, 2017). A second round of national comprehensive assessments for heating and cooling are expected to be submitted by the end of 2020, according to the updated recommendations from the European Commission (European Commission, 2019).

In the absence of granular household end-use consumption data, studies analysing the EU's current space cooling energy use involve estimates obtained mostly through bottom-up technology-based energy models. These in turn depend on technical parameters gathered over tiny time frames, overlooking past variation of AC use (RESCUE, 2014; Dittmann et al., 2017). These models provide limited value to the policy making process as they do not facilitate a broader discussion about the relative importance of the various factors driving air-conditioning use in different EU Member States. These historical estimates are subsequently mixed with crude assumptions about the future development of modelled parameters, such as a 100% AC technology saturation rate (Sparber and Pezzutto, 2014; Werner, 2016) or using current diffusion data from United States as a proxy (Henderson, 2005; Jakubcionis and Carlsson, 2017), to define ceiling values for EU-28 space cooling electricity consumption. The adoption of such simplified methodologies limits understanding about the potential trajectories residential AC markets could follow in the near-future and how different factors, including climate change and economic growth, could affect its evolution. Even if the impact of these two factors is taken into consideration, projections of AC diffusion are based on functions which were not calibrated using historical data for the EU-28 region only (Mima and Criqui, 2009; Mima and Criqui, 2015; JRC, 2018a).

6.1.2 Specific research objectives

Chapter 6 first aims to improve understanding about the components of historical AC electricity use growth (2000-15) in the EU-28 residential sector. The chapter then examines the specific drivers of the climate-sensitive components of space cooling electricity use, including the diffusion of AC technologies in households. Finally, Chapter 6 evaluates different scenarios of future (2016-50) residential AC electricity use under various assumptions about the pace of development of the space cooling market and technical efficiency improvements. In general, this chapter adopts methodologies and modelling tools which are different from those utilised in Chapter 4 and 5 for the United States studies, since these are tailored to the small, but quickly growing, AC market of the EU-28 region.

This chapter uses the novel JRC-IDEES database, which provides consistent and detailed data about the residential space cooling sector of EU-28 countries over an extended time period (2000-15) (JRC, 2017). This permits the development of a multi-method modelling framework, previously presented in Chapter 3 (section 3.3.2) for studying historical trends of space cooling electricity use, which is inclusive of the broader non-technology factors. Moreover, it adopts a more scenario-based approach to evaluate potential future pathways of residential AC electricity consumption for different EU-28 countries. More specifically, this chapter tackles the following research objectives:

(a) Identify the main driving force of EU's residential space cooling electricity use in the time period 2000-15. This question is tackled with traditional decomposition analysis, which helps link the variation of household air-conditioning electricity consumption to relevant activity, structural and intensity components.

(b) Determine the specific drivers of the climate-sensitive components of space cooling electricity consumption. This objective is achieved by extending decomposition analysis to a set of panel data econometric models aiming to explain the influence of climatic and non-climatic factors on national AC penetration rates and households' useful space cooling energy demand.

(c) Evaluate the impacts of future AC diffusion trajectories on electricity-based final energy use for space cooling in the EU-28 residential sectors and potential peak cooling electricity demand, as projected up to 2050. This chapter develops baseline AC diffusion scenarios incorporating projections of socio-economic and climatic data, while alternative policy cases consider unit efficiency targets and AC installation rates in new and renovated buildings.

6.1.3 Chapter structure

Section 6.2 describes the adopted novel multi-method modelling framework in more detail and summarises the data requirements. Section 6.3 presents the results of the historical analysis (section 6.3.1 and 6.3.2) and the future scenario modelling (section 6.3.3). Section 6.4 then discusses potential extensions of the historical analysis framework (section 6.4.1) and compares scenario projections in 2050 with those obtained by other studies (section 6.4.2). Finally, section 6.5 summarises the conclusions of this chapter.

6.2 Data and Methodology

6.2.1 Modelling framework

As explained in section 3.3.2, the historical and future analysis is performed across two overlapping layers, which are connected together via different links visualised through the schematic diagram in Figure 3-3. (A) First, IDA is employed to quantify the effect of changes in different components (i.e., household numbers, unit AC efficiency, useful specific cooling demand and AC diffusion) on the historical variation (2000-15) of EU-28 aggregate residential AC electricity use. This helps identify the main contributing factors of observed past increases in space cooling electricity consumption at the EU level. Panel data approaches then complement analysis by relating the temporal variation of these factors at the country-level to specific socio-economic and climatic effects. Panel data models are specifically used to study the responses of AC penetration rates and useful specific cooling demand to climatic and non-climatic effects. (B) Scenarios are constructed to evaluate the impact of different AC diffusion trajectories on EU-28 sectoral space cooling electricity use and potential peak cooling electricity

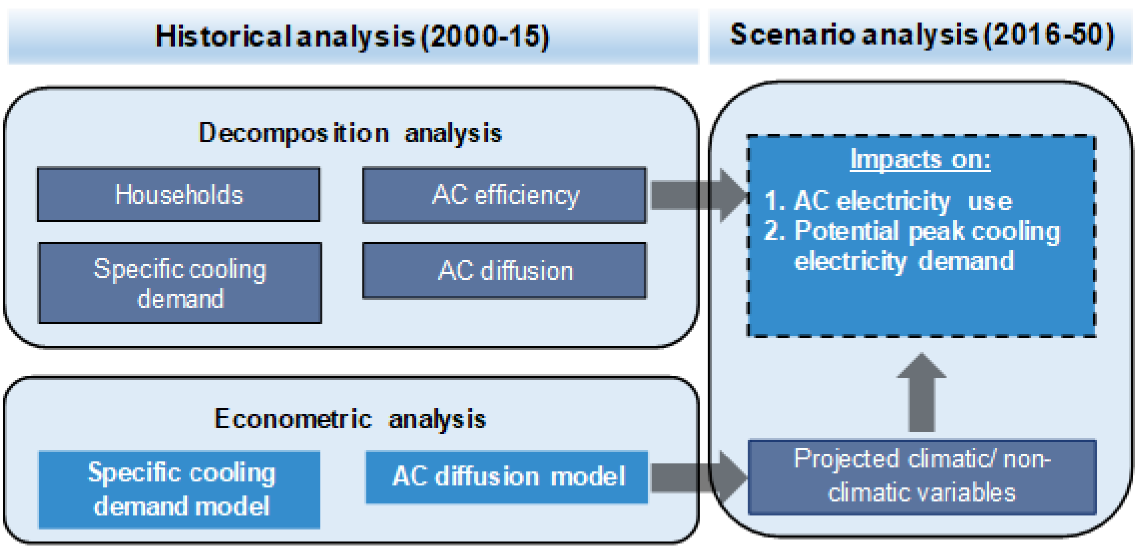


Figure 3-3 Modelling framework for the EU-28 case study

demand in the time period 2016-50. Baseline estimates of future country-level AC take-up levels are derived from the econometric model developed in (A), when used together with projections of climatic and socio-economic data. Impacts on residential electricity demand for the baseline diffusion scenario are finally benchmarked against corresponding impacts for two policy cases, concerning unit efficiency improvements and diversified installation rates.

6.2.2 Historical analysis of EU-28 residential AC electricity use

6.2.2.1 Index decomposition analysis (2000-15)

Sectoral-level decomposition analysis is a very useful tool for energy policy-making, especially in the context of residential sector mitigation strategies where it has been applied to understand the temporal dynamics of energy consumption and the corresponding carbon emissions (Xu and Ang, 2014). The IDA approach offers the advantage of attributing changes of final energy use to a set of pre-specified factors which can be unique for each end-use service, thus facilitating the design of more tailored energy reduction policies. In its simplest form, IDA is performed via eqn. (6-1):

$$FEU = Activity \times Structure \times Intensity \qquad (6\text{-}1)$$

where *FEU*, final energy use of a sector or for a specific end-use, is expressed as the product of *Activity*, *Structural* and Energy *Intensity* factors. The *Activity* component denotes the primary driver of final energy use, while *Structure* captures additional parameters having an impact on its size. On the other hand, the *Intensity* factor represents energy consumed per unit of activity, which is influenced by weather, building and AC technology characteristics, as well as lifestyle patterns (Isaac and van Vuuren, 2009). In the case of residential space cooling electricity consumption, the number of households and diffusion rate of AC equipment is respectively ascribed to the activity and structural parameter (Jakubcionis and Carlsson, 2017). The intensity indicator is then defined as space cooling electricity consumed per air-conditioned household. Space cooling electricity use (FEU_{AC}) in EU-28 countries is therefore expressed in annual steps (TWh/yr) between 2000 and 2015, using eqn. (6-2):

$$FEU_{AC} = Hou \times Diff \times Qspec \div Eff \qquad (6\text{-}2)$$

where *Hou* is the number of households (hh) and *Diff* the share of residential buildings equipped with air-conditioning (%), conforming to the adopted framework. Moreover, useful specific cooling demand (useful kWh/hh), captured through *Qspec*, is converted into units of specific space cooling electricity consumption (kWh/hh) via the cooling system's efficiency indicator, *Eff*.

Log Mean Divisia Index – method I (LMDI-I) is the preferred tool to explain the year-to-year variation of residential AC electricity consumption via the contribution of the 4 pre-selected components, due to its theoretical and methodological advantages (Ang, 2004). These advantages include leaving no residual term since absolute annual FEU_{AC} changes over time can be completely decomposed to individual components, in an additive fashion through eqn. (6-3):

$$\Delta FEU_{AC} = \Delta {FEU_{AC}}^{Hou} + \Delta {FEU_{AC}}^{Diff} + \Delta {FEU_{AC}}^{Qspec} - \Delta {FEU_{AC}}^{Eff} \qquad (6\text{-}3)$$

where differences in FEU_{AC} between a specific year, *yr*, and base year, 0, equates to the sum of partial temporal effects arising from changes in household numbers, AC appliance ownership, useful specific cooling demand and efficiency improvements. Given the logarithmic form of the decomposition, the impact of individual components on FEU_{AC}, such as that of the housing stock is calculated via eqn. (6-4):

$$\Delta {FEU_{AC}}^{Hou} = \frac{FEU_{AC_{yr}} - FEU_{AC_0}}{lnFEU_{AC_{yr}} - lnFEU_{AC_0}} \times (lnHou_{yr} - lnHou_0) \qquad (6\text{-}4)$$

6.2.2.2 Panel data econometric modelling (2000-15)

Diffusion (*Diff*) of residential AC units in EU-28 households during the historical period 2000-15 is studied in a panel data setting through an s-shaped logistic growth curve given by eqn. (3-12), which was developed in section 3.6:

$$\ln\left(\frac{Sat_c}{Diff_{c,yr}} - 1\right) = \ln(\gamma_c) + \underbrace{\delta_1}_{(-)} trend + \underbrace{\delta_2}_{(-)} INC_{c,yr} + \sum_{r=0}^{R} \underbrace{\delta_{3yr-r}}_{(-)} TMP^{JJA}_{c,yr-r} + \varepsilon_{c,yr} \qquad (3\text{-}12)$$

Drawing from previous findings in the literature, the econometric model explicitly accounts for personal income and weather changes in country (*c*) and year (*yr*). The variable *INC* quantifies annual personal income in EU-28 countries, as approximated by per capita GDP which is PPP-adjusted to represent between-country price-level differences. The variable TMP^{JJA} accounts for mean outdoor temperature during the summer period, while a TMP^{JJA} lag (*R*=1) is subsequently added to capture the effect of previous year's extreme heat episodes on AC ownership rates (Auffhammer, 2014). The variable TMP^{JJA} is first adjusted to account for disproportionate temperature impacts on diffusion in areas within a country with larger population, through weights corresponding to NUTS-3 sub-regions population for 2014. On the other hand, the econometric model implicitly controls for evolving energy efficiency standards and AC equipment prices through a time *trend*.

Saturation (*Sat*) represents the maximum attainable penetration rate of air-conditioning in residential buildings which is invariant with time and is assumed to differ between cold and warm EU-28 countries. EU-28 countries are therefore first divided in two groups according to long-term (1995-2015) *CDD* statistics, each of them assumed to reach a unique *Sat* level: countries having higher than average *CDDs* are labelled as warm, while the rest of them are ascribed to the cold group. The performance of the diffusion model in eqn. (3-12) is evaluated in iterations (at steps of 10%) for various group-level saturation values through the adj. R^2 criterion. $\mathrm{Sat}_{\mathrm{cold}}$ is constrained to be always smaller or equal to $\mathrm{Sat}_{\mathrm{warm}}$, while both are set to vary above the highest AC diffusion level recorded in each region during the 2000-15 period. A combination of Sat_{cold} and Sat_{warm} points which maximise the model's goodness-of-fit are adopted. It should be noted that unlike the U.S. case study, this chapter does not compare the explanatory power of different historical models based on their AIC and BIC criteria, since all candidate specifications have the same number of explanatory parameters.

The effect of personal income and mean summer temperature on residential AC diffusion is more accurately identified via FE panel data estimation. The FE estimator additionally generates 28 country-specific intercepts, γ_c, which represent time-invariant characteristics which are unique for each EU-28 country and are allowed to be correlated with explanatory parameters (Auffhammer and Mansur, 2014). As with previous econometric analysis in Chapter 4 and 5, an F-test and a Hausman test are executed to confirm the superiority of the FE estimator to the pooling and RE one.

Useful demand for space cooling per unit of activity (*Qspec*) has been previously econometrically estimated based on cross-sectional models using climatic variables, in the form of *CDDs*, and economic development indicators, such as personal income (Isaac and van Vuuren, 2009) and household expenditures (van Ruijven et al., 2011; Daioglou et al., 2012). In a cross-sectional setting, the positive effect of income on specific cooling demand was demonstrated to diminish in wealthier countries, as occupants choose to use their AC equipment irrespective of their financial status (Levesque et al., 2018). Since the vast majority EU-28 nations are high-income economies (World Bank, 2018b) a different model specification, described in eqn. (6-5), has been chosen to study the within-country variation of *Qspec*:

$$Qspec_{c,yr} = \eta_c + \theta_1 AREA_{c,yr} + \theta_2 AREASQ_{c,yr} + \theta_3 CDD_{c,yr} + \varepsilon_{c,yr} \qquad (6\text{-}5)$$

Useful floor area (*AREA*) is selected as a more straightforward explanatory parameter of *Qspec*; in larger households containing more rooms and communal areas, maintaining desired indoor temperature level demands either more intense use of existing space cooling equipment or acquisition of additional AC units, both having a significant effect on *Qspec* (Yun and Steemers, 2011). Moreover, past research has shown that household floor area is strongly connected with personal income (Santamouris, 2016) and so the inclusion of both variables in the FE panel data model has been avoided. A quadratic *AREA* term (*AREASQ*) is also included to capture any additional non-linear effects.

CDDs characterize the climate-sensitive part of useful specific cooling demand. They quantify the annual sum of daily deviations of mean outdoor air temperature from a pre-specified fixed threshold (Fazeli et al., 2016), in line with Eurostat's definition[14], below which no mechanical space cooling is needed to restore thermal comfort in households. Using a high temperature threshold (here set at 24 ℃) ensures that days with low average temperature, when building electricity demand is essentially climate-insensitive, are excluded from *CDD* calculations. *CDDs* in essence capture the cumulative effect of warm temperatures on specific AC electricity demand more effectively than using an absolute measure of temperature, which was the approach used in the AC diffusion model. As in the standard FE model specification, *η*s refer to country-level factors and *ε* to the residual error term.

6.2.3 Scenario analysis of future EU-28 residential AC electricity use (2016-50)

Future pathways of space cooling electricity consumption (FEU_{AC}) and potential peak cooling electricity demand ($Peak_{AC}$) in the EU-28 region are evaluated though a scenario modelling process which extends the analysis to the period 2016-50. The scenarios focus on incorporating anticipated changes in the stock and efficiency of residential air-conditioners in accordance with the specifications of a baseline and two policy cases. In the baseline case, country-level AC penetration rates are projected in annual steps up to 2050 via the diffusion model in eqn. (3-12), for combinations of personal income (*INC*) and mean summer temperature (TMP^{JJA}) trajectories.

[14] $CDD_{yr} = \sum_{i=1}^{d} \begin{cases} (TMP_{out} - 21℃), & TMP_{out} > 24℃ \\ 0, & TMP_{out} \leq 24℃ \end{cases}$, where d is the number of days in year, *yr*, and TMP_{out} is daily mean outdoor temperature (ESTAT, 2019).

Future personal income is derived from the Intergovernmental Panel on Climate Change's Shared Socio-economic Pathways (SSPs), which provide plausible narratives for the long-term evolution of various socio-economic drivers (Riahi et al., 2017). Baseline AC diffusion scenarios adhere to 3 SSPs which cover the full spectrum of projection uncertainty, including a "middle-of-the-road" trajectory (SSP2) and a fast vs. slow economic growth case (SSP5/SSP3). With respect to increasing summer temperatures across the EU-28 region, RCP8.5 was again selected since it describes the high-end of projected climate change in 2050.

The sensitivity of country-level FEU_{AC} to growing AC up-take is assessed in 2016-50 by adjusting the *Diff* factor in eqn. (6-2) to match the respective scenario's value, while holding household count (*Hou*), AC efficiency (*Eff*) and useful specific cooling demand (*Qspec*) constant at the level in 2015. Future residential AC electricity consumption is therefore estimated using eqn. (6-6):

$$FEU_{AC_{c,yr}} = FEU_{AC_{c,2015}} \times \frac{Diff_{c,yr}}{Diff_{c,2015}} \tag{6-6}$$

Potential peak cooling demand is defined as the maximum theoretical load which a national electricity system would have to sustain if the full residential AC stock in a given year was operating at nameplate capacity; a condition which is more likely be fulfilled during periods of high extreme temperature. Maximum peak cooling demand ($Peak_{AC}$) is then calculated as the product of total annual AC stock in a country and full space cooling (electric) load. Stock size is first obtained as a percentage from the projections performed through the AC diffusion model (eqn. (3-12)) in the 2016-50 period and then converted into stock of units (*StAC*) using the number of houses in 2015. The latter parameter is estimated with the help of EU-15 inventory data obtained from Pezzutto et al. (2017), including different RAC systems' rated capacity (*Cap*) and seasonal energy efficiency ratio (*SEER*), as well as their respective share (*w*) in total buildings' sector stock. Estimation of potential peak cooling demand during 2016-50 is given in eqn. (6-7):

$$Peak_{AC_{c,yr}} = StAC_{c,yr} \times \frac{\sum_{tech=1}^{4} w_{tech} \times Cap_{tech} \div SEER_{tech}}{\sum_{tech=1}^{4} w_{tech}} \tag{6-7}$$

where *tech*= split, multi-split, single-duct and packed systems; which are currently the technologies with highest diffusion in the household sector. Amongst available room systems (Table 6-1), split AC units form the largest portion of the installed RAC stock (~60%), while they have the smallest average capacity size and highest conversion efficiency factor. Given the absence of data about the future composition of residential AC stock, peak cooling electricity demand scenarios in 2050 are built based on the assumption that the relative share of individual technologies remains unchanged.

Table 6-1 Composition and technical parameters of buildings RAC stock at the EU-15 level

AC technology	w (%)	Cap (kW)	SEER
Split systems	61.8	3.50	3.22
Multi-split systems	5.3	16.0	2.12
Single-duct systems	15.7	10.5	4.75
Packed units	17.2	4.75	2.12

Source: Pezzutto et al. (2017)

Two policy cases are subsequently devised, whose aim is to assess the sensitivity of future AC electricity use trajectories to varying assumptions for factors which can be tackled by policy makers, namely the level of AC unit efficiency improvements and diffusion rates in new and renovated buildings. While the baseline scenario keeps the efficiency parameter of national AC systems constant at 2015's levels, the 'Unit efficiency improvement' case applies different assumptions about the evolution of the *Eff* factor up to 2050. Conversely, the 'New Buildings AC rates' scenario incorporates alternative assumptions about the future fraction of new and renovated households installing an air-conditioner, while keeping the *Eff* factor fixed at 2015's levels. In this way, scenario analysis showcases the wide range of possible outcomes in 2050 under various policy regimes, instead of attempting to quantify the possibility of each scenario being realised in the future. The main assumptions made about the modelled variables up to 2050 under the two alternative scenarios are summarised in Table 6-2.

Table 6-2 Assumptions about the evolution of key variables up to 2050 for the two alternative scenarios

	Unit Efficiency improvement		New Buildings AC rates	
Time frame	Variable	Value (relative to 2015)	Variable	Value (absolute)
2021-2030	Eff	+20%	$Diff_{new}$	80%
2031-2040	Eff	+30%	$Diff_{new}$	90%
2041-2050	Eff	+40%	$Diff_{new}$	100%

Case 1 - Unit Efficiency Improvement: This case explores the size of energy savings which could be achieved due to significant increases in AC equipment efficiency. Tighter minimum energy performance standards (MEPS) and labelling schemes are the main mechanisms which currently enforce improvements in the performance of air-conditioners in EU-28 markets (Santamouris, 2016; IEA, 2018). These measures along with technological change are expected to have a major contribution in alleviating the foreseen pressure on electricity systems exerted by peak AC demand (Phadke et al., 2014; Shah et al., 2015).

This scenario adopts the 20% and 30% general efficiency goals endorsed through the EU's mid-term energy strategy for 2020 and 2030, while it assumes that super-efficient units dominate the market by the end of mid-21st century, increasing average AC efficiency by 40% in 2050, relative to 2015. Based on JRC-IDEES data, the efficiency parameter (*Eff*) of residential AC systems at the EU-28 level is equal to 3.0 in 2015. Incremental technical improvements, imposed in the future through this policy scenario, result in assumed EU-level *Eff* factors of 3.6, 3.9 and 4.2 in 2021-30, 2031-40 and 2041-50, respectively for our study. While my assumed average AC efficiency of 4.2 in 2050 is slightly higher than the one adopted by JRC (2019b) (~4.0), this is a feasible target since it is still lower than the *Eff* value of the best available technology currently marketed in the EU-28 region (IEA, 2018). Electricity-based FEU for space cooling in 2016-50 is calculated via eqn. (6-8), after expanding eqn. (6-6) to incorporate assumed changes in space cooling efficiency:

$$FEU_{AC_{c,yr}} = FEU_{AC_{c,2015}} \times \frac{Diff_{c,yr}}{Diff_{c,2015}} \times \frac{Eff_{c,yr}}{Eff_{c,2015}} \tag{6-8}$$

A similar approach is followed in obtaining modified potential peak cooling electricity demand ($Peak_{AC}$) estimates through applying efficiency improvements on the current SEER values of individual RAC technologies in Table 6-1.

Case 2 - New Buildings AC Rates: About 3% of housing stock across the EU-28 region every year (2000-15) consists of new and renovated buildings, which generally display higher AC diffusion rates than existing, non-renovated, ones (JRC, 2017). In 2015, 17.1% of new and renovated EU-28 households were equipped with an air-conditioner, while only 8.9% of old residential buildings had one installed. Future developments in the construction industry could facilitate easier installation of air-conditioning in the former group of buildings, as shown by the experience of the USA (Biddle, 2008). A drop in installation costs could work as an incentive for investing in RAC units; an economic behaviour which if mimicked by more and more newly-constructed households could abruptly transform the EU's residential space cooling market.

This "bad case" scenario is assumed to have an additive effect on baseline residential AC diffusion trajectories. The diffusion parameter is modified each year (*Diff'*) to account for the growing number of new and renovated units, $StAC'_{new}$, in total air-conditioning stock, added to the previous year's stock, $StAC'_{y-1}$, as well as to old households' AC equipment replacements and additions, $StAC'_{old}$, as demonstrated through eqn. (6-9):

$$Diff'_{c,yr} = Diff_{c,yr} + \frac{(StAC'_{new} - StAC_{new})}{Hou_{c,2015}} + \frac{(StAC'_{old} - StAC_{old})}{Hou_{c,2015}} + \frac{(StAC'_{yr-1} - StAC_{yr-1})}{Hou_{c,2015}} \quad (6\text{-}9)$$

My assumptions for this high penetration scenario is that diffusion rates for air-conditioning in new and renovated buildings, $Diff'_{new}$, increase from around 17% in 2015, in 10-year time steps, from 80% in 2021-2030, to 90% in 2031-40, and eventually reach full saturation (100%) in 2041-50. These values are benchmarked against baseline $Diff_{new}$ projections constructed to 2050 by means of linear extrapolation based on historical AC diffusion data (2000-15). The fraction of new and renovated buildings in the total housing stock per year in EU-28 countries is assumed to remain constant at 3% in the future; which equals the ambitious building stock renovation target set in the EU's Energy Performance of Buildings Directive (European Parliament, 2018) and lies within the range of renovation rates selected in (Olonscheck et al., 2011) for Germany's household sector. Since this set of rules does not affect AC purchasing decisions in old households, the $StAC_{old}$ terms can be removed from eqn. (6-9) as they cancel each other. Based on these assumptions, the modified AC diffusion parameter can be calculated under this scenario using eqn. (6-10):

$$Diff'_{c,yr} = Diff_{c,yr} + 3\% \times (StAC'_{new} - StAC_{new}) + \frac{(StAC'_{yr-1} - StAC_{yr-1})}{Hou_{c,2015}} \quad (6\text{-}10)$$

6.2.4 Data requirements

For the purposes of IDA, the JRC-IDEES database was accessed to obtain information regarding space cooling electricity consumption (FEU_{AC}), household numbers (*Hou*), air-conditioning stock and efficiency status of AC systems (*Eff*) (JRC, 2017). Based on these data, response variables of panel data models (i.e., useful specific cooling demand (*Qspec*) and AC diffusion (*Diff*)) were derived. Moreover, econometric modelling required the input of PPP-adjusted GDP data which were obtained from the World Bank (World Bank, 2018a), expressed in constant international dollars for the year 2011. National and NUTS-3 EU-28 population statistics, as well as annual (1995-2015) *CDDs* were sourced from Eurostat (ESTAT, 2014; ESTAT, 2015).

Monthly mean, near-surface, temperatures during the historical period (2000-15) were retrieved for every EU-28 country from Climatic Research Unit's (CRU's) time-series dataset, which is available in 0.5°x0.5° resolution (Harris et al., 2014). For this task, the geographic centroid of each NUTS-3 sub-region was previously matched to the 4 nearest grid points of the CRU's files and temperatures were calculated at the NUTS-3 level via the inverse distance weighting interpolation function described trough eqn. (4-1). The coordinates of the geographic centres were extracted from shapefiles depicting the geometries of NUTS-3 regions in 2013 (ESTAT, 2013). These temperatures were then aggregated to the country level after applying NUTS-3 population weightings for 2014, given in eqn. (3-13).

Descriptive statistics for all variables in the 2000-15 period are presented in Table 6-3. In absolute terms, Italy is the country with by far the largest residential AC consumption having mean annual FEU_{AC} levels of 5.4 TWh/yr, which is 4 times larger than the quantity consumed by either Spain or Greece. Italy, Spain and

Table 6-3 Descriptive statistics of country-level variables during the historical period 2000-15

Variable	Sym.	Mean	Std. Dev.	Max	Min
AC electricity use (TWh/yr)	FEU_{AC}	0.40	1.07	7.84	0
Useful specific cooling demand (useful kWh/hh•yr)	Qspec	1,656	1,070	5,241	333
AC diffusion (%)	Diff	6.4	9.3	48.6	0
Number of households (hh)	Hou	7,459,383	9,998,632	40,558,210	134,669
AC system efficiency	Eff	2.18	0.48	3.62	1.40
Personal income (2011$/pop PPP)	INC	32,684	14,914	98,646	8,811
Household area (m^2/hh)	AREA	89.9	21.9	142.6	41.8
mean JJA temperature (℃)	TMP^{JJA}	19.35	3.35	29.19	13.19
Cooling degree days	CDD	108	174	781	0

Greece were collectively responsible for 70% of EU-aggregate residential space cooling electricity consumption in 2015. Small northern EU-28 countries such as Estonia and Latvia had negligible FEU_{AC} levels in 2015 (<0.001 TWh/yr). In per household terms, Cyprus and Malta, which are the two hottest EU-28 countries according to the long-term *CDD* criterion (1995-2015), recorded the highest levels of useful specific cooling demand, with *Qspec* values of 4974 useful kWh/hh•yr and 3977 useful kWh/hh•yr, respectively, when averaged over the 2000-15 period. On the other hand, EU-28 countries found on the low-end of the annual *Qspec* distribution - Latvia (364 useful kWh/hh•yr) and Lithuania (392 useful kWh/hh•yr) - do not coincide with those having the lowest number of long-term *CDDs*, namely Ireland and Sweden.

Figure 6-2 displays the cross-sectional variation of AC diffusion rates across the EU-28 region for the last year in the sample (2015) and compares it respectively with that of personal income and long-run (2000-15) average summer temperature. The LHS plot presents a weak relationship between national AC penetration rates and personal income level, since the correlation coefficient between the two variables in 2015 is slightly negative (-0.18). On the other hand, the RHS plot shows that space cooling diffusion is positively correlated with mean JJA temperature (correlation coefficient ~ +0.64), implying that hotter EU-28 regions have generally higher penetration levels. The highest residential AC diffusion rates in 2015 were recorded in Croatia (48%), Greece (33%), Italy (30%) and Cyprus (27%). Croatia's exceptionally high penetration rates is unexpected, given its milder summer seasons.

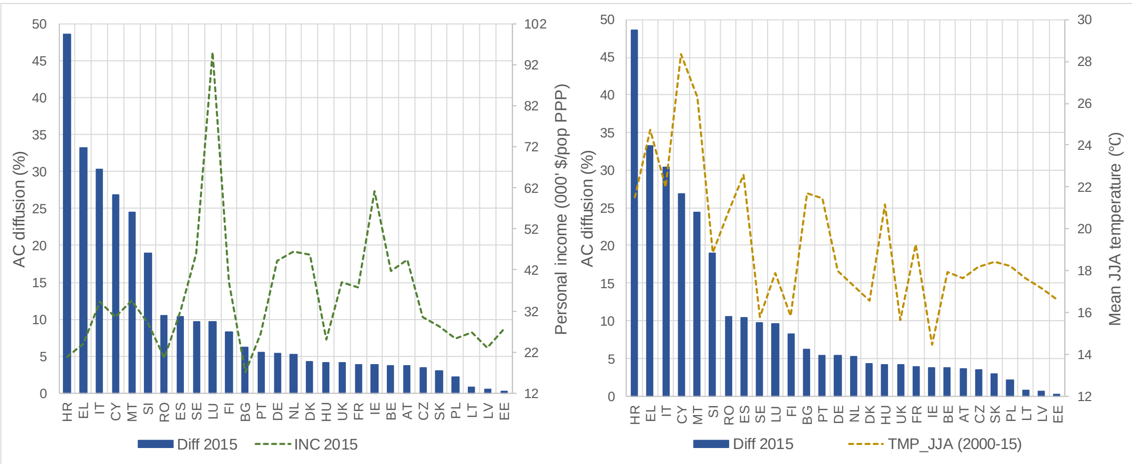


Figure 6-2 Country-level AC diffusion vs. personal income (left panel) and long-run mean summer temperature (right panel) in the EU-28 region

[AT: Austria, BE: Belgium, BG: Bulgaria, CY: Cyprus, CZ: Czech Republic, DE: Germany, DK: Denmark, EE: Estonia, EL: Greece, ES: Spain, FI: Finland, FR: France, HR: Croatia, HU: Hungary, IE: Ireland, IT: Italy, LT: Lithuania, LU: Luxembourg, LV: Latvia, MT: Malta, NL: Netherlands, PL: Poland, PT: Portugal, RO: Romania, SE: Sweden, SI: Slovenia, SK: Slovakia, UK: United Kingdom]

In order to devise baseline scenarios of AC penetration rates in EU-28 households, long-term projections regarding the annual growth of GDP per capita (PPP-adjusted) were collected for 3 SSP storylines from the database of International Institute for Applied Systems Analysis (Riahi et al., 2017) and then averaged over the time period 2015-50. Daily mean, near-surface, temperatures were extracted for the same timeframe from 19 regional climate projections (Table A-3), which have been performed under the EURO-CORDEX downscaling experiment and simulate the effects of an extreme climate change case (RCP8.5) (Jacob et al., 2014). These projections were then translated into monthly, country-level, temperature statistics following the same interpolation/ aggregation procedure as before. Table 6-4 provides a summary of climatic and non-climatic assumptions governing AC diffusion projections under the baseline case.

Table 6-4 Long-term mean (2015-50) annual growth rates of baseline variables in the EU-28 region

		Annual growth rate (%)		
Category	Variable	Low-Range	Mid-Range	High-range
Socio-economic	INC	1.1	1.2	2.2
Climatic	TMP^{JJA}	+0.65 ℃ (-2.01 to +4.01 ℃) [a]		

[a] This statistic shows the increase in TMP^{JJA} (℃) between 2000-15 and 2050 for mid-range RCP8.5 projections. Numbers in the parenthesis represent the full range of climate projections uncertainty.

6.3 Results

The Results section is organised as follows: section 6.3.1 presents findings with respect to the decomposition of the historical variation of EU-28 residential electricity use for space cooling (2000-15) to the annual effects of individual components (i.e. *Diff*, *Eff*, *Qspec* and *Hou*). Following this, sub-section 6.3.2 provides FE econometric estimation results for the historical model of AC diffusion and useful specific cooling demand. Finally, section 6.3.3 explores a baseline and two policy-based scenarios of residential AC electricity use (FEU_{AC}) and potential peak electricity demand ($Peak_{AC}$) in the time period 2016-50.

6.3.1 Decomposition analysis of EU-28 residential AC electricity use (2000-15)

During the time period 2000-15, EU-28 residential space cooling electricity use grew from 6.4 to 15.8 TWh/yr, representing a 2.5-fold increase. The percentage of EU-28 households with an air-conditioner (*Diff*) grew from 2.3% in 2000 to 9.2% in 2015 (4-fold increase), while the efficiency indicator of cooling systems (*Eff*) increased from 1.6 to 3.0 during the same time period (2-fold increase). On the other hand, the growth of useful specific cooling demand (*Qspec*) and housing stock (*Hou*) was modest in 2000-15 compared to that displayed by the other components. At the EU level, *Qspec* rose from 2236 useful kWh/hh•yr in 2000 to 2355 useful kWh/hh•yr in 2015, equalling an overall change of 5.3%. The number of households increased only by 11.8% between 2000 and 2015 (197 to 221 million units), with annual growth rates showing very little fluctuation between successive years.

Figure 6-3 displays the results of the additive decomposition for all 1-year time bands, whereby the annual variation in EU-aggregate FEU_{AC} levels, represented by diamond markers, is broken down into the contribution of single components (*Hou*, *Diff*, *Qspec*, *Eff*), illustrated by the uniquely coloured column bars. As an example of this method, the +0.88 TWh/yr change in FEU_{AC} observed between 2007 and 2008 comprises the 0.12, 1.23 and 0.08 TWh/yr positive impact

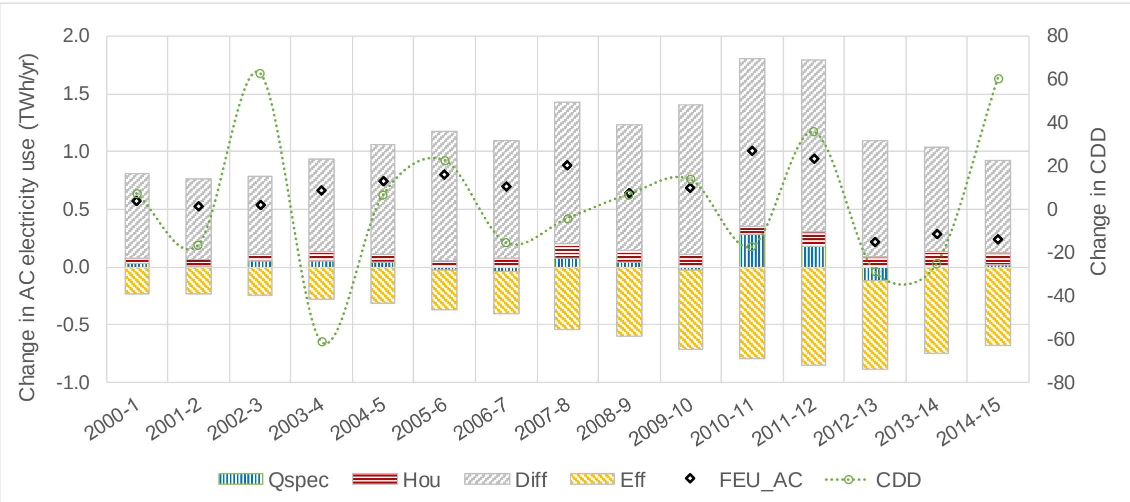


Figure 6-3 Decomposition of residential space cooling electricity use at the EU28-level with comparison to change in CDDs

[LHS: Decomposition of 4 drivers of annual residential AC energy consumption (FEU_{AC}): Useful specific cooling demand (*Qspec*); Number of households (*Hou*); AC diffusion (*Diff*); AC system efficiency (*Eff*) and RHS: Annual change in cooling degree days (*CDD*)] attributed respectively to housing stock, AC diffusion and specific cooling demand, and to the 0.55 TWh/yr negative effect from efficiency improvements.

Figure 6-3 shows that the diffusion of AC units in residential buildings had the strongest increasing impact on EU-28 space cooling electricity consumption across all 15 time bands, having a mean effect (2000-15) on FEU_{AC} of +1.02 TWh/yr. The second largest contribution to FEU_{AC} variation is attributed to AC system efficiency, with an average decreasing effect being half the size of diffusion-related one (-0.51 TWh/yr). Useful specific cooling demand and housing stock size had smaller influences on annual AC electricity consumption levels in the EU-28 region, with an average impact amounting to +0.04 and +0.08 TWh/yr, respectively. This highlights the significance of studying extensive margins in more detail, relating partly to understanding the role climatic and non-climatic factors play in residential AC adoption.

Moreover, the largest diffusion effect on FEU_{AC} (+1.5 TWh/yr) is found for the 2011-12 time band, which co-occurs with a 49.3% relative increase in EU-wide *CDDs*, whose annual change is also plotted in Figure 6-3. One would expect that the *Diff* effect would have peaked in 2002-3, as a result of the severe heatwave which struck the European continent; however, this is not evident from EU-aggregate trends. On the other hand, useful specific cooling demand influences FEU_{AC} the most in the 2010-11 time band, during which mean *CDDs* across the EU dropped by 19.2%. While this finding is counterintuitive, one should also note that this effect peaks due to a sharp increase in *Qspec* levels across Italy, which indeed faced increasing *CDDs* in 2010-11. It is therefore vital to evaluate the specific drivers of *Diff* and *Qspec*, while accounting for the heterogeneous behaviour of EU-28 countries; a need which was also identified by Serrano et al. (2017) when analysing combined heating and cooling demand trends for Europe. This is tackled next through econometric analysis.

6.3.2 Panel data modelling of AC diffusion and specific useful demand (2000-2015)

According to Figure 6-5, EU-28 countries qualifying in the warm group, exceeding the region's average long-term annual *CDDs* (102), are in ascending arithmetical order Croatia (121), Bulgaria (145), Portugal (170), Italy (201), Spain (205), Greece (300), Malta (606) and Cyprus (678), which together represented 26.2% of total EU-28 housing stock in 2015 (57.7 million units). The rest 20 EU-28 countries (i.e., Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Romania, Slovakia, Slovenia, Sweden and United Kingdom) were assigned to the cold group.

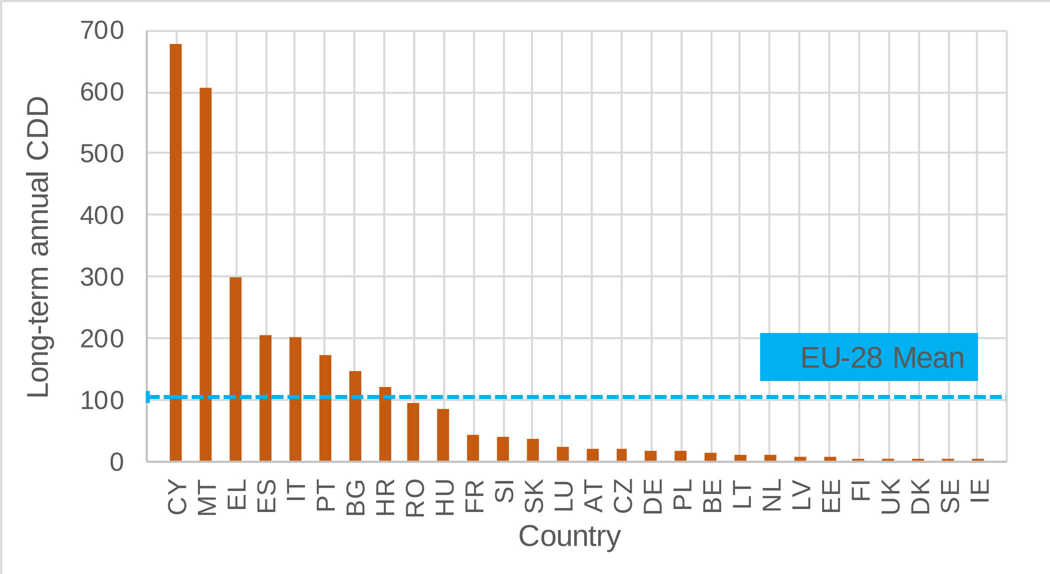


Figure 6-5 Long-term (1995-2015) annual CDDs for EU-28 countries

The residential AC diffusion model in eqn. (3-12) is run initially without a lagged temperature variable, while the obtained R^2 (adj.) statistic is compared for all potential combinations of Sat_{warm} (50-100%) and $Sat_{cold.}$ (20-100%). Model diagnostics which involved application of an F-test for country-specific effects and a Hausman test demonstrated the suitability of FE over the pooling and RE panel data estimator, accordingly. The optimal model fit is achieved when the saturation parameter for warm countries is set at 60%, while that for cold ones at 30%, as demonstrated by the heat map in Figure 6-4 portraying adj. R^2 statistic for all potential Sat_{warm}-Sat_{cold} groupings.

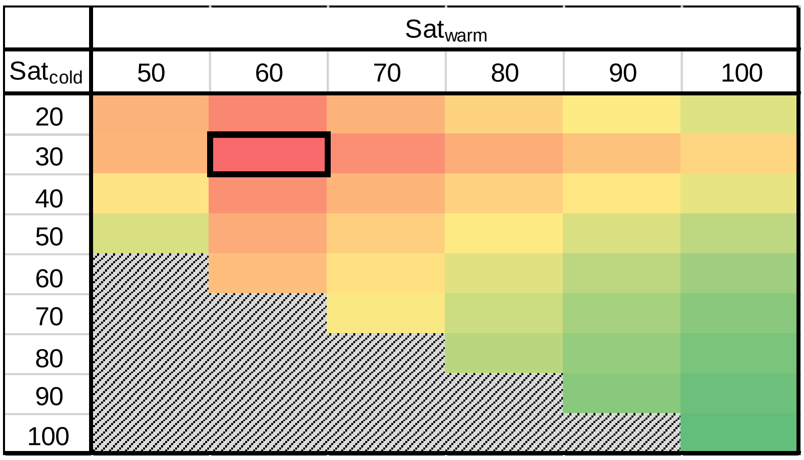


Figure 6-4 Heat map of R^2 (adj.) under all combinations of AC saturation points for warm and cold EU-28 countries

[the colour scaling scheme dictates that high (~0.75), medium (~0.74) and low (~0.73) R^2 values are displayed in red, yellow, green colour, respectively.]

Table 6-5 reports the FE estimator's output following implementation of the empirically-derived saturation levels. Column (1) includes generated coefficients, along with their robust standard errors. Results show that both personal income (*INC*) and contemporaneous mean summer temperature (TMP^{JJA}) exhibited a highly statistically-significant ($p<0.01$) positive effect on AC up-take in households during the time period 2000-15, while a strong trend is also present. Overall model performance is deemed very good, since the independent variables collectively explain 75% of observed variation in data.

Table 6-5 FE estimation results of AC diffusion model with Sat_{warm}=60% and Sat_{cold}=30%

Variables	(1)	(2)	(3)
INC (000' $/pop)	-0.086***	-0.078**	-0.150***
	(0.033)	(0.031)	(0.046)
TMP_{y}^{JJA} (°C)	-0.043***	-0.034*	-0.030***
	(0.014)	(0.019)	(0.009)
TMP_{y-1}^{JJA}(°C)		-0.025*	
		(0.014)	
Trend	-0.137***	-0.142***	-0.152***
	(0.011)	(0.012)	(0.013)
$\overline{\ln(\gamma_c)}$	7.503***	7.570***	3.964***
	(1.117)	(1.095)	(0.110)
Observations	448	420	448
F-test	128.5***	130.8***	
Hausman test	18.0***	11.5**	
R^2 (adj.)	0.753	0.745	0.727

Statistically significant * at the 10%, ** at the 5% and *** at the 1% confidence level. Note: Standard errors in the parenthesis are clustered by country (a la Arellano covariance matrix).

Delayed temperature effects are assessed by re-running the AC diffusion model with a summer temperature variable lag (Column (2)). Interestingly, the coefficient of TMP_{yr-1}^{JJA} also turns out to be statistically significant, albeit at lower confidence level ($p<0.1$). This finding suggests that EU-28 households respond to warmer weather through purchasing AC units at two time steps, one occurring the same year during which a heat event took place and another the year after. The marginal impact of lagged temperature on the response variable is however smaller than the one attributed to contemporaneous TMP^{JJA}. One should also note that inclusion of a lagged TMP^{JJA} term in the model does not come without a cost, as model parameter estimation is less accurate and resulting R^2 (adj.) statistic is smaller compared to the basic specification.

Comparing the size of temperature and income marginal effects on AC diffusion requires a standardization procedure which puts both predictors on the same measurement scale. Re-scaling variables effectively harmonizes FE regression coefficients as they now represent the response of dependent variable due to a standard deviation of either TMP^{JJA} or *INC* (Column (3)). The new income estimate is about 5 times larger than the one for temperature, implying that growing household affluence levels have larger influence on AC purchasing decisions in the EU-28 region, compared to increasing outdoor temperatures. The greater importance of income versus temperature on AC diffusion is reflected in the ratio of *INC* to TMP^{JJA} effect on penetration, which is obtained as around ~5 in this chapter, being roughly similar to a study reported for Chinese provinces (~6) (Auffhammer, 2014).

The model of useful specific cooling demand in eqn. (6-5) is run after ensuring the suitability of the FE estimator via the same confirmatory tests. Ireland is the only EU-28 country with zero cooling degree days for all years in the sample (2000-15), thus it is excluded from the analysis. The estimated FE model generally has less explanatory power relative to the AC diffusion one, with an R^2 (adj.) statistic close to 0.4 (Table 6-6). Parameter estimation shows the presence of a non-linear relationship between useful specific cooling demand and household area, since the *AREASQ* term has a statistically-significant coefficient ($p<0.05$). The marginal effect of *AREA* on *Qspec* ($\theta_{AREA} + 2\theta_{AREASQ}AREA$) becomes positive when household area exceeds 54 m^2/hh. This is much lower than the EU's average household area recorded for the 2000-15 period (89.5 m^2/hh).

On the other hand, the temporal effect of weather on useful specific cooling demand is less evident. Although the estimated *CDD* coefficient exhibits the correct (+) sign, it is only marginally significant ($p \approx 0.097$), while its inclusion has a minor impact on model performance. It is expected that with future revisions of historical *Qspec* data by JRC, the accuracy of parameter identification will be further refined. Nevertheless, the soft link between *Qspec* and *CDD* demonstrated through these results supports the argument brought forward later in peak cooling electricity demand calculations that simultaneous AC use across multiple households would more likely occur during extreme heat conditions.

Table 6-6 FE estimation results of specific cooling demand Qspec (useful kWh/hh•yr) model

Variables	
AREA (m^2/hh)	-36.595$^{\#}$
	(23.465)
AREASQ	0.339**
	(0.145)
CDD	0.103*
	(0.062)
$\overline{(\eta_c)}$	2004.117**
	(907.279)
Observations	432
F-test	440.2***
Hausman test	8.3**
R^2 (adj.)	0.394

Statistically significant at # at the 12%, * at the 10%, ** at the 5% and *** at the 1% confidence level.

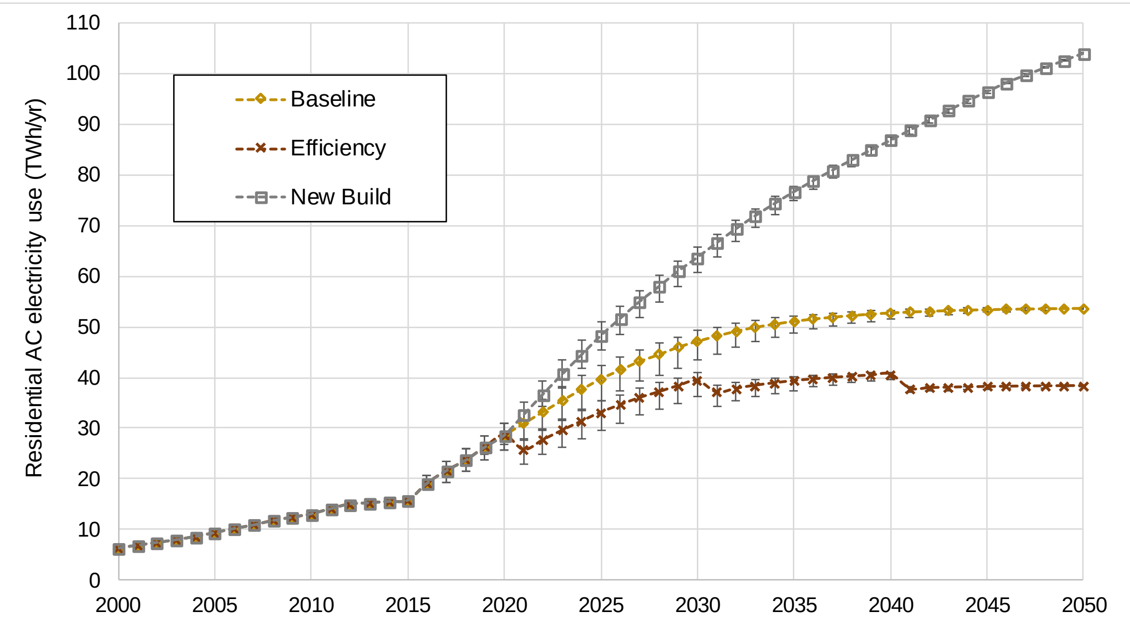
6.3.3 Scenarios of future EU-28 residential AC electricity use (2016-2050)

This section explores the range of potential FEU_{AC} *and* $Peak_{AC}$ outcomes under different trajectories of air-conditioning market development in the 2016-50 period. Space cooling penetration rates are projected in the future using the basic *Diff* model specification (without a TMP^{JJA} lag). In the baseline case, residential air-conditioning markets across warm and cold countries reach almost full saturation by the end of the projection period, increasing EU-aggregate, mid-range, AC diffusion from 9.2% in 2015 to 37.6% in 2050. This is equivalent to the addition of 62.8 million new units to the exiting AC stock in 2015 of which about two-thirds are attributed to cold EU-28 countries. Saturation is virtually reached under all personal income and summer temperature projections in 2050, albeit at varying paces. A steeper AC diffusion curve at intermediate market development stages, arising from a high-income (SSP5) and extreme temperature trajectory (maximum of multi-model ensemble), would result in a higher amount of cumulative electricity consumption over the period (2016-50).

Penetration levels of residential air-conditioning deviate significantly from the Baseline scenario in the "New Buildings AC rates" case, with the largest impact observed in cold countries where new and renovated buildings have low installation rates during the historical analysis period. Under mid-range trajectories, residential AC ownership rate in cold countries reaches 87.5% in 2050 without any signs of saturation, while diffusion in warm countries stagnates at 78.5%. Overall, aggregate space cooling diffusion in the EU-28 region reaches 85.1% in 2050 under this "bad-case" scenario, which translates to a surplus of 104.7 million AC units in 2050 relative to the baseline case.

Residential space cooling electricity consumption is calculated at one-year time steps from 2016-50, under each of the 3 scenarios (Figure 6-6). In the baseline case, mid-range FEU_{AC} across the EU increases by a factor of 3.4 in 2050 (53.7 TWh/yr) relative to 2015. The contribution of cold countries to total FEU_{AC} levels rises from 21.9% in 2015 to 39.5% in 2050, whereas that of warm states declines from 78.1% to 60.5% in the same time period. Italy and Spain together represent the largest portion of EU-28 space cooling energy consumption (46.4% compared to 59.8% in 2015). Despite its growth, AC electricity consumption in the baseline case still accounts for a modest share of EU's residential total (1.9%) and electricity-based (6 %) final energy use in 2050, as projected by the IEA's ETP model in their RTS case (IEA, 2017).

As expected, the sharpest increase of EU-28 residential AC electricity use in the future is estimated under the "New Buildings AC rates" scenario (104.1 TWh/yr

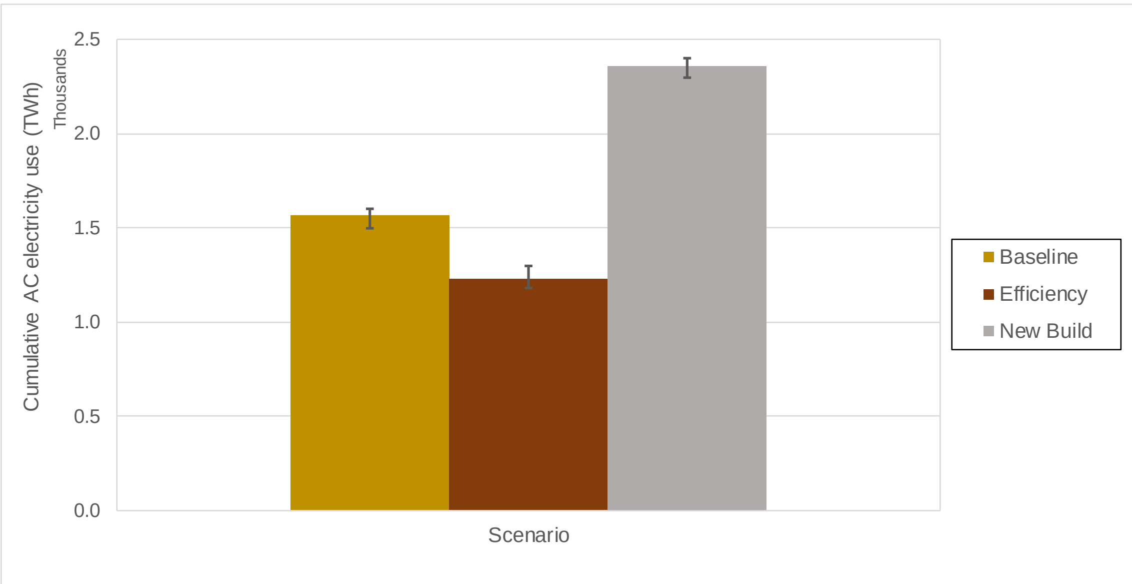


Note: Error bars represent the range of uncertainty in RCP and SSP projections.

Figure 6-6 Residential AC electricity use at the EU-28 level under different scenarios

in 2050 for the mid-range trajectory). Due to the radical transformation of national AC markets, the cold group of countries account for the largest share of household space cooling electricity consumption in 2050 (60.1%), with Germany and France having a combined contribution of 54.7% to total FEU_{AC}, as opposed to 11.5% in 2015. On the other hand, the future share of Spain, Italy and Greece in FEU_{AC} drops to a third. Under this scenario, space cooling in 2050 represents about 3.7% of final residential energy and 11.7% of electricity use at the EU level. Finally, for the strong efficiency case policies aimed at improving the performance of RAC technologies lead to lower end-use electricity use levels in 2050 (38.4 TWh) relative to the baseline scenario. The relative contribution of warm and cold EU-28 countries to total space cooling consumption is comparable to that for baseline trajectories, as this scenario reflects efficiency goals shared across the EU that have not been harmonised with national efficiency targets. Under this scenario, the share of space cooling in final residential energy use (1.4%) and sectoral electricity consumption (4.3%) in 2050 is still higher than that in 2015.

As already stated, emphasis is not only placed on end-point estimates of space cooling electricity use in 2050, but also on the potential trajectories traced in the interim based on different scenarios. The accelerated penetration of air-conditioners in households predicted by the “New buildings AC rates” case, would cause space cooling demand to grow more rapidly in the mid-term, thereby leading to overall higher cumulative electricity use requirements from 2016 to 2050. The important between-scenario differences in the cumulative amount of AC-based electricity consumed in 2016-50 are clearly marked in Figure 6-7. For



Note: Error bars represent the range of uncertainty in RCP and SSP projections.

Figure 6-7 Cumulative residential AC electricity use at the EU-28 level in the 2016-50 period

example, cumulative AC consumption under the “New buildings AC rates” scenario is about 1.5 times and 1.9 times as large as the amount which corresponds to the baseline and strong unit efficiency scenario. Moreover, assumptions about a high-income (SSP5) and maximum RCP8.5 trajectory lead to 5.5% higher cumulative AC electricity use requirements in 2016-50, relative to the mid-range case, under the baseline scenario.

Assessing the magnitude of peak AC electricity demand in EU-28 countries and the associated implications for the electrical system’s peak load requires knowledge about the seasonal distribution of AC usage in relation to the annual profile of power sector’s output. For warm EU-28 countries, contribution of space cooling to the total system’s maximum demand is deemed quite substantial, given their co-occurrence during the summer period. For the vast majority of EU-28 cold countries, on the other hand, annual loads are primarily driven by space heating electrical demand in winter, and much less by space cooling demand, due to cooler summer temperatures and lower AC penetration rates. This is clearly demonstrated by Figure 6-8 in which the annual profile (2010-15) of daily peak demand is compared for a warm (Italy) and cold (Germany) EU-28 country (ENTSO-E, 2017). While a well-defined wintertime peak is observed in the German load profile, two distinct seasonal spikes appear in the Italian one, with the one occurring in summer being persistently more extreme than the winter-based one.

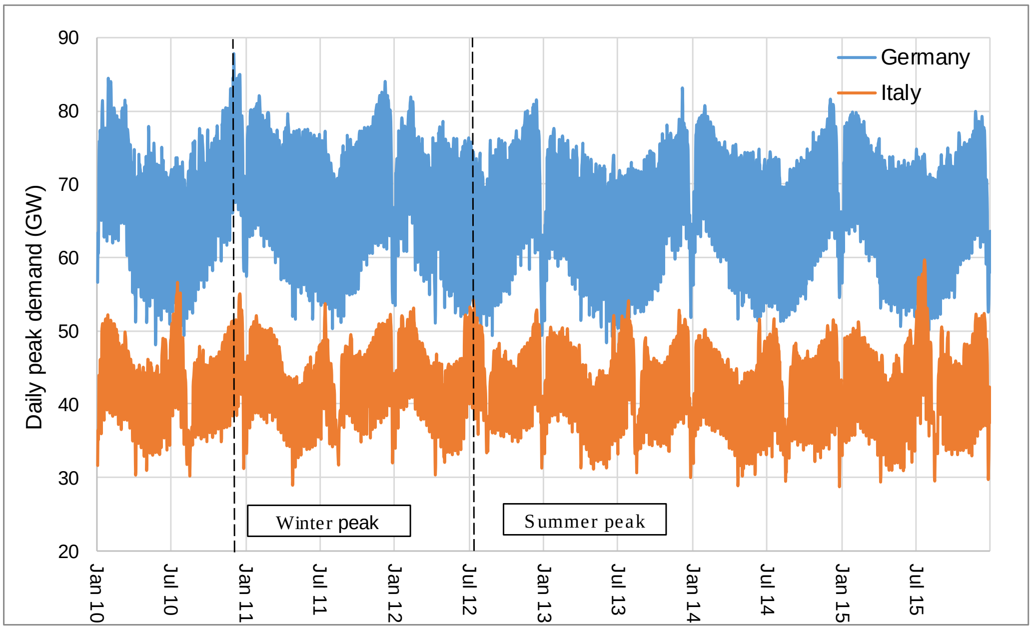


Figure 6-8 Daily peak electricity load in Germany and Italy (2006-15) Source: ENTSO-E (2017)

Furthermore, the peak coincidence factor for residential space cooling, defined as the probability of AC technologies being used at the time of system’s peak demand, is respectively high and low for warm and cold EU-28 countries. Evidence however suggests that under an extreme climate change scenario (RCP8.5), peak electricity demand could shift from winter to summer months for many northern European countries (Wenz et al., 2017), reflecting the more intense use of AC equipment. Since quantifying the probability of future system's peak demand shifting seasons is extremely uncertain, this task remains outside the scope of this paper. This chapter instead establishes a maximum level of instantaneous peak AC electricity demand for EU-28 countries, which reflects the potential stress on the electricity network from the coordinated use of residential air-conditioners during the summer period.

Potential peak cooling electricity demand in the EU-28 residential sector is estimated to increase from 43.3 GW in 2015 (26.7/16.6 GW in warm/cold countries) to 177.7 GW in 2050, under the mid-range baseline projection, with 103.7 GW attributed to cold countries. Moreover, in agreement with FEU_{AC} findings, $Peak_{AC}$ is affected the most under the extreme AC diffusion scenario, recording a 9-fold increase by 2050 (401.9 GW, of which 304.9 GW is in cold countries). As anticipated, the smallest change in peak cooling electricity demand is projected for the strong unit efficiency case (127 GW in 2050, of which 74.1 GW is in cold countries).

While knowledge about the future size of potential peak cooling demand is essential for electricity capacity upgrades, what is also of principal value for electricity network operators is the timing of integration of new plants to the grid. Given the fast-growing residential AC markets and ambitious EU plans to decarbonise electricity grids by 2050, adequate provision of renewable capacity will be required to manage peak loads emerging during summer. The generating potential for different renewable sources varies significantly across the EU-28 region and between different seasons, as shown in Figure 6-9, which compares the monthly generation from main renewable sources (i.e., wind, solar and hydro) for Germany and Italy averaged in 2013-15 (ENTSO-E, 2017). Wind, despite constituting a major source of clean energy for Germany, has maximum generation potential during the winter season. On the other hand, solar energy which presents higher utilisation rates than wind for Italy, has maximum generation potential during summer months, thereby matching the annual profile of AC electricity demand. Finally, hydroelectric power typically peaks during the spring season. Based on these profiles, solar is deemed the most suitable energy source for meeting future potential peak AC demand in the EU-28 region.

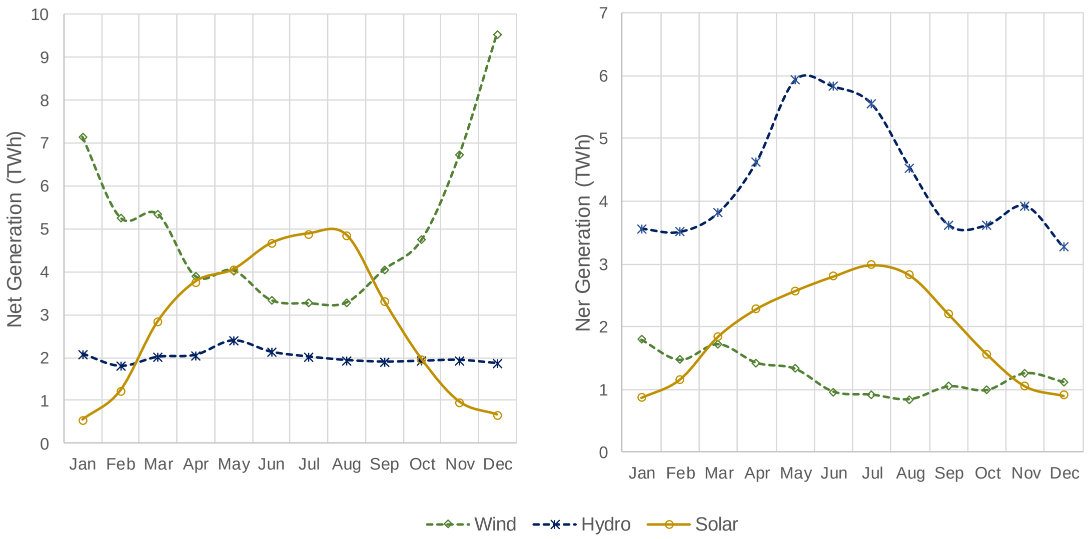


Figure 6-9 Average (2013-15) monthly electricity generation by renewable source in Germany (left) and Italy (right) Source: ENTSO-E (2017).

Figure 6-10 benchmarks the growth of $Peak_{AC}$ under the 3 scenarios against the projected expansion of solar-based generating capacity (European Commission, 2016b), separately for warm and cold EU-28 countries. While solar currently has the same deployment rate in cold and warm EU-28 countries, representing about 10% of total generating capacity, its proportion in the electricity mix increases respectively by a factor of 2 and 3 by 2050 in cold and warm Member States. Furthermore, potential peak residential AC demand across cold countries is shown to outgrow forecasted expansion of solar capacity during most of the

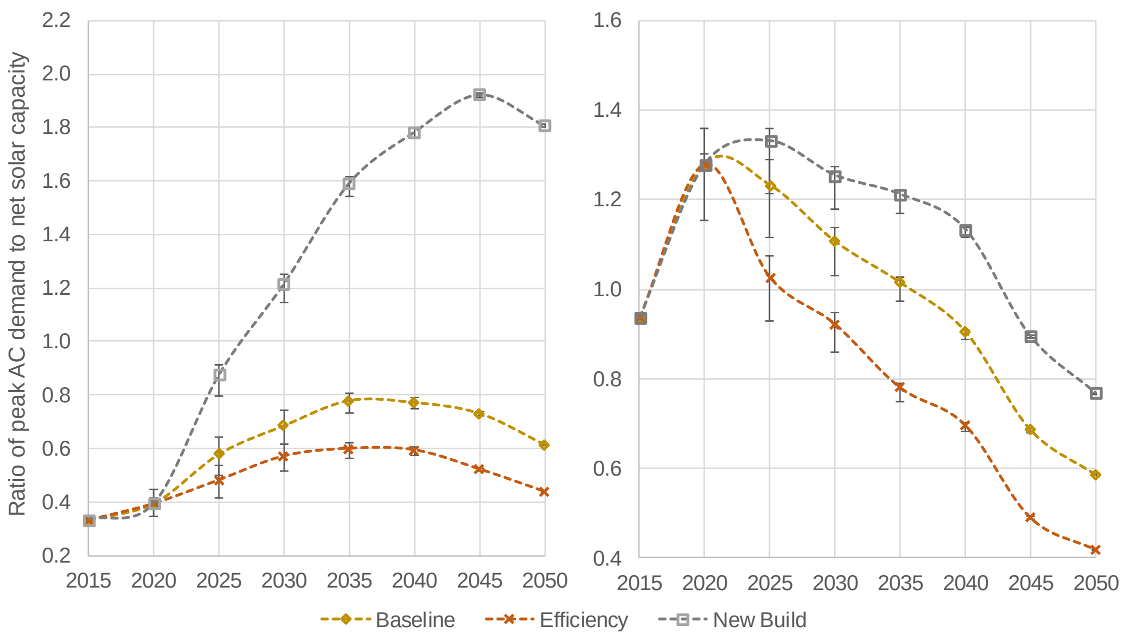


Figure 6-10 Ratio of potential peak cooling electricity demand to solar-based capacity for cold (left) and warm (right) EU-28 countries

projections period. This is especially the case for the “New buildings AC rates” scenario, whereby aggregate $Peak_{AC}$ increases by as much as twice (~1.9) the size of total solar capacity in cold countries, highlighting potential risks of electricity system failure if other sources of generating capacity are not added to meet peaking demand and alternative cooling options are not provided. In contrast to cold Member States, growth in solar capacity in warm countries catches up with that of potential peak cooling demand much earlier in the 2016-50 period, with the latest turning point occurring by 2025 under the extreme AC diffusion scenario.

6.4 Discussion

This section first discusses in qualitative terms the potential implications for historical modelling and future projections of AC electricity use from using an extended version of the AC diffusion model described in 6.2.2.2; one which accommodates regionally-differentiated responses to temperature and income changes. Since the EU-28 region extends over a large geographical area it is characterised by a variety of climate types including temperate with a dry and hot summer (Mediterranean), temperate without a dry season and with warm summer and cold climate without a dry season and with warm summer (Continental) (Peel et al., 2007). Important discrepancies are also observed with regards to the stage of economic development each EU-28 country is currently in, as shown by the significant variation of national personal income in Figure 6-2. It is therefore possible that residents in different parts of Europe may respond differently to changing personal income or summer temperature in adjusting their AC electricity use through the extensive margin (i.e. via AC diffusion); a hypothesis which is tested in section 6.4.1. Following this, section 6.4.2 compares my scenario analysis results regarding the level of residential AC electricity consumption in 2050 with projections from the literature.

6.4.1 Heterogeneous responses of AC diffusion across the EU-28 region

Diffusion of air-conditioners in households was found in section 6.3.1 to be the single most important contributor to the past increases in space cooling electricity consumption for the EU-28 region. In order to better understand the climatic and non-climatic drivers of historical space cooling penetration, the diffusion parameter (*Diff*) was further analysed in section 6.3.2 via the means of panel data modelling. A “s-shaped” logistic growth model incorporating personal income, mean summer temperature and a time trend as explanatory factors, was capable of explaining three quarters of past AC diffusion variation. It is important to remind the reader that parameter estimates, generated via the FE model, represent the average response of AC diffusion across the EU-28 region to a marginal change in any of the independent variables (*INC*, TMP^{JJA} and *trend*).

However, households located in the warm or cold EU-28 region may respond differently to changes in personal income or summer temperature, due to behavioural or cultural exogenous factors not currently captured by the country-specific intercepts, γ_c. A convenient way to investigate the regional heterogeneity of diffusion responses to external stimuli, is to interact the main explanatory parameters (i.e., *INC* and TMP^{JJA}) with a categorical variable separating warm from cold EU-28 counties. (i.e., *DumW*=1 if *c* belongs to the warm region). The results of this exercise are presented for personal income in column (1) and for mean summer temperature in column (2) of Table 6-7.

Table 6-7 AC diffusion model results considering differences in cold and warm countries

Variables	(1)	(2)	(3)	(4)
INC (000$/pop)	-0.105**	-0.086**	-0.029	-0.090*
	(0.043)	(0.033)	(0.027)	(0.047)
TMP_y^{JJA} (°C)	-0.044***	-0.055***	-0.030***	-0.047***
	(0.015)	(0.019)	(0.010)	(0.017)
DumW × INC	0.082#			
	(0.054)			
DumW × TMP_y^{JJA}		0.052*		
		(0.030)		
Trend	-0.133***	-0.138***	-0.121***	-0.145***
	(0.012)	(0.014)	(0.011)	(0.022)
$\overline{\ln(\gamma_c)}$	7.434***	7.372***	3.880***	8.392***
	(1.088)	(1.079)	(0.759)	(1.579)
Observations	448	448	128	320
F-test	129.76***	121.34***	411.41***	102.98***
Hausman test	28.972***	7.930*	0.169	3.999
R^2 (adj.)	0.761	0.752	0.859	0.749

Statistically significant at # at 13%, * at 10%, ** at 5% and *** at 1% confidence level. Note: Standard errors in the parenthesis are clustered by country (a la Arellano covariance matrix).

According to the new estimation results, the interaction term between warm EU-28 countries and *INC* is positive but only statistically significant at 13%, thus not permitting any inference for the existence of between-group differences in the effect of income on AC diffusion. A different classification system of EU-28 countries based on their long-term, per capita, GDP indicator could have produced a more meaningful output. On the other hand, the TMP^{JJA}-*DumW* interaction is statistically significant at 10% and has a positively signed coefficient, implying that the marginal effect of temperature on AC diffusion is respectively equal to –0.055 and -0.003 for cold and warm EU-28 countries. In other words, an increase in mean JJA temperature has a larger influence on AC purchasing decisions across cold EU-28 countries (remember that due to the model's functional form, the more negative a coefficient is, the stronger its effect on diffusion becomes). This outcome suggests that residents in cold EU-28 countries with lower capacity to adapt to hot weather are more inclined to purchase an AC unit during a warm summer season. Furthermore, while annual AC demand requirements under the baseline scenario are projected to be higher for warm EU-28 countries, climate change is expected to encourage more people residing in cold regions to purchase an AC unit. This suggests that there is a higher possibility that air-conditioning is adopted during periods of extreme heat, which may contribute to an increase in peak electricity demand during summer.

The robustness of the previous result is verified by re-running the original AC diffusion model separately for warm and cold EU-28 countries, while retaining the previously-adopted 60% and 30% regional saturation levels (Table 6-7, columns (3) and (4), accordingly). The estimated effect for TMP^{JJA} is highly statistically significant ($p<0.01$) for both EU-28 regions, with the coefficient for cold countries being about 1.5 times as large as that for warm countries. This finding comes in disagreement with De Cian et al. (2019) which studied adaptation mechanisms for a cross-section of European households and found that the response of AC adoption rates to changing *CDD* levels is weaker in colder areas. Nevertheless, it agrees with findings in Li et al. (2018) which showed that Chinese AC penetration rates are more sensitive to outdoor temperature deviations for households located in the northern colder part of the country, compared to those in the southern warmer region. This highlights the need for more assessments about the spatial variation of climatic and non-climatic impacts on residential AC diffusion trajectories in the EU-28 region.

6.4.2 Comparison of future projections with previous studies

Comparison with previous studies is performed in order to detect potential common trends amongst available projections and identify specific modelling assumptions which lead to different AC electricity use estimates in 2050. In general, my findings agree with the general trend found in previous studies, which predict a significant increase of final electricity use for space cooling in the EU's residential sector (Figure 2-1). However, discrepancies arise between projections about the exact level of AC electricity consumption in 2050. My baseline FEU_{AC} estimate for the EU-28 region in 2050 is roughly 2.5 times as large as the IEA's RTS projection for space cooling electricity consumption (21.8 TWh/yr) (IEA, 2017). The latest FEU_{AC} estimate for 2050 for the EU-28 region is found in the JRC POTEnCIA central scenario (42.5 TWh/yr) (JRC, 2019b), which compares well with my strong unit efficiency projection (38.4 TWh/yr). Unlike this study's modelling approach, these assessments did not examine potential implications of climate change on future residential AC electricity use.

More importantly, these studies predict a substantially lower growth rate for future EU-28 space cooling electricity use up to 2050 relative to baseline projections in my study. This is illustrated graphically in the left plot of Figure 6-11, which compares the indexed evolution of future EU-level residential AC electricity use as projected through my study, and via the IEA's and JRC's models. The annual growth rate of space cooling electricity use between 2014 and 2050 is respectively estimated to be 3.6%, 2.8% and 0.5% under my mid-range baseline scenario, the POTEnCIA central and RTS scenario. Detailed statistics obtained from the POTEnCIA database suggest that the lower growth rate of space cooling consumption is to a large degree attributed to modelling assumptions about the slower penetration of air-conditioning in EU-28 households in 2015-50 (right plot of Figure 6-11). Although EU-level AC diffusion under the POTEnCIA central scenario (24.5%) is significantly lower than my baseline estimate in 2050 (37.6%), its predicted trajectory does not show any signs of saturation.

This chapter generally finds important differences from other studies which also accounted for the effects of temperature and income on AC diffusion and useful

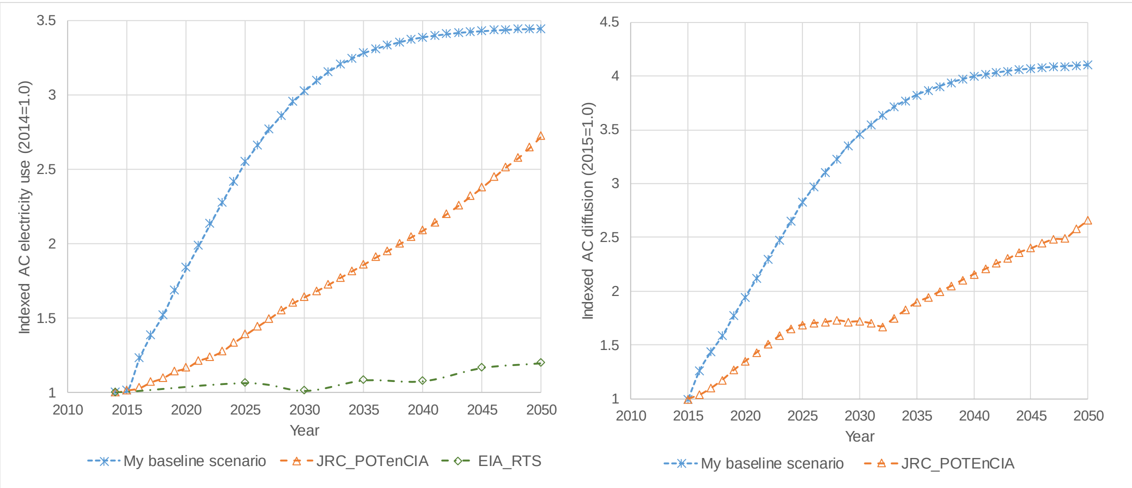


Figure 6-11 Indexed evolution of future residential AC electricity use (left panel) and diffusion (right panel) according to my baseline scenario and other studies

specific cooling demand. The JRC projected EU-28 residential AC electricity consumption to reach 33 TWh/yr by 2050, without the influence of climate change, and to increase up to 78 TWh/yr under an RCP8.5-like set of climate simulations (JRC, 2018a). While the JRC's highest FEU_{AC} estimate lies within the range of values obtained in this chapter (38-104 TWh/yr), they predict a much stronger impact on the growth of AC penetration rates for southern European countries in 2050 than my baseline case. These were shown to exceed the 80% diffusion level by 2050 and continue to ascend thereafter, due to higher assumed saturation rates and the determinant role of climate. On the other hand, mid-21st century's AC ownership rates across northern European countries in (JRC, 2018a) were found to remain well below the 30% saturation point adopted for my analysis.

Dittmann et al. (2017) presented similar trends to JRC (2018) about the spatial heterogeneity of future climatic impacts on the share of residential cooled areas in southern and northern EU-28 countries. For a moderate climate change trajectory (RCP4.5), their EU-level estimate of FEU_{AC} in 2050 amounts to 31 TWh/yr, which is lower than the range of my estimates. Mima and Criqui (2009) and (2015) were the only studies which projected a significantly larger increase of future levels of space cooling electricity consumption. They estimated EU-27 residential final electricity use for space cooling to reach 129-233 TWh/yr (Mima and Criqui, 2015) and 634-754 TWh/yr (Mima and Criqui, 2009) in 2050. Each range represents the difference in predicted AC electricity consumption levels for a constant climate case and a medium-high greenhouse emissions scenario in 2050.

Summarising the above, the full range of my projections for EU-28 residential electricity use in 2050 exceed the majority of those originating from recently published studies. In most cases, this is attributed to my modelling assumptions about the fast diffusion of AC technologies in the EU-28 household sector which already reaches the effective saturation point by the mid-21st century. On the other hand, AC diffusion and electricity use projections from my study are much less sensitive to the future effect of climate change compared to other studies, whose predictions especially for warm EU-28 countries vary greatly according to the followed climatic trajectory. Unlike my modelling approach, revenue does not seem to be an important driver of space cooling diffusion in other studies.

6.5 Conclusions

This chapter has developed and applied new approaches to deciphering drivers of past and future trends of electricity-based final energy use for air-conditioning in the EU's residential sector; an end-use characterised by tremendous growth potential. A novel multi-method modelling framework was constructed, which used index decomposition analysis as a reference point for understanding the drivers of past space cooling electricity consumption (2000-15), then extended this to a set of panel data models estimating climatic and non-climatic effects on AC components. Finally, a combination of the two methods led to the creation of scenarios of residential AC electricity consumption and potential peak cooling electricity demand in EU-28 countries up to 2050. Three key conclusions can be drawn from my analysis.

First, index decomposition analysis showed that penetration of air-conditioning and technical efficiency improvements, to a lesser extent, shaped past trends (2000-15) of space cooling electricity use in EU-28 households. AC diffusion was by far the largest driver in the past, contributing to the annual increase of EU-28 space cooling electricity consumption on average by 1 TWh each year. This increasing effect was only partly counterbalanced by unit efficiency gains over the same time period, causing AC electricity use to still grow on average by 0.6 TWh each year. Econometric analysis also suggested that both the diffusion of air-conditioning in households and useful specific energy demand depend on temperature variation. However, personal income was found to be the most important determinant of past AC diffusion, having a five times larger marginal effect compared to mean summer temperature. Moreover, the sensitivity of AC adoption rates to a unit increase of mean summer temperature was shown to be stronger for cold EU-28 countries.

Second, three potential trajectories of AC diffusion and unit efficiency were devised through scenario analysis, based on which EU-28 aggregate residential space cooling electricity use grows from 16 TWh/yr in 2015 to 38-104 TWh/yr in 2050. This represents an increase in the share of space cooling in EU-level residential final electricity use from 2% in 2015 to 4-12% in 2050. My baseline estimate of household AC electricity consumption in 2050 (54 TWh/yr) is 32 TWh/yr and 11 TWh/yr higher than projections from IEA (IEA, 2017) and JRC (JRC, 2019b), respectively, which do not forecast potential climate change-driven increases of AC usage and more importantly assume slower diffusion rates of AC equipment in households in the future. When compared to other climate change impact assessments, my study generally finds important differences regarding the degree of north-south polarisation of AC up-take in the EU-28 region (Dittmann et al., 2017; JRC, 2018a) and the aggregate level of residential AC electricity consumption in 2050 (Mima and Criqui, 2009; Mima and Criqui, 2015).

Third, my study showed that electricity systems will have to sustain a higher level of potential peak cooling demand in the future (4-fold increase in 2015-50 under my baseline case) if met by mechanical air-conditioners, which could challenge generation and network performance, subject to the size of electrical capacity installed (Connolly, 2017). This could be a particular issue in EU-28 countries whose power infrastructure is currently designed to face the highest loads during the winter season (Wenz et al., 2017); a potential seasonal shift of peak electricity demand to summer months, as a result of increased AC usage, would have implications for improved inter-seasonal storage of renewable electricity, which could be then transmitted across the EU to places with high peak cooling demand. Future work could focus on devising future projections of actual peak cooling demand in EU-28 countries, which are based on functions that explain the number of residential AC units being active in a region based on a set of climatic and non-climatic conditions, similar to Burillo et al. (2017).

The next chapter performs a synthesis of results obtained from Chapter 4, Chapter 5 and Chapter 6 corresponding to the south U.S., contiguous U.S. and EU-28 case study and links them back to the research questions specified in Chapter 1, as well as the research gaps identified the literature review (Chapter 2). It also discusses the implications of these findings and of the modelling frameworks proposed in Chapter 3 for the energy modelling community and the development of future generation energy reduction policies.

Chapter 7

Discussion: advancing knowledge about space cooling demand in the residential sector

7.1 Overview

This PhD thesis focused on past and future trends of residential energy demand attributed to space cooling; the building end-use recording the highest growth rate in the period 1990-2015 across OECD (2.9% per year) and non-OECD (6.8% per year) countries (IEA, 2017). Demand for air-conditioning is also distinguished from that for other residential end-use services by its large growth potential in the future, as a result of many contributing factors such as the warming climate and increasing affluence levels. Mid-range global projections summarised in Figure 1-6, show that residential electricity use for space cooling could grow from 0.9 PWh/yr in 2016 to 3.2-9.4 PWh/yr in 2050, which is equal to a future growth rate of 8-28% per annum. This development has significant implications for the global energy system, primarily in primary energy consumption terms as increasing demand for residential space cooling shifts fuel mix towards electricity (Zhou et al., 2013). Despite the important role of space cooling in driving sectoral demand for electricity that needs to be provided by the power sector, estimates of its size in 2050 display important variability at a global (Figure 1-6) and regional (Figure 2-1 and Table 2-1) level. This stresses the great uncertainty in the modelling process of the future drivers of residential AC electricity use.

Furthermore, this project aimed at improving current methodologies used to model the drivers of residential space cooling demand in seeking to improve future projections of AC-driven residential electricity use up to 2050. The evolution of space cooling electricity use to 2050 was compared for two regions which are currently at a different stage concerning the evolution of the residential AC market. Chapter 4 and Chapter 5 focused respectively on different parts of the contiguous U.S. region, in which penetration of AC systems has almost reached an effective saturation point (~90%). Space cooling is already an important residential end-use with a contribution to total and peak U.S. electricity demand set to increase in the future. On the other hand, Chapter 6 revolves around AC electricity demand in the residential sector of the EU-28 region, where the current adoption rate for space cooling is much lower at 10% and its contribution to sectoral electricity consumption levels is minimal. Nevertheless, the size of EU-28 space cooling electricity use was shown to increase rapidly in the future as a result of growing AC adoption. Due to the uncertainty in EU-28 future AC saturation rates coupled to the near saturation of the U.S. market, projections of space cooling electricity use for the 2050 horizon show much more variability for the EU-28 (Figure 2-1) than for the U.S. region (Table 2-1).

From the literature review, methodology and analysis chapters (2-6) there are four cross-analysis / chapter aspects worth further discussion. First, section 7.2 considers the scale of projected impacts on final electricity use and generation requirements from growing space cooling demand in the saturated U.S. and un-saturated EU-28 AC market. Second, section 7.3 discusses the methodological implications from tailoring general modelling frameworks to study past and future space cooling demand in a nearly-saturated and a small, but quickly-growing, AC market. Third, section 7.4 provides recommendations with respect to potential improvements in the way space cooling demand is currently represented in large-scale whole energy system models. Section 7.5 discusses the ways through which policies can be effective in limiting increasing demand for space cooling, while differentiating between regulatory measures which are more suitable for a saturated and non-saturated residential AC market. Finally, section 7.6 summarises the main findings of the Discussion chapter.

7.2 How large are the projected impacts on electricity generation systems?

7.2.1 Saturated AC market

In the case of the nearly-saturated U.S. AC market (Chapter 4 and Chapter 5), important impacts on annual and seasonal residential electricity use are projected in the mid-21st century both at the regional and national level. The climate-sensitive component of residential electricity use is indirectly measured via monthly degree days (and other climate metrics), whose relative change in the future multiplied by the corresponding historical sensitivity parameter determines the impact of climate change on residential electricity use. Due to modelling limitations pertaining to the large-scale collection of future specific humidity data, climatic impacts on future residential electricity use are simulated only via changing *CDD* levels. Projections of residential electricity use also incorporate non-climatic impacts, including the effect of growing personal income and electricity prices. In per capita terms, warming temperatures (approximated via the *CDD* effect) has the second largest contribution to the projected increase of U.S.-wide annual residential electricity use in 2050, lagging only behind that of personal income. Under the 18 possible scenarios, annual per capita residential electricity use in the contiguous U.S. region grows by 6-12% between the 2000-18 to the 2046-55 period. Growing space cooling requirements as a result of climate change will lead to more importance increases of per capita electricity use levels in 2046-50 (relative to 2000-18) during the summer which range from 10% to 22%.

Under the full set of projections (which incorporate population expansion), annual U.S.-wide residential electricity use in 2046-55 was shown to increase by 10.3-17.3% relative to 2018's levels. In absolute terms, this represents an increase from 1.46 PWh/yr in 2018, which is equal to 38% of total U.S. electricity use[15] (U.S. EIA, 2020b), to 1.61-1.72 PWh/yr in 2050, which forms 29-37% of total electricity use based on the EIA's NEMS reference scenario (U.S. EIA, 2019a). Projections undertaken with EIA's NEMS predict that residential electricity use will reach 1.64 PWh/yr in 2050, which overlaps with my estimates, while the IEA's RTS forecast is slightly lower at 1.59 PWh/yr. The lower overall contribution of residential buildings to future U.S. electricity use levels is attributed to growing electricity demand in the transportation sector. Still, the residential sector remains the largest electricity consumer, contributing to 18-30% of the increase in total U.S. electricity use in 2050.

On a seasonal basis, the difference between future (2046-55) and present (2018) residential electricity use levels is higher at 16-29% during the summer period as a result of the disproportionate increase in residential AC demand. Intensified demand for space cooling increases the "peakiness" of monthly residential electricity demand in summer which has important implications for long-term electricity systems planning, as adequate reserve capacity would need to be installed to meet future AC-driven peak demand. Applying the same set of calculations as in section 4.4.2, monthly electricity use estimates are converted into average instantaneous load projections in the summer period. Instantaneous electricity demand during the summer season is set to increase from 197 GW in 2018, which is equal to 18.0% of net summer U.S. electricity generating capacity (U.S. EIA, 2019b), to 229-254 GW in 2050, which equates to 15.2-16.8% of projected net summer generating capacity (U.S. EIA, 2019a).

Furthermore, growing summertime residential electricity use contributes to 8-14% of the increase in U.S. generating capacity in 2050. According to the EIA's NEMS reference projections, 30% of the U.S. electricity generating capacity in 2050 consists of renewable sources (447 GW), of which about half (216 GW) will be made of solar PV plants (U.S. EIA, 2019a). As a result, growing residential demand for space cooling as a result of warmer summer seasons will put strain on solar-based renewable resources. Any space cooling demand not met by renewables will be supplied through natural gas combined-cycle power plants and combustion-turbine diesel plants which respectively shape 33% and 12% of

[15] This figure includes electricity sold to all sectors, minus the amount of self-generated electricity consumed by commercial and industrial facilities.

total U.S. generating capacity in 2050. Another effect of growing summertime electricity use will therefore be an increase in GHG emissions, which will depend on the mismatch between space cooling demand variation and solar PV output.

Impacts of rising residential electricity use levels on future electricity systems also vary between different U.S. regions. While projections of future electricity use are not available at the climatic region level, these impacts are compared for the South and (Mid-west + Northeast) census region which resemble the previous division made between cold-warm U.S. states. Annual residential electricity use in the South census region (16 states) increases from 0.62 PWh/yr in 2018, which is equal to 35% of regional electricity use, to 0.66-0.75 PWh/yr in 2050, which is equivalent to 29-33% of regional electricity use based on the EIA's NEMS reference scenario (U.S. EIA, 2019a). Annual residential electricity use in the Mid-west and Northeast census regions (21 states) grows from 0.46 PWh/yr in 2018, which equals to 34% of total regional electricity use, to 0.60-0.70 PWh/yr in 2050, which represents 39-45% of future regional aggregate electricity use.

According to my seasonal projections, instantaneous summertime electricity load across the South census region increases from 86 GW (8% of net summer electricity generating capacity in the USA) in 2018 to 101-113 GW (7-8% of net summer generating capacity in the USA) in 2050. Instantaneous electricity demand across the Northeast/Mid-west census region increases from 60 GW (5% of net summer electricity generating capacity in the United States) in 2018 to 79-97 GW (5-6% of net summer generating capacity in the United States) in 2050. So, while in absolute terms the South census region has a higher level of annual and seasonal residential electricity use in the future, Southeast and Mid-west regions have a greater impact on future total electricity use and potential peak electricity demand. This can be explained through the higher saturation level of personal income effects in northern U.S. states compared to southern ones. The spatial and seasonal heterogeneity of climatic and non-climatic impacts has therefore consequences on electricity infrastructure planning (including generation, transmission and distribution networks).

7.2.2 Non-saturated AC market

In the case of the growing EU-28 AC market (Chapter 6), modelled demand for space cooling electricity use was projected to increase from 15.8 TWh/yr, which is equal to 2% and 1% of residential and total final electricity use in the EU-28 region, to reach 38.4-104.1 TWh/yr in 2050. This range is higher than the majority of projections reviewed in section 6.4.2. While the change from 2015 to mid-21st century consumption levels is substantial in relative terms, space cooling electricity use in 2050 still represents respectively a modest 5-13% and 1-3%

share of EU-28 residential and total final electricity use as predicted by JRC (2019b) for the POTEnCIA central scenario. In other words, space cooling contributes to a 3-12% increase of total final electricity use in the EU-28 region. Despite space cooling increasing its share in final electricity consumption as a result of the more widespread adoption of AC equipment, it does not become the most important electrical residential end-use by 2050. According to JRC (2019b), appliances and lighting will shape about half of final EU-28 residential electricity use in 2050, followed by space heating with a contribution at 20%. It is important to note that impacts relating to increased unit AC demand, for example as a result of warmer weather or a larger floor area, were not considered here due to the very small effect of that component on historical space cooling electricity use.

Chapter 6 also demonstrates that the EU-28 power sector will have to sustain a higher level of summertime maximum peak cooling electricity demand in the future: this increases from 43 GW in 2015 (this represents 4% of net electricity generating capacity in the EU-28 region based on JRC (2019b)) to 127-402 GW in 2050 (this forms 9-27% of net generating capacity in the EU-28 region). That is to say that growing diffusion of air-conditioners will contribute to a 17% of the increase in net generating capacity by 2050 for the baseline case, an impact which is substantially higher under the extreme diffusion scenario (~70%). According to the POTEnCIA central case, about 70% of the EU-28 electricity generating capacity in 2050 consists of renewable sources (1051 GW), of which 40% (403 GW) will be made of solar PV plants. The significant growth in space cooling electricity use in the EU-28 region will therefore place strain on solar-based renewable energy sources.

It is worth to mention that impacts on future final electricity use levels can vary considerably between the warm and cold group of EU-28 countries. Residential electricity use in warm EU-28 countries can increase from 12.4 TWh/yr in 2015 (2% of total final electricity use in warm countries), to 23.2-41.6 TWh/yr in 2050 (3-5% of total final electricity use in warm countries). On the other hand, household AC electricity use for cold EU-28 countries is projected to grow from 3.5 TWh/yr in 2015 (0.2% of total final electricity use in cold countries) to 15.1-62.6 TWh/yr in 2050 (1-2% of total final electricity use in cold countries). The larger positive impact on final electricity use in 2050 for warm EU-28 countries (8-20% vs. 2-10% for cold EU-28 countries) is justified by the higher assumed saturation rate of AC equipment for warm EU-28 countries under the baseline scenario. In the “New buildings AC rates” case, the between-group difference in final electricity use impacts becomes smaller, as the rapidly-growing penetration rates in new and renovated buildings accelerate the growth of space cooling electricity use for cold countries.

Potential peak cooling demand across warm EU-28 countries increases from 27 GW in 2015 (9% of net electricity generation capacity in warm countries) to 53-97 GW in 2050 (15-28% of net generation capacity in warm countries). On the other hand, the same quantity across the cold group of EU-28 countries increases from 17 GW in 2015 (2% of net generation capacity in cold countries) to 74-305 GW in 2050 (7-27% of net generation capacity in cold countries). That is to say that growing residential AC demand contributes to a 37-100% increase of future net electricity generation capacity in warm countries, while the impact is lower at 13-66% for cold EU-28 countries.

Moreover, potential peak cooling electricity demand was shown in Figure 6-10 to outgrow the predicted increase of solar-based capacity in cold EU-28 countries, whose energy system is designed to sustain the highest heating electricity loads during winter months. These are some indications that greater AC adoption could potentially challenge generation and network performance, if there is not adequate available capacity during the summer period. This has also implications for improved inter-seasonal storage of renewable electricity, which could be then transmitted across the EU to regions with high peak cooling demand. However, evidence from Denholm and Mai (2019) suggests that there is little capacity and energy value from employing seasonal storage at high (55%) penetration rates of variable renewable electricity generation.

Results concerning the impacts on total final electricity use and net generation capacity from growing residential electricity use in the saturated U.S. market (section 7.2.1) and space cooling demand in the un-saturated EU-28 AC market (section 7.2.2) are summarised in Table 7-1. In the saturated (U.S.-wide) AC market, increasing residential electricity use has a larger effect on total final electricity use than on net generating capacity requirements in 2050, while this pattern is reversed in the un-saturated (EU-wide) market. When impacts for the saturated AC market are disaggregated at the regional level, future changes in residential electricity use across north U.S. states have a greater impact on the electricity system given the larger influence of personal income growth compared to south states. When impacts for the un-saturated AC market are disaggregated at the regional level, future increases in space cooling electricity use have a larger impact on the electricity system across warm EU-28 countries instead.

It should be noted that a direct comparison of the size of capacity-related impacts between the saturated and non-saturated case cannot be performed given the key differences in the definition of peak AC electric demand. In the saturated case total electricity demand is distributed equally among the hours in a month which may *underestimate* the resulting impact on peak generating capacity. In the un-saturated case, estimates of peak electricity demand are based on the maximum

Table 7-1 Summary of impacts on the electricity system for the saturated and non-saturated AC market in 2050

	Impacts in 2050	
Type of AC market	Final electricity use	Net generating capacity
Saturated (U.S.)		
U.S.-wide	18-30%	8-14%
Southeast	7-26%	4-7% (8-15%)[a]
Northeast/ Mid-west	78-139%	5-9% (13-26%)[a]
Un-saturated (EU-28)		
EU-wide	3-12%	17-71%
Warm	8-20%	37-100%
Cold	2-10%	13-66%

[a] The first range of percentages without the parenthesis represents impacts on national net electricity generating capacity. Alternatively, the range in the parenthesis shows the impact on the region's total generating capacity when assuming that its future share in U.S.-wide generating capacity is the same as in 2018.

number of AC units which can operate simultaneously at a given time which may *overestimate* the resulting impact on peak generating capacity.

A higher demand for electricity supply in the residential sector will need to be satisfied through additional investments in generating capacity, placed in areas with high cooling demand density. The resulting economic impact will not only involve generation and capacity costs, but also costs attributed to the transmission, distribution and storage of energy (Auffhammer et al., 2017). For example, Wenz et al. (2017) provide an estimate about the discounted capacity cost associated with the operation of a single additional AC unit at 1 kW in the United States, which amounts to 455$ per kW. Based on this figure, one could obtain an estimate of the economic cost incurring from future capacity upgrades driven by growing space cooling demand. This is not plausible for the U.S. case study where residential electricity use is modelled on a monthly basis and the exact future number of AC units is unknown.

The 134 GW extra capacity required at the EU-level due to the increase in the number of air-conditioners corresponds to a cumulative cost of 61.2 billion dollars in the 2016-50 period, which if converted to Euros (exchange currency rate at 0.9 in 2016 (ESTAT, 2016)) amounts to 55.1 billion €. This represents a 0.4% of GDP in 2015 for the EU-28 region (at 2016 values). Under the "Unit efficiency improvement" scenario, the economic impact from expanding AC-based capacity in the period 2016-50 is lower at 34.3 billion € (representing 0.2% of GDP in 2015). On the hand, the corresponding cost for the "New buildings AC rates" case is notably higher at 146.8 billion €, which is equal to 1% of the region's GDP in 2015. It is therefore evident that these capacity expansion costs will not be negligible, especially under the fast diffusion case.

7.3 Tailoring modelling frameworks to the state of AC diffusion

In the previous section two very different states of space cooling diffusion were analysed. In the case of U.S., the residential market for space cooling is moving towards saturation (~90% in 2015), whereas in the EU-28 region very low levels of diffusion were present which did not exceed 10% in 2015. In the saturated case personal income and *CDDs* were shown in Chapter 5 to be the most important drivers of future residential electricity use, respectively on an annual and seasonal scale. In the un-saturated case in Chapter 6, AC diffusion and unit efficiency improvements to a lesser degree were the most significant modelling features of residential AC electricity use. These modelling features are also summarised in Table 7-2. Therefore, the second key aspect to discuss is how to adapt general modelling frameworks to the state of diffusion.

Table 7-2 The most important AC modelling features for a saturated and un-saturated market

Type of AC market	Modelling feature					
Saturated (U.S.-like)	Personal income	Electricity prices	CDD	HDD	Extreme weather metrics	Humidity
	✓		✓			
Un-saturated (EU-like)	Diffusion	Efficiency	Specific electricity use	Housing stock		
	✓	✓				

In a nearly-saturated AC market, most of the variability in projections of future residential space cooling electricity use is caused by changing end-use demand patterns in households which are already equipped with an air-conditioner (Huang and Gurney, 2016a), namely the intensive margin. Aside from climatic impacts, projections of residential electricity use are clouded by the uncertainty in future population, GDP and technological trends (Zhou et al., 2014). These assumptions justified the decision of not incorporating an explicit control of AC ownership rates in the econometric model of residential electricity use for the U.S. case study. Nevertheless, any small effect that increased penetration of space cooling had on historical residential electricity use levels was to some extent controlled by the personal income and the various climatic metrics (based on U.S. EIA (2001) the fraction of U.S. households with some form of air-conditioning in 2001 was 10% lower than in 2015). Alternative metrics of climate-sensitive energy use (i.e. degree days with optimised temperature set points, heat and cold wave days, and air humidity metrics) were subsequently applied to improve the overall performance of traditional degree day-based metrics.

On the other hand, in regions where there is no widespread AC adoption, as it was the case with the EU-28 residential sector, variability in projections of future residential AC electricity use is mainly caused by the uncertainty in AC diffusion trajectories (i.e., the extensive margin). Using a traditional econometric-type approach to explain past and future trends of space cooling electricity use, similar to that adopted in Chapter 4 and Chapter 5 and previous studies like Eskeland and Mideksa (2010) and Damm et al. (2017), generally falls short of fully encompassing the anticipated impacts from growing AC diffusion. These assessments project future electricity use based on the constant response coefficient of historical electricity use to outdoor temperature variation, without controlling for the progressive shifts in capital stock levels of HVAC equipment in households, which in turn amplify overall electricity demand (Davis and Gertler, 2015). Alternatively, the multi-method approach which was developed for Chapter 6, combining econometric and technological-based methods, was adapted to the emerging residential space cooling market in the EU-28 region.

This multi-method modelling framework was effective in isolating the component of AC electricity use relating to extensive margin adjustments, via decomposition analysis (section 6.3.1), and in explicitly modelling the drivers of AC diffusion via FE panel data estimation (section 6.3.2). Breaking down space cooling electricity use variation to the effect of different components is also a standard practice in bottom-up assessments (see for example Levesque et al. (2018) and Clarke et al. (2018)). However, the specific drivers of these components, are subsequently modelled based on (a) a limited number of data points (a caveat expressed by Mima and Criqui (2015) and JRC (2018)) and (b) usually assuming that the path to demand saturation is identical for all countries (see for example the assumptions about a universal AC affordability curve in Isaac and van Vuuren (2009)). My study addresses both of these drawbacks by employing an extensive dataset with 16 years of data and using econometric techniques which account for unobserved between-country differences. The developed framework also offers a flexible way of assessing potential energy savings from improvements in the efficiency of RAC systems (a feature which is omitted from typical top-down approaches). Since AC diffusion is probably the largest (IEA, 2018) and most uncertain parameter (Santamouris, 2016) in global projections of future space cooling demand, the framework designed for the un-saturated EU-28 market can also be applied in other regions with large AC diffusion growth potential, like China and India.

7.4 AC modelling aspects to include in whole energy system models

Section 7.3 has explained the main differences between modelling frameworks designed to analyse residential AC demand trends in the two case studies of my research. This section extends the previous discussion by proposing ways through which the most important modelling features of residential AC demand, as summarised for a saturated and a non-saturated market in Table 7-2, can be more effectively integrated into whole energy system models, such as IAMs. These recommendations are also aligned with the limitations of large-scale bottom-up models, as those identified in section 2.2.3.

7.4.1 Saturated AC market

Results from Chapter 5 demonstrated that for a saturated AC market personal income is the key driver as it contributed to an 8-9% increase in annual per capita electricity use in 2046-55 (relative to 2000-18), while the impact of *CDDs* was lower at 3-6%. While personal income is the key driver, its marginal impact on residential electricity use becomes progressively smaller in the future at higher income levels as demand for electricity becomes partly satiated. In that regard, the two streams of bottom-up assessments identified in section 2.2.2 are both correct in the general use of a logarithmic function to model the dependence of country-level space cooling demand respectively on personal/household income (McNeil and Letschert, 2008; Isaac and van Vuuren, 2009) and on the affordability level (i.e., personal income divided over the price of delivering the space cooling service as in Eom et al. (2012) and Clarke et al. (2018)).

However, evidence concerning the first stream of bottom-up assessments points to the direction that a universal logarithmic personal income function fits better AC demand data obtained for un-saturated AC markets and is much less accurate for saturated markets. Figure 7-1 (obtained from Levesque et al. (2018)) presents the function calibrated to model the dependency of historical building space cooling demand for different countries and regions (CDD and U-value adjusted) on personal income. While this function works well for countries with low income, the quality of fit is low for countries at the high-end of personal income distribution, like the United States and Japan, which also happen to have nearly-saturated AC markets. While it was not possible to find any other papers presenting results for the model calibration process, my first recommendation is that more regionally-disaggregated approaches are employed to better model the relationship between of space cooling demand and personal income variation for saturated and non-saturated AC markets. Nevertheless, it is important to note that the use of a consistent time series of space cooling demand data in Levesque et al. (2018) provides a major advancement from previous bottom-up studies in the same category which calibrate these logarithmic income functions based on single year's cross-sectional statistics.

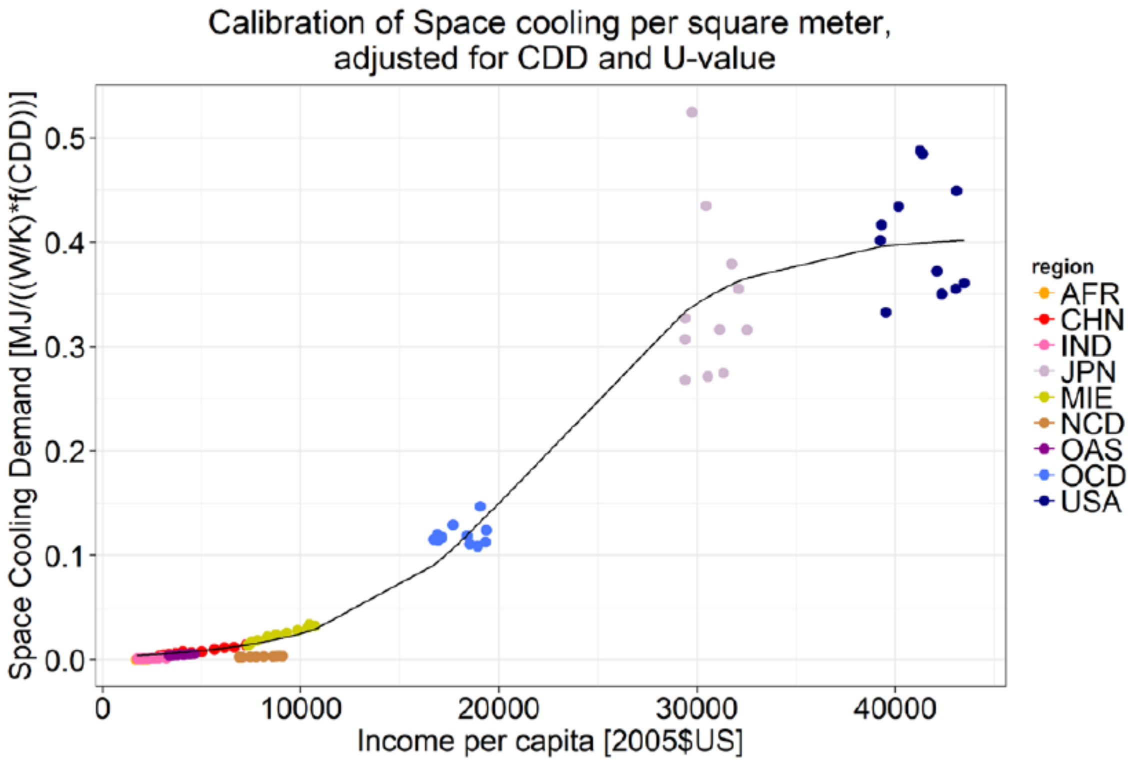


Figure 7-1 Modelling dependency of building space cooling demand on personal income in bottom-up models. Source: Levesque et al. (2018)

Furthermore, econometric estimation results from Chapter 5 (Table 4-6 and Table B-2) showed that the rate by which personal income impacts on residential electricity use become saturated varies considerably across the contiguous U.S. region, which could also explain the important dispersion of U.S. data in Figure 7-1. In general, warm states in the south U.S. climatic region have a lower demand saturation level (at US$ (constant 2018) 51,000) than cold states in the north U.S. climatic region (at US$ (constant 2018) 92, 000). This can be attributed to within-country differences in the diffusion of space cooling equipment (but also electric heating), as warm states in the South are moving much closer to achieving 100% AC saturation. My second recommendation would be that for geographically-large and climatically-diverse nearly-saturated AC markets, such as the U.S. one, dependency of space cooling (but also heating) demand on personal income variation is modelled at the regional, rather than the national level. In that regard, model calibration results from the state-level bottom-up model of space cooling and heating demand in Zhou et al. (2014) for the U.S. region could be integrated into large-scale IAMs.

According to estimation results in Table 5-4, residential electricity use in the contiguous U.S. regions is also affected by changing electricity prices. However, the function developed in Figure 7-1 to depict the relationship between space cooling demand (CDD and U-value adjusted) and personal income does not take into account between-country differences in electricity prices. For example, 2018's residential electricity prices in Japan were twice as large as corresponding prices in the United States (IEA, 2020). Electricity price is part of the energy-related cost of delivering space cooling in buildings and could have an effect, together with non-energy related (capital) costs, on the amount of electricity consumed each year for AC purposes. Moreover, my third recommendation for modelling space cooling demand for saturated AC markets is accounting for regional differences in the price of electricity. In that regard, the second stream of identified bottom-up methodologies in section 2.2.2 adds extra value in assessments of space cooling demand by adopting a composite affordability metric, based on the ratio of personal income and the price of AC services. However, more empirical evidence is needed to assess the explanatory power of an affordability metric in in models of space cooling demand compared to that of the single income parameter.

Another potential reason for the dispersion of U.S. data in Figure 7-1 could be due to the inadequate description of climatic effects via the *CDD* metric. Degree days have long been the established climatic metric for relating weather, and more specifically outdoor temperature variation, with climate-sensitive energy demand in buildings. This is especially the case with bottom-up, service-oriented, IAMs (Zhou et al., 2014; Labriet et al., 2015; Clarke et al., 2018), where degree days are employed as a metric for capturing the future impacts of climate change on building heating and cooling energy use. Chapter 2 on literature review attempted to challenge the view that temperature-based (dry-bulb) degree days, built according to a universal 18.3 ℃ set point applied to both heating and cooling energy demand elements, are a comprehensive measure of climate-sensitive energy use. This was performed by presenting a number of modelling features which are omitted from current climatic metrics and could improve future projections of residential electricity use in saturated AC markets.

Reviewed climatic metrics comprised degree day metrics with empirically-derived set-point temperatures, *HWD* and *CWD* metrics and a specific humidity variable. Section 5.4.1 facilitated a broad discussion about the statistical benefits arising from modelling south, north and contiguous U.S. residential electricity use via the constructed alternative metrics in terms of the model's (a) ability to fit historical data, and (b) its seasonal and annual forecasting accuracy. In general, findings for the south and north U.S. climatic region, suggest that there is indeed a value in introducing the new climate metrics in econometric models of electricity use, still the positive impact is *moderate* under both categories. From an estimation accuracy perspective, modelling south and north U.S. residential electricity use (2000-15) using the full set of alternative climate metrics increased the fraction of explained data variation by 2% and 5%, respectively, relative to the reference model which employs NOAA's external degree days. From a forecasting ability perspective, the fully-fledge residential electricity use model for the south and north U.S. climatic region decreased the annual forecasting error by 1% relative to the reference model in the 2016-18 forecasting period.

Amongst reviewed metrics, fine-tuning the set point temperature in degree day calculations and controlling for specific humidity had the largest effect on model performance for the south U.S. region. In line with expectations, the sensitivity analysis showed that residential consumers in the south U.S. states switch on their HVAC systems at higher outdoor temperatures than the customary 18.3 ℃ level, as they are more accustomed to warmer regional weather conditions. In the case of the north U.S. region, only the addition of specific humidity improved the performance of the historical residential electricity use model. The extreme heat and cold metrics had a minor influence on the estimation and prediction accuracy estimators of the two regional models; still their explanatory power can become greater in the future as extreme temperature events become more frequent and intense. Also, the impact of *HWDs* on residential electricity use depends strongly on the level of JJA specific humidity, which is also set to increase in the future.

Overall, the above results from Chapter 4 and Chapter 5 suggest that the proposed climate metrics can indeed help improve knowledge about the statistical relationship between residential electricity use and weather, ideally for regions with more homogeneous climatic characteristics. Similar to the south U.S. region, metrics of temperature extremity combined with air humidity controls could be applied in electricity demand modelling for other warm and humid areas, such as the Saudi Arabia (Howarth et al., 2020) and United Arab Emirates (Radhi, 2009), where air-conditioning is used throughout the year contributing to more than 50% of annual residential electricity use (Lapillonne, 2019). In the same fashion, addition of a specific humidity variable can explain the variation in residential electricity use that is attributed to the extensive use of dehumidifiers, in places like the north U.S. climatic region. Aside from improving overall model fitting, introduction of the reviewed metrics can theoretically help reduce omitted variable bias in identifying the statistical effect of weather variables on residential electricity consumption (Barreca et al., 2016), which in turn improves future projections of residential electricity use. These projections can then be used by utility planners to ensure that adequate generating capacity is put in place to meet seasonal electricity loads under different climate change outcomes.

The question then arises: Is the presented empirical evidence robust enough to suggest that the reviewed climatic metrics are also included in large-scale IAMs to improve representation of space cooling demand/heating in saturated AC markets? Chapter 5 on residential electricity use trends across the contiguous U.S. region demonstrated that the improvement in historical model fitting following inclusion of the additional modelling features is less significant at the national level. This could be attributed to heterogeneous responses of space cooling and heating electricity demand to air temperature and humidity variation in different climatic regions, which cannot be adequately described through a single model coefficient in the national model. Bottom-up IAMs with global coverage typically aggregate their output for a number of countries which may combine different types of climate. The important spatial variability of climatic impacts makes it therefore difficult to generalise conclusions about the practical usefulness of using these alternative metrics as extra parameters in national-level residential space cooling demand/heating functions in IAMs.

Nevertheless, the evidence presented in the previous paragraphs suggests that similar to personal income, climate dependency of residential space cooling demand in large saturated AC markets needs to be modelled at finer spatial scales. In the case of the U.S. market, this would imply that annual demand for space cooling is not represented by a single data point, as in Figure 7-1, but rather as a collection of data points describing demand for different states with similar climate characteristics. Degree day metrics can then be designed in such way that they reflect regional differences in the response of residential space cooling demand/heating to weather variation. Calculating regional *CDDs* and *HDDs* against empirically-determined cut-off temperatures (4th recommendation), which is the approach followed in Chapter 4 and Chapter 5, is a first step for moving away from the single 18.3 ℃ baseline temperature model adopted by the majority of large-scale bottom up models. As explained in Chapter 2 (section

2.3.2), degree day set points can vary between regions based on climatic, building-stock, socio-economic and cultural characteristics. Building space cooling demand functions in bottom-up IAMs could also allow for the potential adaptation of occupants to increased heat through acclimatisation by progressively raising the base temperature in *CDD* calculations in the long-run (Azevedo et al., 2015).To my knowledge only Levesque et al. (2018) is an example of bottom-up model which uses an evolving set-point for *CDD* calculations, still that is not deduced from empirical research.

Another category of climatic impacts which needs to be addressed in IAMs relates to the adoption and use of dehumidifiers. Air humidity was shown to directly increase the amount of electricity consumed in north U.S. states where there is a more widespread adoption of dehumidifiers. A metric of air humidity needs to be therefore integrated into bottom-up IAMs to account for potential latent cooling loads (5th recommendation). To my knowledge, only the IEA's ETP model has a description of space cooling demand including for dehumidifiers (IEA, 2018), however there is no information as to how humidity variation directly affects demand for dehumidifying purposes.

7.4.2 Non-saturated AC market

This thesis developed an alternative approach towards modelling the adoption of mechanical air-conditioning in EU-28 households, which was shown to have the strongest effect on space cooling electricity use (having a partial effect of +1 TWh on space cooling consumption per year during the period 2000-15, when total AC electricity use increased by 0.6 TWh per annum). Combining information from both the cross-sectional and temporal dimension of data helped identify the climatic and non-climatic drivers of AC diffusion. In line with the original hypothesis, both personal income and mean JJA temperature were found to have a statistically significant impact on past residential AC diffusion, with the former variable being its key driver.

More importantly, Chapter 6 highlighted the implications for projections of future AC diffusion and electricity use for a non-saturated AC market from not adopting the “Climate Maximum” approach (section 3.6) to determine future saturation rates of space cooling equipment. As discussed in section 2.2.3, the crude assumption that current diffusion rates in the United States can be used as a proxy for future saturation in non-saturated markets has significant implications for projections of AC electricity use performed via bottom-up models (limitation no. 2). Instead of deriving EU-28 saturation levels using current penetration rates in the U.S. as an analogue for the potential growth of space cooling sectors with similar climatic type, these were determined via empirical analysis. This involved fitting AC diffusion curves to historical stock data (2000-15) applying alternative assumptions about the future level of saturation in the warm and cold group of EU-28 countries. Optimal model fit was achieved when saturation was set at 60% for warm and 30% for cold EU-28 countries. This had 2 important implications for the projections of AC diffusion and electricity use in the EU-28 region:

(a) These empirically-derived regional saturation points for warm and cold EU-28 countries were substantially different from those derived via the climate maximum approach in Jakubcionis and Carlsson (2017). My study found that based on historical data the effective saturation rate for space cooling is at 38% in the EU-28 region, while Jakubcionis and Carlsson (2017) calculated that to be at 50%. Deviations were much larger for countries at the high and low-end of the distribution of long-term *CDD* values with the “Climate Maximum” approach respectively overestimating and underestimating potential saturation rates for the hottest and coldest EU-28 countries, respectively, when compared to my values. For example, they estimated the potential saturation point for Cyprus and Malta to be at 97%, which is different from the 60% saturation rate adopted in my study, and much higher than the current 27% and 24% AC diffusion rate in these countries (Figure 6-2). On the other hand, they estimated the saturation level for space cooling in the United Kingdom and Sweden to be respectively at 17% and 12%, which is much lower than the adopted 30% saturation rate in my study. The current AC diffusion rate in the residential sector of Sweden is at 10% and shows an ascending trend, meaning that the saturation level adopted through the climate maximum approach will be soon surpassed.

(b) Residential AC diffusion in the EU-28 region as econometrically estimated in Chapter 6 shows strong dependency on the year-to-year variation of personal income, and less on temperature variation. Assessments with bottom-up orientation such as JRC (2018), portray dependency of AC diffusion on personal/ household income based on a universal availability curve. Due to its logarithmic shape, diffusion grows rapidly with personal income in low-income countries, with that growth subsequently slowing down at higher income levels. Household “revenue effects” are less important for high-income EU-28 countries and warming temperatures become instead the key driver of space cooling diffusion for these economies. This can also explain why diffusion grows faster in southern EU-28 countries than northern ones in JRC (2018). However, econometric results in Table 6-7 from my study showed that historical AC diffusion in cold EU-28 countries responds more strongly to annual changes in personal income and JJA temperature relative to warm ones.

As a result of point (a) and (b), bottom-up assessments predict a much stronger impact on future space cooling electricity use for the southern EU-28 countries, with much of the variability in projections caused by climate model uncertainty (Mima and Criqui, 2015). On the other hand, these impacts are much less pronounced for north EU-28 countries. Moreover, as future diffusion rates of residential space cooling in bottom-up assessments are driven by the *CDD* function (i.e., the Climate Maximum function), their growth does not show any signs of stagnation before 2050. This comes in sharp contrast with findings from Chapter 6 which predicts space cooling adoption rates to saturate by 2050 in both warm and cold EU-28 countries. While AC diffusion (and electricity use) as modelled in Chapter 6 reaches a satiation point at a relatively early time point in the future, it increases at a much faster rate in the interim compared to other projections (Figure 6-11).

In light of the methodological and practical differences, my recommendations for enabling better modelling of space cooling demand in un-saturated AC markets via whole energy systems are as follows:

(a) **1st recommendation - Improving AC saturation functions:** Instead of imposing the crude assumption that future AC saturation rates will reach current diffusion rates observed in U.S. regions with similar climate, this parameter can be calibrated based on historical diffusion data collected for different countries/ regions. Similar to the analysis performed in Chapter 6, countries can be first split into different groups according to their climate type (e.g. cold, mild and hot ones as in de Cian et al. (2013)) and different group diffusion curves can be fitted to historical data, assuming a different effective saturation rate each time. The saturation value which produces the best model fit for each group of countries can be finally adopted. The sensitivity of this result can be tested for excluding and including data points obtained for the U.S. region as a way to understand the impact of a potential behavioural shift from a moderate to an intensive U.S.-like cooling lifestyle in households.

(b) **2nd recommendation - Improving the depiction of personal income effects**: After each climate type is assigned with a unique saturation value, countries in each group can be further divided into sub-groups according to their personal income status (high vs. low-income, industrialised vs. developing countries). Then instead of assuming that diffusion in all countries will follow a universal affordability curve, different diffusion trajectories can be fitted which are specific to each sub-group. This would essentially lead to a set of distinct AC diffusion trajectories, which vary according to the climate and income-based group each country belongs to. This would improve understanding about the spatial-heterogeneity of AC adoption decisions with respect to the prevailing climatic and socio-economic decisions. It will also assist in better quantifying the uncertainty in impacts on regional and global-level space cooling electricity use from different potential AC diffusion trajectories.

7.5 The effectiveness of different energy reduction policies

Improvements in **(a) AC equipment performance** and **(b) building envelope characteristics** are in general the key elements of policies aiming to reduce the amount of fuel required for space cooling end-use services in buildings. Scott et al. (2008) signified the importance of energy efficiency programmes (e.g., Energy star labelling scheme, appliance research and development programmes, and state building energy codes) in offsetting the anticipated growth in climate-sensitive energy use in 2020 for the U.S. building sector, as result of higher temperatures and evolving building stock. Eom et al. (2012) found that policies aiming to improve building shell characteristics in China can reduce useful residential specific demand for space cooling in 2050 by 13% and 11% for urban and rural areas, respectively. IEA's (2017) ETP future scenario analysis for the buildings sector predicts that switching to highly energy-efficient and renewable AC systems and improving building envelopes can together reduce global residential AC electricity use by 33% by 2050. More radical interventions in the residential sector are predicted to yield an additional 9% of AC-related energy savings by 2050.

Phadke et al. (2014) investigated the impact of different AC technology efficiency measures on residential electricity use for space cooling in India. They showed that 40% of the projected AC electricity use in 2030 can be reduced in a cost-effective way, which also reduces the contribution of air-conditioners to the system's peak demand by 60 GW (from 143 GW). Shah et al. (2015) estimated the benefits in terms of global peak electricity demand and GHG emissions reduction from using more energy efficient RAC units, in addition to switching to refrigerants with a lower global warming potential. If these two measures are applied concurrently, 1090-2540 peaker power plants (with 500 MW capacity) would be avoided in 2050, as well as 4 billion tons of CO_2 equivalent, that is equal to 8% of total GHG emissions in 2015 (IEA, 2019a).

IEA (2018) estimated that more stringent MEPS can reduce the baseline projection of global space cooling energy consumption in buildings by 45% in 2050, while upgraded building envelopes and behavioural change can bring 23%

additional energy savings. Tighter MEPS also lead to a 53% reduction of the global requirement for extra generating capacity in the 2016-50 period to meet growing AC demand. JRC (2018a) assessed the magnitude of AC-related energy demand reductions for the EU-28 residential sector achieved via improved AC technical efficiency and building insulation up to 2100. Upgrading building insulation achieves a 10% reduction in space cooling demand by 2050 (compared to the reference case), while unit AC efficiency improvements is responsible for a further 30% reduction.

Furthermore, policies which maximise the benefits relating to the energy saved through promoting highly energy-efficient AC units (policy action (a)) and building stock (policy action (b)) will probably be the most effective for a saturated AC market, like the U.S. one, where owning a central or a room air-conditioner has become the norm. Policy actions will need to be complemented with government funding directed towards cooling-related research, consumer information programmes about the benefits of using energy efficient AC units and financial incentives which increase the market availability of these products (IEA, 2018). According to Clarke et al. (2018), the efficiency of AC technologies will increase more quickly in the future (2010-2100) relative to that of heating devices (e.g., boilers and furnaces), with an annual growth rate of 0.25% in industrialised nations (vs. 0.1% for heating). There is also evidence from technology adoption studies (Rapson, 2014), which suggests that U.S. households are forward-looking with respect to their AC purchasing decisions, implying that they value the economic benefits stemming from the installation of a more efficient AC unit.

In the case of the un-saturated EU-28 AC market, what was found to be of particular interest for electricity supply systems reliability was the exceptionally fast rates with which residential AC electricity use approaches its effective saturation point in the mid-21st century (4% growth per year in 2015-50 under the baseline scenario compared to 0.1% predicted annual growth rate for total EU-28 residential electricity use in the same time period (JRC, 2019b)). Moreover, despite the implementation of ambitious energy efficiency targets for RAC systems in the “Unit efficiency improvement” case, reductions of AC-based space cooling electricity use were completely compensated by increases due to higher AC diffusion rates. This resulted in space cooling electricity use still increasing by 3% per annum during the 2015-50 period under this scenario.

Furthermore, the enforcement of more efficient technologies (policy action (a)) and building envelopes (policy action (b)) in the EU-28 region may only party reduce the growing seasonal requirements of space cooling electricity use. It could also lead to rebound effects which reduce the energy savings (Gillingham et al., 2016). A more comprehensive set of policies for an un-saturated AC market would additionally seek to mitigate the fast growth of space cooling demand by decelerating the adoption of mechanical AC devices in households. This portfolio of policies which target EU-28 countries includes the following preventing actions:

(c) Amendment of renovation strategies in existing buildings

EU-28 Member States are obliged, under the Energy Efficiency Directive (European Parliament, 2012), to publish long-term renovation strategies with a description of current housing stock and cost-effective approaches to achieve deep decarbonisation. While the majority of countries were found to be compliant with this requirement (JRC, 2019a), there is still not a unifying approach towards curbing energy demand for space cooling. Moreover, the growing role of air-conditioning in achieving renovation goals has been overlooked by many of the cold EU-28 countries. Updated strategies should parameterise anticipated changes in local climate characteristics, and also address other risk factors, such as increased consumers' thermal comfort expectations (Aebischer et al., 2007).

Furthermore, for national renovation strategies to achieve maximum potential energy savings in the residential sector, the socio-economic and dwelling-specific factors which influence the adoption of refurbishment measures should be examined on a country-by-country basis. For example, Hamilton et al. (2014) and Hamilton et al. (2016) showed that the probability for the uptake of energy efficiency retrofits in English dwellings is associated with household income and dwelling age. One of their most important finding was that as household income increases owners spend less on dwelling efficiency measures.

(d) Effective promotion of passive cooling designs in new buildings

Passive cooling comprises all those natural or passive techniques that can help maintain indoor thermal comfort, while requiring minimal or zero energy input (Santamouris, 2016). These can be split into processes preventing solar heat gains (e.g., better shading systems, roof and glazing properties), those modulating heat through utilisation of buildings' thermal mass and those dissipating heat (e.g., natural ventilation and evaporative cooling) (Santamouris and Kolokotsa, 2013). Passive cooling needs to receive further support in the Energy Performance of Buildings Directive (European Parliament, 2018), as a tool which can not only enhance energy conservation efforts in residential buildings, but more importantly can help minimise the chance of mass penetration of mechanical space cooling technologies in the future. However, this policy action may not be as effective as point (c) on renovation policies due to the small percentage of new households comprising each year's housing stock (Lapillonne, 2019).

(e) Diversification of space cooling supply

While residential space cooling is usually supplied through electric room air-conditioners, decentralised, small-scale, production sites are emerging as alternative cold providers. Amongst available technologies, district cooling is considered by the EU as an integral part of a future highly-efficient space cooling sector, as it offers substantial environmental and primary energy savings benefits (ECOHEATCOOL, 2006). Installing decentralised district cooling plants in urban areas with high cold demand density can more importantly increase flexibility of space cooling supply by reducing the anticipated stress on European electricity systems.

However, the size of district cooling systems in terms of peak demand capacity is presently limited to 1.7 GW in cold EU-28 countries and 0.5 GW in warm ones (DG ENER, 2016), which represents only 10% and 2% of the cold and warm sub-regions' potential peak cooling electricity demand in 2015, respectively. Furthermore, local authorities need to design a combination of fiscal incentives and bonus mechanisms for district cooling suppliers to overcome market obstacles and increase this technology's share in EU-28 space cooling supply. In addition to minimising market risks, innovation in building engineering could facilitate easier connection of buildings to nearby decentralised systems.

7.6 Summary of Discussion

This chapter explored the general implications of this research across three central themes: (a) the anticipated impacts on electricity generation systems, (b) the implications for future whole energy system modelling, and (c) the practical usefulness of different energy reduction policies. With respect to the first key discussion theme, synthesis of results from Chapter 5 and Chapter 6 highlighted the difference in the nature of anticipated consequences for future power generation between the saturated (U.S.) and un-saturated (EU-28) AC market. While for the saturated type of market growing residential electricity use has more important implications for baseload electricity use requirements, increasing demand for space cooling affects peak electricity generating capacity the most for the un-saturated market. For both examples (but more importantly in the EU-28 case), additional demand for space cooling purposes in 2050 will need to be met to a great extent through solar-based renewable electricity production. This stresses the importance of flexibly incorporating and storing solar PV electricity production in the power grid which can be employed later during periods of high AC demand. A potential mismatch between renewable-based electricity supply and space cooling demand will require non-renewable based power plants to be dispatched, thus increasing GHG emissions disposed to the environment.

Second, the discussion chapter highlighted the need for adapting general modelling frameworks to the state of AC diffusion in each country (Chapter 3), so that they more effectively capture the effect of the most important AC modelling features. That is personal income and *CDDs* for saturated markets, and space cooling diffusion and unit efficiency improvements for un-saturated markets, according to Chapter 5 and Chapter 6. A number of recommendations were provided relating to potential improvements for the representation of these modelling features in bottom-up IAM demand functions, drawing also evidence from the literature review (Chapter 2). The key suggestions revolved around the need for more spatially-disaggregated approaches to model the dependence of space cooling demand on personal income variation for saturated AC markets (Chapter 5). They also underlined the value of using reviewed climatic metrics which encompass degree days with region-specific thresholds and air humidity statistics (Chapter 4 and Chapter 5). For the un-saturated AC markets, recommendations concern advanced approaches for setting space cooling saturation rates and better integrating personal income effects on diffusion (Chapter 6).

Finally, the discussion chapter presented evidence from previous studies about the effectiveness of different policy tools in limiting energy demand for space cooling, thereby reducing overall impacts on electricity generation systems and GHG emissions. In addition to improving the performance standards of AC technologies and building envelopes, which are the key policy instruments for saturated AC markets, additional policies were presented which can limit the dispersion of space cooling equipment in un-saturated markets.

The following chapter (Chapter 8) revisits the overarching and specific research objectives of this PhD thesis and provides concluding remarks with respect to the significance of this study. Chapter 8 also discusses some of the limitations of this study and suggests potential routes for future research work.

Chapter 8

Conclusions

8.1 Answer to the overarching research question

This PhD thesis aimed at improving current methods and metrics for understanding the drivers of the past evolution of AC demand, which has been the fastest growing end-use service in the global residential sector. Moreover, this thesis aimed at using these new approaches to improve projections of future electricity use in the residential sector, thereby aiding our understanding of the consequences for regional power supply systems from growing residential space cooling demand. The overarching research question that this thesis aimed at answering is the following:

> *With increasing residential energy demand allocated to space cooling how can AC-driven impacts be better modelled to understand the potential future implications for electricity systems in a carbon-constrained world?*

Improvements in future electricity use projections were evaluated separately for two regions with a very different status regarding the current size and future growth potential of their residential AC market, namely the nearly-saturated U.S. and the small, but quickly-growing, EU-28 market. Future AC-driven impacts involved those relating to direct increases in the amount of electricity consumed for space cooling purposes in U.S. households based on the existing stock of AC equipment (i.e., the intensive margin). Moreover, they refer to indirect electricity use increases encouraged through the penetration of additional AC units in EU-28 households (i.e., the extensive margin).

First, my findings showcase the value for regional studies in developing more sophisticated metrics which capture features of climate-sensitive electricity use not described via current approaches. These advanced metrics were shown to improve modelling of the relationship between weather and historical residential electricity use for regions with different climate types. Application of these metrics together with future climatic data in the warm region of the United States also resulted in higher projected levels of seasonal residential electricity use relative to traditional tools. Second, while the evolution of climatic metrics has important implications for summertime electricity use, scenario analysis showed that that the most important driver of annual (per capita) residential electricity use for the saturated contiguous U.S. market is growing affluence levels. Third, personal income was also found to be most influential driver of residential AC diffusion in the non-saturated EU-28 market, which in turn had made the largest contribution to past increases of sectoral space cooling electricity use. On the other hand, mean weather conditions were shown to have much less influence on annual AC purchasing decisions for the un-saturated AC market.

Fourth, with regards to long-term implications, my findings showed that electricity generation requirements during the summer period will increase across both the U.S. and EU-28 region. This means that regional power capacity up-scaling needs to match the predicted growth of residential space cooling demand. However, there are differences in the nature of AC electricity use impacts experienced in these two regions: In the case of the nearly-saturated U.S. market, space cooling is already an important contributor to total final electricity use, with the national electricity system currently facing the highest level of electricity demand during the summer. Increasing residential electricity use in the U.S. residential sector as a result of climate change and growing personal income will therefore amplify pressure on baseload and peak power supply, demanding that more renewable resources are allocated for summer consumption purposes. On the other hand, space cooling presently forms a minor fraction of total final electricity use in the non-saturated EU-28 market, with the majority of national power sectors facing their peak electricity demand in the winter season. The impact of space cooling on total residential electricity use and thus on baseload generating capacity requirements is projected to remain low in the future (Table 7-1). Nevertheless, the expected rapid diffusion of air-conditioners in the EU-28 area can create new pressure points on national power sectors in the summer; if not enough flexible renewable peak capacity is connected.

Section 8.2 provides answers to the specific research objectives addressed in this research. More specifically, section 8.2.1 presents conclusions about the practical usefulness of developing alternative climatic metrics to model past and future climate-sensitive electricity use in a nearly-saturated (U.S.) AC market. Section 8.2.2 provides conclusions concerning projections of future residential electricity use in a nearly-saturated AC market, which integrate climatic with non-climatic impacts. Finally, section 8.2.3 concludes about the development of new methods to understand the impact of climatic and non-climatic factors on future space cooling electricity use in an un-saturated (EU-28) AC market. Then, section 8.3 elaborates on the high-level findings of this research and their implications for utility planning, the energy modelling community and climate policy. Finally, section 8.4 concludes with presenting the key limitations of this work and potential future routes for advancing knowledge in this field.

8.2 Answers to specific research objectives

8.2.1 Improving metrics of space cooling and heating residential electricity use

Research question 1 (RQ1): *What set of metrics could be designed which would improve modelling the relationship between residential electricity use and weather, and what are their implications for long-term projections of space cooling and heating loads?*

The first objective of this research was to develop new metrics of climate-sensitive residential energy use and compare them with existing ones, namely cooling (*CDD*) and heating (*HDD*) degree days adhering to the single 18.3 ℃ base temperature model. This research looked specifically at three types of metrics: (1) *CDDs* and *HDDs* with adjustable base temperatures for different regions, (2) temperature metrics, incorporating different attributes (i.e., duration, frequency and intensity) of heat and cold wave events, and (3) a raw specific humidity variable which is interacted with the extreme heat variables developed in point (2). The reviewed climatic metrics are summarised in section 4.2.2.1.

8.2.1.1 Specific humidity metric

Amongst tested metrics in Chapter 4 and Chapter 5, the specific humidity metric was the one achieving the most significant improvement in the overall performance of regional state-level residential electricity use models (Table 5-5). Incorporating air humidity statistics, increases the fraction of data variance (2000-15) explained by the south U.S. (per capita) electricity model and its annual prediction error (2016-18) respectively by 0.6% and 0.3%, compared to the specification addressing only modelling features (1) and (2) (Figure 4-9 and Figure 4-10). The reduction in prediction error is more pronounced for wintertime electricity use (0.9%). Overall, the south U.S. model encapsulating modelling features (1), (2) and (3) had a 2% higher adj. R^2 and a 1% lower annual MAPE level relative to the reference (NOAA) degree day model.

In the case of the north U.S. climatic region, adding the air humidity variable had an even larger influence on the historical model's performance due to direct consumption from dehumidifiers. Its addition increased the fraction of explained data variation by 5% in 2000-15 and lowered the annual forecasting error by 1% in 2016-18 (this is both relative to the specification adopting features (1) and (2), and to the reference degree day model as shown in Figure 5-2 and Figure 5-3). The interaction variable between humidity and the heat wave day metric was associated with a statistically-significant, positively-signed, coefficient in both the south (Table 4-6), north (Table B-2) and contiguous U.S. (Table 5-4) model. This implies that the former variable amplifies the effect of the latter one on monthly residential electricity use. However, it has proven more difficult to encapsulate the effect of specific humidity at the national (contiguous U.S.) level as this was shown to vary between climatic regions, by exerting a “cooling” effect across southern states and a “heating” effect across northern ones. Still, the contiguous U.S. model of residential electricity use encapsulating modelling features (1), (2) and (3) slightly outperforms the reference (NOAA) degree day model (Table 5-5).

8.2.1.2 Empirically-determined degree days

The next more useful reviewed metric for explaining climate-sensitive residential electricity use was shown to be *CDD* and *HDD* metrics tailored to account for regional differences in climatic, socio-economic and building characteristics via empirically-determined set points. Adopting a higher base temperature for heating (19.3 ℃) and cooling (21.3 ℃) demand calculations was more effective in improving modelling of past residential electricity use for the south U.S. climatic region (Figure 4-8). The impact on adj. R^2 and annual MAPE statistics was roughly the same with that from adding the air humidity metric in section 8.2.1.1.

While the improvement in historical model fitting was much less significant at 0.1% for the north U.S. climatic region (Figure 5-2), lowering the regional threshold temperature for *HDDs* to 15.3 ℃ still managed to reduce the forecasting error (2016-18) during winter months by 1% (Figure 5-3). As a result, the method of fine-tuning cut-off temperatures based on which heating and cooling electricity demand calculations are performed is essential for seasonal electricity demand modelling and climate change impact assessments, in regions with similar climatic characteristics. On the other hand, the contiguous U.S. model of residential electricity use using *CDDs* and *HDDs* with country-specific set-point temperatures did not outperform the reference (NOAA) degree day model (Figure 5-4). This highlights the degree of uncertainty in constructing degree days which are representative of the average behaviour towards space cooling and heating electricity use across the whole of U.S. residential sector.

8.2.1.3 Heat and cold wave day metrics

Lastly, alternative climatic metrics including a description of extreme heat and cold events had the smallest effect on the overall performance of the residential electricity use models. When applied to the south U.S. case study, these metrics increased slightly (0.4%) the fraction of historical electricity use variation (2000-15) which is explained by the econometric model, compared to the one using optimised degree day metrics (Figure 4-9). It is more straightforward to interpret the model coefficient for the cold wave metric, as its positive sign implies that more electricity is used to heat households in response of extreme cold events

(Table 4-6). On the other hand, the total effect of heat waves on south U.S. residential electricity use is not directly interpretable, as its sign becomes positive only above a certain value of specific humidity; a finding which is verified in the U.S.-wide analysis (Table 5-4).

Incorporating the extreme temperatures metrics in the residential electricity use model for the north U.S. climatic region, had a negligible effect on the quality of econometric estimation and forecasting accuracy (Table 5-5). The absence of a statistically-significant response to cold wave days (Table B-1) could be attributed to substitution effects for alternative heating energy sources (e.g., natural gas and heating fuel oil) during periods of extreme cold, due to the higher marginal cost of electricity.

8.2.1.4 Implications for future space cooling and heating electricity loads

Summarising conclusions from section 8.2.1.1 to 8.2.1.3, it is found that only the statistical performance of the south U.S. historical model of residential electricity use was enhanced by the application of each separate modelling feature (1), (2) and (3). In the case of the north U.S. region, only integration of modelling feature (3), namely specific humidity effects, had an effect on the quality of the historical electricity use model. Still the improvement from accounting for specific humidity in the north U.S. model was stronger compared with the combined effect of modelling features (1) -(3) on the model’s performance for the south U.S. region. While the statistical properties of the contiguous U.S. model of residential electricity use showed incremental improvements through the application of each reviewed metric, the fully-extended model was only marginally better than the reference (NOAA) degree day one.

Chapter 4 allowed assessing the influence of encapsulating modelling features (1), (2) and (3) on projections of future residential electricity use for the south U.S. region, while allowing a distinction between cooling and heating loads. Adoption of *CDD* and *HDD* metrics with optimised set-point temperatures (modelling feature (1)) increased the amount of predicted residential electricity use in 2050 for south U.S. states by 2% in summer, relative to the fixed 18.3 ℃ base temperature model (Figure 4-11). At the same time, the optimised degree day model predicts a 0.4% smaller increase in wintertime residential electricity use by 2050 in the south U.S. region, relative to the 18.3 ℃ base temperature model. This implies that scenario projections based on the standard degree day approach may underestimate (overestimate) the magnitude of space cooling (heating) electricity use increases in 2050 and corresponding seasonal capacity requirements.

The highest projection of summertime residential electricity use in the mid-21st century for the south U.S. region was generated through the econometric model encompassing all the three new modelling features, which exceeded the one produced via the 18.3 ℃ base temperature degree day model by 3%. This difference was approximated to equal the size of 3 (8) coal (natural gas) power plants (Table 4-8). Divergence between summertime electricity use model projections in 2050 was even more pronounced at 5% for sub-regions experiencing extremely high humidity levels during the summer season (Figure 4-12). On the heating side, projections for the south U.S. region with a description of cold wave day impacts project a 2% higher level of wintertime electricity use in 2050, relative to the standard degree day model. This was due to extreme cold events becoming more intensified in the future despite the gradual warming of average annual and seasonal temperatures.

Overall, the intensified “peakiness” of monthly residential electricity loads in the south U.S. region highlights the need for expanding generating capacity to cope with the stress on electricity systems from complex climatic effects on space cooling and heating loads. For the contiguous U.S. region, while inclusion of the three modelling features did not improve the historical model significantly, it can be expected that the explanatory power of the reviewed metrics will become more important in the future in a warming world. As temperature extremes become longer and more frequent with climate change, and specific humidity levels rise, understanding their combined influence on future AC and heating-driven electricity loads will be essential for building enough electricity generating capacity across the whole of U.S. residential sector.

8.2.2 Improving projections of residential electricity use for a saturated AC market

Research question 2 (RQ2): *How can climatic impacts be integrated into projections of future residential electricity use for a saturated AC market and how do they compare with the impacts of non-climatic drivers?*

The second research objective was to assess the interaction of climatic and non-climatic sources of uncertainty in future projections of residential electricity use for the nearly-saturated contiguous U.S. AC market. The climatic metrics which were shown to improve the performance of the historical model (**RQ1**) were integrated into projections for the impact of climate change on national-level residential electricity use in the mid-21st century (2046-55). These impacts included increased space cooling and decreased heating electricity use, respectively via the predicted growth and reduction in the number of *CDDs* and *HDDs* with improved set-point temperatures (i.e., modelling feature (1)), for the potential range of climatic trajectories in 2050. It should be noted that the interaction of specific humidity-extreme heat effects (i.e., modelling feature (2) and (3)) was not accommodated in national-level electricity use projections due to the large memory requirements for processing high-resolution humidity data. Nevertheless, these climatic metrics were introduced in the historical model of contiguous U.S. electricity use to reduce potential omitted variable bias. In addition to climatic impacts, projections for the contiguous U.S. region accommodated an array of non-climatic impacts on future residential electricity use, including that of growing affluence levels and increasing fuel prices.

Evolving personal income was shown to be the single most important driver of the future increases in annual residential electricity use, in per capita terms. Annual-mean contiguous U.S. (per capita) residential electricity increases by 8-9% in 2046-55 under the range of economic growth pathways, when compared to 2000-18 levels (Figure 5-8). On the other hand, the increasing effect of climate change on annual residential electricity use levels in 2046-55 (relative to 2000-18) is lower at 1-4%, which can still offset the decreasing effect of growing electricity prices (-2 to -4%). Nevertheless, the impact of climate on residential electricity use becomes much more pronounced and more uncertain at the seasonal/monthly level, particularly via the projected increases in AC-related electricity demand. Climate change is going to be responsible for a 7-15% increase in summertime (per capita) electricity use relative to 2000-18 levels (Figure 5-11). The effect of climate on per capita electricity use during summer months far exceeds that of non-climatic drivers, as well as the corresponding *HDD* effect in the winter season (-2 to -3%). This is also reflected in the mid-21st projections of total residential electricity use across the contiguous U.S. region; summertime consumption increases by 26-40% in 2046-55 relative to present levels, whereas annual consumption grows only by 19-27% (Figure 5-12).

8.2.3 Improving projections of residential space cooling electricity use for a non-saturated AC market

Research question 3 (RQ3): *How can climatic and non-climatic metrics be integrated into models of residential space cooling diffusion in a non-saturated AC market, and what are the implications for long-term projections of residential electricity use?*

The third objective of this thesis was to develop a multi-method framework for analysing past and future trends of residential space cooling electricity use in the non-saturated EU-28 AC market. The framework enables a comparison between the influence of different drivers on AC electricity demand. The decomposition analysis performed using data for the 2000-15 period allowed identifying the variation of past residential AC electricity use (~+0.6 TWh per year) which is attributed to the effect of different components, including that for growing AC penetration levels (Figure 6-3). The effect of the diffusion-related component (~+1 TWh per year) on past space cooling electricity use far exceeded the contribution of other components, including the decreasing effect of AC unit efficiency improvements. Econometric analysis demonstrated the strong dependence of residential AC diffusion on personal income variation, whose marginal effect was about 5 times as large as that for mean JJA temperature (Table 6-5).

Constructed scenarios of AC diffusion for the 2016-50 period, stressed the large future growth potential for residential space cooling electricity use in the EU-28 region, which was projected to increase by up to factor of 7 in 2050 relative to 2015 levels (16 TWh/yr) (Figure 6-6). While the future growth potential for EU-28 residential space cooling electricity use is huge, its impact on the region's electricity system is small in terms of its contribution to sectoral final electricity use levels, which grows from just 2% to 13% in 2050 under the extreme AC diffusion scenario. Still, my model predicts a stronger dependence of AC diffusion on personal income growth compared to other assessments (Figure 6-11) which results in faster growth rates of space cooling electricity use in the mid-term. Moreover, important increases in residential AC electricity demand levels are estimated across cold EU-28 countries in 2050 which are not evident in other studies, as growing affluence levels and not climate is the main determinant of AC diffusion according to my research.

8.3 Wider significance and implications of this research

The focus of the previous section was around the specific methods and metrics developed to improve understanding about the evolution of historical residential electricity use and space cooling demand, respectively for the U.S. and EU-28 region. They also identified the AC modelling features which had the strongest influence in projections of residential electricity use in the mid-21st century, separately for the saturated (personal income and *CDDs*) and non-saturated (AC diffusion and efficiency improvement) AC market. This section elaborates on the significance and general implications of the findings of this research for three separate areas: (a) future electricity systems planning, (b) whole energy systems modelling, and (c) energy demand reduction policies:

(a) Future electricity systems planning

Electricity generation and transmission systems will face more intense electricity loads in the future as a result of increasing space cooling demand. Section 7.2 found that the consequences of growing demand for electricity in the saturated U.S. AC market are more severe for future baseload rather than for peak electricity use, although my approach may underestimate net impacts in the second category. As a result, increases in residential electricity demand will raise average electricity generation requirements in the U.S. power sector, while also exacerbating to some degree the stress of space cooling demand on peak generating capacity, with the effect being larger in north U.S. states. The opposite trend was observed for the un-saturated EU-28 AC market: impacts on peak electricity demand are much more significant than impacts on baseload electricity use (although it is noted that my approach may overestimate the impacts in the first category), while warm EU-28 countries are affected the most.

These findings imply that regulatory measures will need to promote the flexible integration of renewable sources in national electricity systems, in accordance to energy supply decarbonisation targets. Renewable generating capacity, especially solar PV, can be deployed to provide a significant part of the electricity required to meet increasing summertime residential cooling loads, as its output varies closely with AC demand variation. According to forecasts (JRC, 2019b), solar PV will shape a large fraction of net generating capacity for the EU-28 (27%) power sector, given the deep decarbonisation goals set by the European Union. EU's strategic shift towards a climate-neutral economy (European Commission, 2018), recently expressed via the European Green Deal, dictates that electricity systems will have to move towards net-zero GHG emissions by 2050 to meet obligations under the Paris Agreement. This means that of foremost concern for utility planners will be the effective balancing of peak electricity demand for space cooling with renewable-based supply, to avoid system failure. The flexibility of the integration of renewables in the electricity system can be increased significantly through decentralised production centres and energy storage solutions which can shift excess supply to periods when high electricity demand occurs (Denholm et al., 2010). Additionally, electricity stored in the summer can be moved around Europe via an interconnection system to places with high AC demand.

On the other hand, only 15% of the U.S. net generating electricity capacity in 2050 will be made of solar PV technologies, as forecasted by U.S. EIA (2019a). Since the national power grid will be dominated by non-renewable energy sources (mainly natural gas combined-cycle power plants), increases in space cooling and total electricity use in the residential sector will not only challenge the stable operation of the electricity network, but also lead to the further growth of GHG emissions from the power sector. Despite the absence of power sector decarbonisation goals at the federal level, 30 U.S. states have already implemented renewable portfolio standards which can drive up the fraction of electricity generated through renewable sources in the future (Barbose, 2019).

(b) Whole energy systems modelling

The second contribution of this research was in identifying gaps and propose improvements to the existing methodologies followed to model space cooling electricity use via demand functions in bottom-up IAM tools. The proposed improvements can be divided into those relating to the depiction of personal income and climatic effects on space cooling demand for saturated AC markets, and into those concerning diffusion effects for un-saturated AC markets.

Improved representation of affluence effects in saturated AC markets: Conclusions regarding the key role of personal income in projecting future levels of residential electricity use in the saturated U.S. market stresses the need for improved income driven space cooling demand functions in IAMs. Designed personal income metrics need to reflect the gradual saturation of personal income effects on residential electricity use across large climatically-diverse countries. These saturation points were shown to vary significantly across the contiguous U.S. region (Table 5-4), based on the current diffusion rate of HVAC equipment, and overall heating and cooling needs. Personal income functions need to also take into account between-country differences in the price of electricity.

Improved representation of climatic effects in saturated AC markets: Whole energy system models with a description for residential space cooling (and heating) demand, will need to accommodate climatic metrics which are not restricted to the effect of *CDDs* and *HDDs* with a uniform 18.3 ℃ temperature threshold. The analysis performed for the south (north) U.S. climatic region showed that *CDDs* and *HDDs* estimated with a higher (lower) than 18.3 ℃ set point temperature explain better monthly residential electricity use data in warmer (colder) regions. Climate-sensitive residential energy demand needs to be modelled for different countries based on degree day metrics with empirically-determined set-point temperatures. Moreover, air humidity effects will need to be integrated into the climatic metrics, to account for the amount of electricity consumed for room dehumidifying purposes.

Improved representation of diffusion effects in non-saturated AC markets: Findings pertaining to the significant role of AC up-take in the growth of residential space cooling electricity use for the non-saturated EU-28 market emphasised the need for improved representation of AC diffusion effects in IAM tools. First, my results suggested that the use of current AC diffusion rates in the U.S. market as a proxy for future potential diffusion rates in non-saturated markets ("Climate Maximum") is not an accurate approach and that space cooling saturation rates need to be instead determined via empirically-driven approaches. More specifically, my model predicted that the saturation rate of AC diffusion in EU-28 countries is close to 40%, rather than 50% based on the climate maximum approach, and found a smaller divergence in saturation rates between cold and warm EU-28 countries. Second, EU-28 residential AC diffusion was shown to grow faster in 2050 relative to other assessments, which was also evident for cold EU countries, since personal income variation and not climate change was the main driver. As a result, the effect of personal income on residential AC diffusion needs be also better modelled for non-saturated AC markets.

(c) Energy demand reduction policies

The anticipated substantial increases in future baseload and peak electricity use from growing residential AC demand will need to be limited through a variety of building energy demand reduction measures. A wide portfolio of energy reduction strategies for the buildings sector found in the literature were discussed in section 7.5, with the most important ones aiming to improve the technical efficiency of AC technologies and thermal characteristics of building envelopes. Moreover, decelerating the diffusion of space cooling equipment specifically across non-saturated AC markets can be achieved through updated renovation strategies and passive-cooling building designs.

Evidence from past assessments shows that AC energy efficiency and building envelope improvements can together bring important benefits in terms of the total energy use avoided in 2050 for AC purposes. Scenarios with highly optimistic assumptions about building and technology performance characteristics predict respectively a more than 40% and 60% reduction in global baseline AC energy use in 2050 across the residential (IEA, 2017) and whole buildings sector (IEA, 2018). Reduced space cooling needs will also lead to the lower contribution of air-conditioning to peak electricity demand, which decreases the costs for building extra electricity generating capacity in the future. In addition to benefits for electricity systems, improving AC energy efficiency can play a determinant role in abating future CO_2 and non-CO_2 GHG emissions from space cooling adoption and use (Lapillonne, 2019).

In order for the identified benefits to be realised, properly-designed national cooling policies will need to be set out which are effective in reducing space cooling consumption in buildings (IEA, 2018). These national strategies need to follow a holistic approach: specific policy tools may include regulations enforcing stricter MEPs for AC units and building energy codes, information programmes promoting the use of more energy-efficient products, and funding for cooling-related research and international collaboration programmes. Moreover, demand-side response programmes could promote the availability of smart-control technologies in the residential sector (IEA, 2019d).

8.4 Limitations of this research and recommendations for future work

The work presented in this PhD thesis has two key limitations which are presented below together with recommendations about how these could be overcome in the future by related work in this field:

Limitation no. 1- The short-run parameters in the FE panel data model for the saturated AC market may not be wholly suited to use in long term 30yr+ forecasts.

The state-level econometric model developed for studying historical residential electricity use in the south (Chapter 4) and north/contiguous (Chapter 5) U.S. region was estimated via a FE estimator, which belongs to the family of static models. This essentially means that FE model parameter estimates represent the short-run effect of weather, socio-economic and fuel price variables on historical U.S. residential electricity use. These effects may not completely portray long-run adjustments of sectoral electricity use via changes in the capital stock and efficiency of electric-consuming equipment (De Cian and Sue Wing, 2019). As an example, residential electricity use could be inelastic to electricity price changes in the short-run as consumers have limited options to alter their consumption levels, whereas in the long-run a more elastic response to growing prices could comprise the purchase of more efficient AC units (Bernstein and Griffin, 2006). In that regard, the estimated short-run parameter for the *EP* variable and its corresponding effect in 2050 may underestimate the decrease in residential electricity use levels from growing electricity prices.

In a similar fashion, growth of personal income may induce the purchase of new household equipment in the long-run that has an additional impact on total electricity consumption levels, which may not be adequately captured by the short-run *INC* coefficient. Nevertheless, addition of the squared income variable (*INCSQ*) in my historical model and use of an extended panel dataset covering years 2000-18 has partly controlled for long-run demand saturation effects in the residential sector. With regards to climatic parameters, the long-run effect of warming climate may also induce increases in the stock of AC equipment (i.e., the extensive margin), thus increasing overall electricity use levels in the residential sector. The estimated FE response coefficient for *CDD*-based and extreme heat metrics may not adequately this additional effect on electricity use. However, this amplifying effect is notably smaller for the nearly-saturated AC market of the United States, even under an extreme climate change scenario (Huang and Gurney, 2016a), relative to the direct impact of warmer weather on seasonal AC-driven electricity use requirements through the intensive margin.

Recommendation no. 1: A dynamic specification of the historical residential electricity use panel data model would permit to obtain the size of potential long-run adjustments of electricity use, especially to varying electricity prices. These dynamic panel data estimators (such as the pooled mean group and the dynamic fixed effect estimator (Gautam and Paudel, 2018)) specifically allow for the inclusion of error correction parameters which determine the delayed responses of residential electricity use to changing climatic and non-climatic conditions. As a result, dynamic models generate two types of coefficient for each explanatory variable relating to its short-run and long-run elasticity value. However, applying these dynamic panel data estimators with monthly electricity consumption data is rare occurrence in the literature as this approach finds mostly application with annual data (van Ruijven et al., 2019; De Cian and Sue Wing, 2019).

Limitation no. 2- The diffusion model for the growing AC market lacks information about the purchasing behaviour of residential consumers in different seasons and regions within a country

On the diffusion side of residential space cooling (Chapter 6), the EU-28 analysis demonstrated that a strong relationship exists between national AC penetration rates and personal income, while the impact of weather on AC adoption is much weaker. However, the literature on the impacts of climate change on space cooling electricity use suggests that these effects become far more pronounced on a seasonal/monthly scale and at the regional level. The historical AC diffusion model developed for the EU-28 residential sector utilises the latest JRC-IDEES data (JRC, 2018b), which are only available at the country level and for successive years (2000-15).

Introduction of a lagged JJA temperature metric in the historical model of AC diffusion for the EU-28 residential sector showed that past hot summer seasons influence AC adoption decisions in the following year. Restriction to annual datasets however hinders any assessments about the climate-sensitivity of AC diffusion rates separately for mean and extreme weather metrics. Overcoming this data limitation issue is very challenging since national-level household surveys, such as the EIA's RECS datasets (U.S. EIA, 2017b) mostly report annual statistics on the penetration rates for different equipment types. Given the long process entailing the collection and analysis of questionnaires for a sample of households which is representative of the national housing stock, it is uncertain whether future household surveys will achieve finer temporal resolution.

Recommendation no. 2: A solution to this reduced data granularity issue is that monthly or seasonal AC sales data for a country/region are collected from different residential AC manufacturers. This time series of AC sales data can be then econometrically analysed to improve understanding about the relationship between AC purchases, and mean and extreme weather effects. This can be performed through an empirical model which tests both for the impact of degree day/ raw temperature and extreme heat-humidity metrics, as those developed in Chapter 4. Availability of detailed AC sales data has the extra benefit of obtaining information regarding the efficiency status and selling price of AC units. The effect of these factors also driving AC diffusion in the residential sector can be modelled via the econometric model and subsequently compared with that of extreme weather effects.

8.5 Reflective epilogue

This PhD thesis aimed at improving the modelling of the drivers of residential space cooling demand, whose future evolution is uncertain under the different sets of climatic and socio-economic trajectories in 2050. Uncertainty primarily stems from modelling approaches which do not account for certain economic behaviours and other factors which can explain differences in residential electricity use across different regions. Uncertainty in modelling past and future residential electricity use can also result from the lack of consistent datasets, which are accessible at different temporal and spatial scales.

Section 8.5.1 therefore reflects on the multiple criteria used to choose between a top-down and a bottom-up modelling approach for fulfilling the objectives of this research. Furthermore, it provides a more elaborated discussion about the specific benefits of employing top-down methodologies with respect to the quantification of rebound effects in households. Section 8.5.2 then reflects on the choice of a suitable functional form for the models developed for the saturated (U.S.) and un-saturated (EU-28) AC market. The discussion revolves both around the factors which were explicitly described in the individual models of U.S. residential and EU-28 space cooling electricity use, as well as other confounding variables which were only considered partially. Section 8.5.3 highlights identified issues relating to the current availability of data and their implications for the design of the two case studies.

Following the discussion on modelling challenges, the reflective epilogue (section 8.5.4) focuses on the general findings of this PhD and, particularly, on those concerning the importance of different modelled parameters for total and AC-specific residential electricity use, accordingly for the U.S. and EU-28 region. A comparison of the significance of modelled parameters is similarly performed at the sub-regional level to identify trends in market development masked in the regional analysis. This section also stresses about the role of air humidity as an explanatory variable in projections of future residential electricity use. Finally, section 8.5.5 concludes by evaluating the magnitude and nature of future impacts on regional electricity systems, as identified in the saturated (U.S.) and un-saturated (EU-28) case study.

8.5.1 Selection of the general modelling approach

This research was unique in developing modelling frameworks which were adapted specifically to the state of diffusion in regional AC markets. This permitted a comparison of the drivers and impacts of increasing space cooling electricity demand between a region with an almost saturated AC market (United States) and a region with low but quickly growing AC penetration rates (European Union). The adopted modelling methodologies (respectively presented in Figure 3-2 and Figure 3-3 for the U.S. and EU-28 case study) share a common feature: they are both of a top-down nature. This essentially required developing reduced-form econometric equations to describe the relationship between residential electricity demand components and macro-level external drivers, which is different from the analytical and highly-disaggregated approach followed by bottom-up models (as described in section 2.2.2). Preference towards top-down over bottom-up modelling approaches was established on the grounds of the identified research objectives and the relative strengths and weaknesses of competing methods under different categories, as summarised in Table 3-1.

Both the U.S. and EU-28 case study included a retrospective analysis component through which they obtained empirical estimates for the effects of climatic and non-climatic factors on residential space cooling diffusion and electricity use. This removed engineering-based bottom-up methodologies from the list of candidate approaches, since they are not suitable for including the wider non-technological factors that influence energy demand (Table 3-1). Moreover, bottom-up statistical modelling tools were not deemed appropriate for this research since generalising the results of statistical analysis to the U.S. and EU-28 regional level would require large amounts of data that were outwith a single PhD project. Top-down models, on the other hand, can quantify the effect of non-technological drivers, like the climate, income and fuel prices, and can be also easily applied over large geographical regions. Apart from the ease of application, top-down models are computationally-efficient tools which were employed in this thesis to project U.S. residential electricity use and EU-28 space cooling demand in the future, without imposing assumptions about the evolution of complex factors relating to technologies and buildings.

An important point regarding the choice of the modelling philosophy, which can be discussed in more detail, relates to the ability of top-down models to observe paradoxical economic behaviours. A key example is the so-called rebound effect (Gillingham et al., 2016), through which improvements in the efficiency of an energy-conversion technology causes its greater use (through lower implicit prices), resulting in a lower level of energy savings for an economic sector than that originally intended. That is, for example, introduction of more efficient AC units in a market will not always lead to the energy savings estimated through engineering-based (bottom-up) calculations, as households may decide to make more use of their space cooling equipment (direct rebound) or re-spend saved income on other energy-consuming activities (indirect rebound). While the first reference to rebound effects dates back to year 1865 (Jevons, 1865), the debate about their significance compared to first-order fuel savings and potential implications for the energy conservation policies became fierce in the early 1990s (Brookes, 1990; Brookes, 1993).

The main argument put forward by advocates of the importance of rebounds, such as in Brookes (2000), is that improved resource productivity forces the equilibrium level between energy supply and demand to be met at a higher (price and consequently) consumption level, compared to the case where no efficiency measures took place. Furthermore, rebound effects are not restricted in the end-use sectors, but their impacts can theoretically extend to the whole of the economy, as expressed via the Khazzoom-Brookes postulate (Saunders, 1992). Interestingly, this postulate showcases that under certain conditions (e.g. the choice of a suitable production function and of a large enough elasticity value for the substitution between energy and capital-labour (Saunders, 2000)), improved efficiency could lead to a “backfire”, whereby overall energy consumption levels rise instead of decreasing. Existence of significant rebound effects would also point to the flaws of policies aiming to reduce final energy use only through energy efficiency measures. It would also stress the need for policy packages to be complimented by actions to encourage the faster penetration of renewables in a country’s energy mix.

On the other hand, scholars, such as Schipper and Grubb (2000) have evaluated micro-rebounds to be responsible for only a small part of end-use energy savings taken back following an efficiency improvement, but acknowledge that this holds only for mature economies. Similarly, a recent study by Brockway et al. (2017) estimated partial rebound effects for the U.S. and the UK (in the order of 13-50%), while finding evidence of backfire (rebound >100%) for an industrialised country, namely China. For space cooling end-use demand, Jenkins et al. (2011) provide a direct rebound estimate of 1-26% for developed countries, while they caution that this value does not account for impacts on the diffusion of air-conditioners and improved thermal comfort standards.

In this PhD, the choice of a top-down modelling approach, whereby the empirical relationships between residential electricity use and explanatory variables are established based on historical data aided in implicitly capturing rebound effects, at least at the micro-level (direct and indirect). In the state-level model of U.S. residential electricity use, this was achieved through the adoption of a FE panel data econometric estimator which captures the relationship between historical electricity demand, economic activity and electricity prices. Also, the effects of energy efficiency improvements were implicitly controlled in the model by the introduction of annual dummies. In the country-level model of AC electricity use for the EU-28 region, historical improvements in the efficiency of the AC stock were explicitly expressed in the index decomposition equation. A separate FE panel data econometric model of AC diffusion and specific useful cooling demand was used to capture historical rebounds linked to space cooling diffusion and use.

The econometric equations built in the historical modelling phase were used in the development of future projections for the U.S. residential electricity use and EU-28 space cooling demand. As a result, the micro-rebound effects captured in the historical models are also implicitly included in long-term projections, although their size is assumed to remain fixed at historical levels. Future rebounds are expected to be small for the contiguous U.S. market, as the growth in floor area of households which is cooled becomes saturated. In the un-saturated EU-28 case study, rebounds will be more significant in the long-run as more efficient AC technologies enter the market, lowering the effective cost of the service and accelerating their diffusion in households. In this context, top-down models are deemed more appropriate than bottom-up ones in modelling the future evolution of residential electricity use, as the latter group of tools ignore the potential effect of the multiple rebound mechanisms.

8.5.2 Choice of a suitable modelling functional form

While the previous section has justified the use of top-down approaches, this part shifts the focus to the functional form of the models developed in each case study and more specifically to the selected model variables. From the review of bottom-up studies in 2.2.2, the variables which were found to be included in assessments of residential energy demand conducted at the macro-level relate to (a) climatic, (b) socio-economic, (c) technology, and (d) building characteristics of energy use. In the case of space cooling, (cooling) degree days have been used as a central metric to treat the climate-sensitive component of building electricity use, representing daily transformations of air temperature relative to a fixed set-point temperature. However, from the critique in section 2.3.2, it was shown that some modelling features are not adequately captured by traditional degree day metrics, such as the effects of extreme heat and of non-temperature weather factors, as well as a limited scope applies around the choice of a base temperature.

As a result, Chapter 4 and Chapter 5 were dedicated to reviewing alternative metrics of climate-sensitive residential electricity use separately for the south and north U.S. climatic area, as well as for the whole of contiguous U.S. region. Aside from *CDDs/HDDs* defined with a uniform 18.3 ℃ threshold, the state-level econometric model of residential electricity use (eqn. (3-10)) included degree days with empirically-determined set-point temperatures, new metrics of extreme heat and cold, and an air humidity control. Population-weighted degree days were calculated (eqn. (4-1)) to control for the concentration of populations in urban centres. Generally, a higher (lower) *CDD* temperature threshold was expected for households in the south (north) U.S. region, due to the acclimatisation of populations to warmer (colder) environments; this was verified in the results. This is also the reason that the *CDD* metric adopted in Chapter 6 to model the climate-sensitivity of specific useful AC demand in the EU-28 region was based on a 24 ℃ set point, as the largest share of consumption occurs in warm countries[16]. One would expect these thresholds to evolve in the long-run, as a result of acclimatisation or environmentally-friendly behaviours; a behavioural shift for which the individual drivers cannot be studied in a top-down setting.

Air humidity was selected to complement temperature-based parameters in the U.S. econometric model as (a) previous studies showed its inclusion improves predictions of summertime electricity loads and (b) it could potentially confound the estimated effect of temperature on electricity use. More specifically, specific humidity is positively correlated with air temperature, as water evaporation increases in warmer environments (Barreca, 2012). If humidity is also linked to the variation of building electricity demand through latent cooling loads and displays a trend, then econometric models controlling only for temperature would be biased. The direction of this bias was found to differ between the south (Table 4-6) and north (Table B-2) U.S. model, since in the former case not controlling for humidity underestimated the effect of *CDDs* on electricity use while the opposite occurred for the latter case.

It is of course possible that other non-temperature confounders exist, such as solar radiation, rainfall, wind speed and direction, snowfall and cloud cover. For example, incoming solar radiation causes air temperature to vary, and at the same time can amplify the need for electrical air-conditioning in summer. Moreover, regional temperature differences lead to fluctuations in air pressure which then affect winds. Wind reduces demand for electric space cooling, although its cooling effect is more of a local character (Chapagain and Kittipiyakul, 2018). This study refrains from including the full set of weather

[16] The climate-sensitivity of AC diffusion was instead modelled via the JJA temperature parameter which is a metric of the average extremity of summertime temperatures.

predictors in the U.S. model of residential electricity use for two reasons: First, this can create multi-collinearity issues (i.e. the existence of highly-correlated variables in the regression) which would essentially undermine the quality of econometric estimates. Second, future high-resolution projections for non-temperature variables are generally difficult to obtain for large-scale case studies; an issue which is further discussed in section 8.5.3.

With respect to socio-economic variables, bottom-up modelling studies typically use population or number of households as the main activity driver of residential energy demand. Similarly, in the top-down econometric model for the U.S. region, state-level electricity use data were adjusted for population changes over the historical and future analysis period. Due to the technological dimension of the AC demand model for the EU-28 region (eqn. (6-2)), the number of households was instead chosen as the activity driver. In addition to activity drivers, personal income (or household expenditures) was found in the literature to be the main structural driver influencing electricity use for space cooling either directly, or indirectly through increased AC up-take. Personal income was therefore included as an explanatory factor in the econometric model of U.S. residential electricity use and EU-28 AC diffusion. For the former study, a quadratic income parameter was added to the linear model specification to control for the saturation of income effects; a model extension which had a profound role in the interpretation of socio-economic impacts at the sub-regional level (further analysed in section 8.5.4).

Technological factors, such as the efficiency and capacity of HVAC technologies, as well as upfront capital costs for the investment in new equipment and fuel costs for its operation cannot be explicitly portrayed in sectoral econometric models. As a result, the U.S. residential electricity use model controls explicitly for average electricity retail prices and implicitly for autonomous technological improvement in the past via the annual dummies. Technological parameters will also affect the future level of energy consumption for an end-use service as they are subject to change via energy efficiency policy measures. The projections of future U.S. residential use should be therefore considered as changes in electricity demand resulting from growing economic activity, the warming climate and altered electricity prices, before technological adaptation and substitution. As van Ruijven et al. (2019) explain, adaptation mechanisms could be subsequently studied by feeding the results of the econometric model to IAMs or Computable General Equilibrium (CGE) models. On the other hand, the technological module of the residential AC electricity use model for the EU-28 region captured key features of the space cooling technologies, such as their efficiency and size, which allowed the creation of high efficiency scenarios for the future.

Similar to technology, information about the building envelope is difficult to embed in macro-level top-down models. Various building characteristics affect useful energy demand levels including heat loss rate from the building shell (expressed as the U-value of floors, walls, roof and windows), air permeability and natural ventilation rates (Collins et al., 2010; Fotiou et al., 2019). Any changes to these parameters over the historical analysis period, were partially controlled by the annual-specific effects in the U.S. econometric model and implicitly accounted by the specific useful AC demand factor in the EU-28 decomposition formula. The EU-28 study further modelled historical useful AC demand using household area (and *CDDs*) as exogenous factors.

Policies may enforce stricter building codes in new structures and accelerate the renovation of old buildings in the future (see section 7.5 for a discussion on the suitability of different policies for saturated and non-saturated AC markets). In the context of climate change, building-level policies need also to promote measures that avoid the accumulation of solar heat gains through windows and overheating in buildings (Aebischer et al., 2007). This will be especially a challenge for cold regions where buildings with deep insulation are designed to keep the indoor environment warm while neglecting the increased importance of space cooling. The overall impact on residential electricity use will be compounded or mitigated through the adoption or non-adoption of energy-intensive lifestyles. An example of such energy-intensive lifestyle was portrayed in the fast AC diffusion scenario in the EU-28 study. This highlighted the importance of measures preventing the mass up-take of air-conditioners, especially in cold EU-28 countries.

8.5.3 Data availability issues

For both case studies, the data collection process involved obtaining information relating to three groups of variables: (a) energy use, (b) socio-economic or/and general information about the housing stock, and (c) climatic.

First, granular data relating to energy use were easier to collect for the U.S. region: electricity sales data (volume and unit price) for the residential sector of individual U.S. states are available on a monthly basis from the EIA (U.S. EIA, 2020b). This level of temporal granularity in the econometric model was suitable for better relating household heating and cooling behaviours to the variation of climatic parameters. As explained in 3.3.2, Eurostat on the other hand publishes final residential electricity use data for individual EU-28 countries only on an annual basis (ESTAT, 2015), which mask the seasonal variation of space heating and cooling demand. Monthly statistics were limited to total electricity available in the internal market which include energy consumption in sectors, other than the residential. Potential availability of monthly residential electricity sales data would permit replicating the assessment performed for contiguous U.S. to the EU-28 region and improve the comparability of results between the saturated and un-saturated market case study.

Second, limited availability of cooling stock data for the EU-28 region lessened the degree to which the residential diffusion model (built in section 3.6) accounts for the variation of purchasing behaviours between seasons and sub-regions of a country. As already discussed in section 8.4, in the absence of seasonal AC sales data, using the JRC-IDEES database (JRC, 2018b) was the best available option as it provides for the first time consistent time series of annual AC stock data for all EU-28 countries. This is still a considerable improvement compared to other EU-28 databases (e.g. Odyssee-Mure) whose information on the penetration rates of space cooling equipment in households is incomplete. The restriction to annual stock datasets did not facilitate an assessment about the various climatic and socio-economic effects on AC up-take over the summer period. Even if seasonal sales data were made available however, another limiting factor would be the non-existence of seasonal personal income data for EU-28 countries (a limitation which was not present in the U.S. case study).

Third, climatic data were more easily traceable at very fine temporal and spatial levels. In the U.S. case study, historical values (2000-18) of daily mean and 3-hour near-surface temperature, as well as of monthly specific humidity, were sourced with spatial resolution of ~1/3 degrees (~32 km) from the NARR project (NCEP, 2016). In the EU-28 case study, historical data (2000-15) of monthly-mean temperature were obtained from the CRU's global datasets with spatial resolution of ~1/2 degrees (Harris et al., 2014). However, unlike for contiguous U.S. states, high-resolution data for air humidity were not available for EU-28 countries which restricted the analysis of climatic impacts on residential AC diffusion to temperature-related effects.

The assessment about the impacts of climate change on south U.S. residential electricity use in Chapter 4 was based on MACA temperature and specific humidity data (Abatzoglou and Brown, 2012), which are available with even finer spatial resolution of ~1/16 degrees(~ 6 km). However, as noted in section 5.2.4.2, it was not computationally efficient to use the same data source for devising projections of residential electricity use over the whole of contiguous U.S. region, given the extremely large size of individual MACA product files. A different source for future downscaled climatic variables was preferred in Chapter 5 (WCRP, 2013), which while it still provides high-resolution data (~1/8 degrees which is roughly equal to 12 km), it contained temperature and precipitation projections only. In general, this highlights issues around the lack of climate data when assessments about the impact of humidity on energy use extend over large territories, like the U.S. or the EU-28 region. The same general issue would arise if one decides to incorporate in the model other secondary weather variables like solar radiation and wind speed.

8.5.4 The relative importance of modelled parameters

The approach used to understand the relative importance of modelled parameters for evolving electricity demand was different for the saturated (U.S.) and non-saturated (EU-28) AC market, as a result of the unique modelling tools adopted in each case. In the U.S. study, this was assessed through evaluating the impact of the modelled parameters on (per capita) residential electricity use, as econometrically projected in the period 2046-55 under different climatic, socio-economic and fuel price trajectories. Therefore, their importance was defined as the amount of increase (or decrease) in future U.S.-wide residential electricity use from 2000-18 levels which is specifically attributed to changing heating and cooling degree days, personal income and electricity prices (section 5.2.3).

In the EU-28 case study, the relative influence of modelled parameters was instead examined through the decomposition identity (6-2) which breaks down the past changes of EU-28 space cooling electricity use to the impact of individual factors. The importance of modelled parameters (i.e. number of households, AC diffusion, useful specific energy demand and technical efficiency) was then quantified as their contribution to the increase of annual AC electricity use in 2000-15. Table 7-2 presented the main conclusions of this assessment for the U.S. and EU-28 region as a whole, by synthesizing results from Chapter 5 and Chapter 6. This section builds on this previous discussion by also evaluating sub-regional differences in results (i.e. cold vs. warm U.S. and EU-28 sub-regions).

8.5.4.1 Saturated AC market

According to the analysis for the saturated U.S. market, personal income was the most important parameter causing annual per capita residential electricity use in 2046-55 to grow by 8-9% (relative to 2000-18) at a national level. In contrast to annual results, seasonal analysis showed that warming temperatures- not increasing income- is the most influential variable with an impact on per capita electricity use ranging from 7 to 15% over the summer period.

Sub-regional projections revealed some peculiar trends. First, income is the main driver of annual residential electricity use for both the north and south U.S. region, however through an effect acting in a different direction. The impact of growing personal income corresponding to north U.S. ranges from 22% to 31%, which is much higher than the previous country-level estimate. The big magnitude of this impact is explained by the high saturation level of income effects in this sub-region (section 5.3.2.2). Furthermore, this demonstrates the future potential for the penetration of AC equipment in households, as well as of electric heating, which is not currently the established heating technology across cold U.S. states. On the other hand, average income effects across the south U.S. region become completely saturated before 2050 due to the more widespread adoption and use of electric heating and cooling equipment. This turns income effects on per capita electricity use in 2046-55 negative (-1 to -11%). Second, the increasing effect of climate on residential electricity use (+1 to +4%) is equally distributed between north and south U.S. states on an annual basis.

Third, climatic impacts are disproportionately distributed between the north and south U.S. sub-region on a seasonal basis. In north U.S. states, the impact of climate in 2046-55 displays a clear peak in the summer, as per capita residential electricity use increases by 9-18% due to increasing cooling requirements. Still, this effect is somewhat lower than the corresponding seasonal income effect (+21 to 29%) which again highlights the high penetration potential of HVAC equipment in the cold U.S. region. In south U.S. states, climate change impacts also peak in the summer (+4 to +11%) but are of lower magnitude compared to those in the north. Still, climatic effects become more important than income-related effects (-1 to -9%) during the cooling season, which signifies the role of climate in the evolution of seasonal residential electricity use in the south sub-region.

Results from Chapter 4 concerning projections of future residential electricity use for the south U.S. region (section 4.3.4) using various combinations of climate metrics allowed a comparison of the relative importance of climate-related effects. Extreme heat episodes, when combined with high levels of humidity (≥ 15 g/kg), were shown to increase the amount of electricity consumed in the summer, which is above the level predicted by conventional dry-bulb degree day metrics. Research suggests that the anticipated growth in extreme heat-humidity events across the globe due to climate change, will have adverse impacts on human health (Schär, 2016; Raymond et al., 2020). Future cooling technologies will inevitably become an essential mechanism for populations to manage adaptation to increased heat exposure (Hanna and Tait, 2015).

Projections for the south U.S. region however showed that summertime impacts on residential electricity use are principally driven by mean temperature changes. The additional growth of electricity use resulting from the combination of high humidity and heat waves is rather a second-order effect. At the regional level, capturing these effects increased summertime residential electricity use in 2050 by ~3% (Figure 4-11), relative to baseline projections via the degree day model. This difference was larger (~5%) in sub-regions experiencing extremely high humidity levels (Figure 4-12). This is another of the main reasons that humidity effects were not integrated into nationwide projections of residential electricity use. It is possible that electricity use in households will become more sensitive to humidity variation in the future with the surge of extreme heat events; a development which would amplify their impact on summer AC electricity demand.

8.5.4.2 Un-saturated AC market

From the decomposition exercise in section 6.3.1, AC diffusion was found to be the most significant driver of space cooling electricity use for the un-saturated EU market, with a mean increasing effect of 1 TWh per year. When compared to the 0.6 TWh/yr mean annual increase of EU-28 space cooling electricity use recorded from 2000 to 2015, the impact of AC penetration amounts to a 160% increase. That contribution is about two times as large as the negative impact corresponding to improved efficiency (-0.5 TWh or -80% per annum). The same conclusions about the dominance of diffusion-related effects are reached when examining separately results for warm and cold countries: For both country sets AC diffusion is the most important parameter accounting for a 150% increase in the sub-region's annual space cooling electricity use. The percentage decrease of annual space cooling electricity use attributed to improved efficiency standards is however higher in warm countries (90%) than in cold ones (60%). This is explained by the faster up-take of air-conditioners in the cold European countries relative to warm ones (12% vs. 8% annual growth rate) whose effect is not compensated by the faster diffusion of more efficient technologies in the market.

Econometric results from the same chapter (section 6.2.2.2), showed that personal income is the most important parameter in modelling AC diffusion for the EU-28 residential sector. Its impact on AC up-take was shown to be about 5 times as large as that of mean summer temperature. Moreover, results from the extended econometric model in section 6.4.1, provided evidence about the stronger dependence of AC diffusion on personal income and temperature in cold EU-28 countries compared to warm ones. This could be justified by the very early stage of AC market development in this group of countries. A further assessment of climatic effects (including that of humidity) was not pursued, since available data did not cover the evolution of residential AC stock for different seasons, when climatic impacts are more pronounced.

8.5.5 The context and materiality of identified impacts on future electricity systems

A better understanding of the factors which influence end-use electricity demand, and especially that for residential space cooling, contributed to assessing the nature and magnitude of anticipated impacts on future electricity systems. The size of projected impacts in the mid-21st century was determined differently in the saturated and un-saturated market case study: In the U.S. case study, the impact of annual residential electricity use, was defined as its contribution to the increase in aggregate final electricity consumption of the U.S. economy between present (2018) and future (2050) levels. In addition to impacts on baseload consumption, this assessment considered the potential implications on peak electricity demand from the increased peakiness of summertime residential electricity loads. The future change in the peakiness component (as defined in section 4.4.2). was then compared to the forecasted increase in total U.S. summer generating capacity.

In the EU-28 case study, the impact on baseload consumption was similarly estimated as the share of increase in EU-aggregate final electricity consumption in 2050 which is attributed to growing residential AC demand. In the absence of seasonal cooling load data, impacts on peak electricity demand were measured through the variable of potential peak cooling demand developed in eqn. (6-7). The growth in potential peak AC electricity demand as projected in 2050 was then benchmarked with the increase in net generating capacity of the EU-28 power sector. For both case studies, the identified impacts were first evaluated at the regional level and subsequently split between the two main sub-regions. Detailed quantitative results of this comparative assessment were presented in Table 7-1. This section elaborates on the implications of the identified impacts from a more qualitative point of view and discusses potential developments which could present additional challenges for the stable operation of future electricity systems.

8.5.5.1 Saturated AC market

First, in the case of the saturated U.S. market, mid-21st-century impacts of growing residential electricity use (due to socio-economic forces and warmer climatic conditions) were found to be more pronounced for baseload electricity consumption than for peak electricity system demand. This is not to say that increasing demand for residential space cooling will not exert more pressure on the electricity system's peak capacity. As explained in 7.2.1, the adopted method may underestimate impacts on peak electricity demand. The disproportionate growth of residential electricity consumption during summer months (peakiness of summertime residential electricity loads increases by 16-29% in 2050) at the very least will call for better allocation of peak capacity to meet cooling demand. This will therefore put strain on solar-based renewable capacity in the future, but also increase CO_2 emissions from fossil-fuelled peaking plants.

Second, impacts on the U.S. electricity system from growing residential electricity use will be reinforced by the expected seasonal increases of AC electricity demand in the services sector. Demand for air-conditioning in the transportation sector could also become increasingly climate-sensitive, which would further amplify this issue given the anticipated electrification of this sector in the future. The drivers of climate-sensitive demand in the transportation sector are however less well known (van Ruijven et al., 2019).

Third, due to the higher saturation level of income effects in north U.S., future impacts on baseload electricity use were found to be considerably larger in this (a 78-139% increase) region compared to south U.S. states (a 7-26% increase). The seasonal distribution of impacts in the north U.S. region remains an important research question as, due to the top-down nature of the model, the dominant income-related effects cannot be decomposed into those relating to increased demand for climate-sensitive or climate-insensitive services. Nevertheless, given the strong north-south polarisation of income effects (section 5.4.2), a plausible interpretation of these findings is that growing income will drive an increase in future residential electricity demand for both heating and cooling purposes. Further adoption of air-conditioners in households will be accompanied by a progressive switch from natural gas central furnaces (which is the primary heating technology in cold areas (U.S. EIA, 2017d)) to electric heat pumps. This will inevitably exacerbate the pressure on the north U.S. power sector from growing electricity loads during both the summer and winter season.

This development also implies that future models of residential energy use in the cold U.S. region need to take into account the structural change brought by the gradual electrification of the heating sector. In south U.S. on the other hand, impacts on future electricity systems can be more easily ascribed to seasonal AC electricity loads, driven by warmer weather, but also by populations migrating to warm areas. While the impacts of migration have not been explicitly included in the model as it was outside the scope of this PhD, one could adapt the projections presented in Chapter 5 to account for regionally-differentiated rates of future population growth.

8.5.5.2 Un-saturated AC market

Fourth, unlike the U.S. case study, impacts on future electricity systems in the un-saturated EU-28 market were evaluated to be more significant with respect to peak, rather than to baseload capacity additions (Table 7-1). The smaller impact on total final electricity use for the EU-28 region is explained by the current insignificant size of residential AC demand which despite its considerable growth in 2050, does not exceed that for other building end-uses, like space and water heating. Of greater importance is the increase in the electricity system's peak demand due to increased AC adoption (the impact on net generating capacity varies between 17 and 71% in 2050), although as discussed in 7.2 the employed method may overestimate the true magnitude of impacts. The dominant contribution of renewable energy sources to the EU-28 power mix in 2050 implies that increased AC electricity demand will primarily place strain on solar-based generating capacity. Similar to the U.S., the anticipated contribution of services and transport on future peak AC demand will add to this problem.

Fourth, spatially-disaggregated results demonstrated that increased adoption of space cooling technologies will have a greater effect on electricity systems in warm than in cold EU-28 countries (37-100% vs. 13-66% concerning the impact on peak capacity in 2050). The stronger impacts for the warm EU-28 sub-region is explained by the higher saturation level of AC equipment reached in 2050 (60%), as well as the very small role of cooling in current final energy demand for cold areas (0.2%). Moreover, while impacts from the annual increase in AC electricity demand are more pronounced in warm countries, the growth rate of potential AC peak demand in the cold EU-28 sub-region was shown to outgrow the forecasted growth of solar-based capacity (Figure 6-11). This finding highlighted challenges for generation and network performance in the electricity systems of cold EU-28 countries, which would emerge if there is not enough capacity to serve growing AC electricity loads. Finally, this finding underlined the increasing role of inter-seasonal storage technologies in the transmission of renewable electricity to regions having high peak cooling demand.

The reflective epilogue concludes this thesis. Sections 8.5.1, 8.5.2 and 8.5.3 highlighted the most important points regarding the choice of an appropriate modelling approach to answer the specific research questions of this PhD, as well as some of the challenges imposed by data unavailability. Section 8.5.4 identified the most important drivers of residential space cooling demand according to the state of diffusion in an AC market (saturated U.S. vs. un-saturated EU-28 region) and the climate (warm vs. cold sub-regions). Finally, section 8.5.5 provided the context about the implications for future electricity systems from the anticipated growth of residential space cooling demand. Undoubtedly, the foreseen increase in space cooling demand across the globe will be a major challenge for the stable operation of electricity systems and the effectiveness of climate change mitigation strategies in 2050. Further understanding its potential trajectories in the future and associated impacts for utility planning and policy should therefore be a constant endeavour for researchers in this area.

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Appendix A Future climate simulation models

Table A-1, Table A-2 and Table A-3 provide a list of CMIP5 climate models used in Chapter 4, 5 and 6 to project the impacts of multiple climatic metrics on future residential electricity use in the south U.S., contiguous U.S. and EU-28 region, respectively.

Table A-1 CMIP5 climate models used in climate data simulations (2046-55) for the south U.S. climatic region

No.	Climate model run with the MACA-LIVNEH downscaling method
1	bcc-csm1-1 (China)
2	bcc-csm1-1-m (China)
3	BNU-ESM (China)
4	CanESM2 (Canada)
5	CCSM4 (USA)
6	CNRM-CM5 (France)
7	CSIRO-Mk3-6-0 (Australia)
8	GFDL-ESM2G (USA)
9	GFDL-ESM2M (USA)
10	HadGEM2-CC365 (United Kingdom)
11	HadGEM2-ES365 (United Kingdom)
12	inmcm4 (Russia)
13	IPSL-CM5A-LR (France)
14	IPSL-CM5A-MR (France)
15	IPSL-CM5B-LR (France)
16	MIROC5 (Japan)
17	MIROC-ESM (Japan)
18	MIROC-ESM-CHEM (Japan)
19	MRI-CGCM3 (Japan)
20	NorESM1-M (Norway)

Table A-2 CMIP5 climate models used in climate data simulations (2046-55) for the contiguous U.S. domain

No.	Climate model run with the BCCA downscaling method
1	bcc-csm1-1 (China)
2	CanESM2 (Canada)
3	CCSM4 (USA)
4	CSIRO-Mk3-6-0 (Australia)
5	GFDL -CM3 (USA)
6	GFDL-ESM2G (USA)
7	GFDL-ESM2M (USA)
8	IPSL-CM5A-LR (France)
9	IPSL-CM5A-MR (France)
10	MIROC-ESM (Japan)
11	MIROC-ESM-CHEM (Japan)
12	MIROC5 (Japan)
13	MPI-ESM-LR (Germany)
14	MPI-ESM-MR (Germany)
15	MRI-CGCM3 (Japan)
16	NorESM1-M (Norway)

Table A-3 CMIP5 earth system and regional climate models used in climate data simulations (2016-50) for the EU-28 region

No.	Climate model configuration
1	CCCma-CanESM2 _SMHI-RCA4_v1
2	CNRM-CERFACS-CNRM-CM5_CLMcom-CCLM5-0-6_v1
3	CNRM-CERFACS-CNRM-CM5_CNRM-ALADIN53_v1
4	CNRM-CERFACS-CNRM-CM5_HMS-ALADIN52_v1
5	CNRM-CERFACS-CNRM-CM5_RMIB-UGent-ALARO-0_v1
6	CNRM-CERFACS-CNRM-CM5_SMHI-RCA4_v1
7	CSIRO-QCCCE-CSIRO-Mk3-6-0_SMHI-RCA4_v1
8	ICHEC-EC-EARTH_KNMI-RACMO22E_v1
9	IPSL-IPSL-CM5A-MR_SMHI-RCA4_v1
10	MIROC-MIROC5_CLMcom-CCLM5-0-6_v1
11	MIROC-MIROC5_SMHI-RCA4_v1
12	MPI-M-MPI-ESM-LR_CLMcom-CCLM4-8-17_v1
13	MPI-M-MPI-ESM-LR_CLMcom-CCLM5-0-6_v1
14	MPI-M-MPI-ESM-LR_MPI-CSC-REMO2009_v1
15	MPI-M-MPI-ESM-LR_SMHI-RCA4_v1
16	NCC-NorESM1-M_SMHI-RCA4_v1
17	NOAA-GFDL-GFDL-ESM2M_SMHI-RCA4_v1
18	MOHC-HadGEM2-ES_CLMcom-CCLM5-0-6_v1
19	MOHC-HadGEM2-ES_SMHI-RCA4_v1

Appendix B Historical electricity use model for the north U.S. climatic region (2000-18)

This section presents detailed results concerning the historical state-level model of per capita residential electricity use, constructed using monthly data for the 21 states belonging to the north U.S. climatic regions (i.e. west north central, east north central and northeast climatic sub-region). Descriptive statistics for the variables used in the analysis of historical (2000-18) residential electricity use in the north U.S. climatic region are provided in Table B-1.

Table B-1 Descriptive statistics of state-level variables for the north U.S. climatic region (2000-18)

Variable	Sym.	Mean	Std. Dev.	Max	Min
Electricity use (TWh/mo)	EL	1.29	1.28	6.32	0.07
Per capita electricity use (kWh/pop•mo)	EL_PC	335.16	103.07	933.78	130.08
Population	POP	4,336,599	4,796,877	19,656,084	493,457
Personal income (000’ 2018 $/pop)	INC	51.73	8.99	81.83	33.08
Electricity price (2018 Cents/kWh)	EP	14.21	3.59	25.25	7.46
Cooling degree days	CDD[a]	58	99	613	0
Heating degree days	HDD[a]	544	474	1941	0

[a] Degree day statistics correspond to NOAA’s published values for a fixed threshold of 18.3^{0}C.

Then, Table B-2 presents the FE estimation results (2000-15) for the north U.S. (per capita) residential electricity use model, under the reference (**Base$_0$**), as well as the best-performing base (**Base$_{opt}$**), extended (**Ext**) and humidity-based

Table B-2 FE estimation results of EL_PC (kWh/pop•mo) model for the north U.S. climatic region (2000-15)

	Base$_0$	Base$_{opt}$	Ext$_{avint}$	Hum$_{int}$
INC (000’ $/pop)	6.946***	5.684**	5.719**	6.588***
	(2.112)	(2.604)	(2.659)	(1.639)
INCSQ	-0.040***	-0.027	-0.028	-0.036***
	(0.014)	(0.018)	(0.018)	(0.013)
EP (cents/kWh)	-6.707***	-6.588***	-6.554***	-5.167***
	(0.737)	(0.773)	(0.783)	(0.655)
CDD	0.404***	0.568***	0.537***	0.164***
	(0.018)	(0.040)	(0.045)	(0.057)
HDD	0.107***	0.280***	0.279***	0.341***
	(0.010)	(0.020)	(0.020)	(0.019)
IHW$_{av}$			4.516***	
			(1.742)	
ICW$_{av}$			1.064	
			(1.518)	
IHW				-0.876
				(0.791)
ICW				-0.152
				(0.114)
HUM (g/kg)				16.484***
				(1.061)
IHW × HUM				0.168**
				(0.067)
Observations	4032	4032	4032	4032
$\overline{\beta_s}$	106.019	99.907	98.137	-15.635
	(73.455)	(87.493)	(88.683)	(57.253)
F-test	322.25***	305.03***	306.31***	400.21***
Hausman test	17.08	2.46	26.04	33.67
R^2 (adj.)	0.704	0.705	0.705	0.756

Statistically significant *** at 1%, ** at 5%, * at 10%, and confidence level. Note: Standard errors in parenthesis are computed via *a la Driscoll and Kraay* estimator which is robust to serial and cross-sectional correlation.

(**Hum**) specification, based on the R^2, AIC and BIC criterion. A discussion about the size and direction of personal income, electricity price and climatic effects on historical residential electricity use is provided in the main text (section 5.4.2). The result of the conducted F-test confirms the superiority of the FE estimator over the pooling one, as it signifies the presence of unit-specific effects in the sample. On the other hand, the Hausman test in this case fails to reject the null hypothesis that there is no correlation between the unit-specific effects and explanatory parameters. Still, the FE estimator is preferred over the RE one, as (a) inference about climatic and non-climatic effects on residential electricity use is conditional on the selected sample of states and not on a wider population and (b) the interest primarily lies in comparing the explanatory power of different specifications; which is independent of the choice between an RE and FE estimator.

Finally, Figure B-1 and Figure B-2 respectively compare the size of year- and month-specific effects, as computed for the north U.S. climatic region in the 2000-15 period under the reference ($Base_0$) and humidity-based specification (Hum_{int})[17]. Figure B-1 shows that while a common trend exists between the two specifications, whereby annual effects grow until year 2010 and decrease thereafter, extending the base specification to incorporate the new modelling features, including specific humidity, effectively reduces the size of yearly effects.

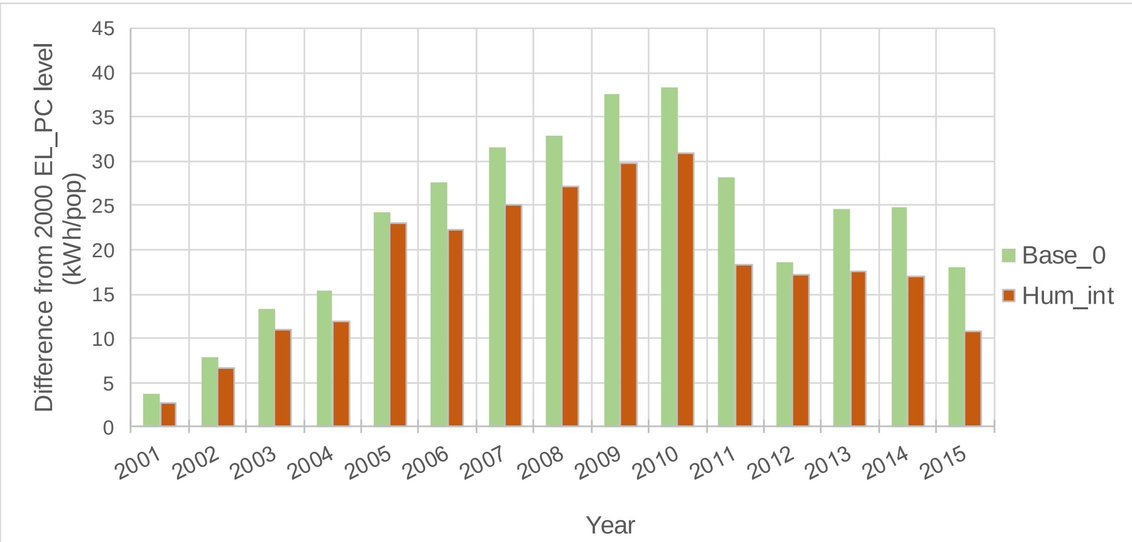

Figure B-1 Variation of annual-specific effects under the reference and humidity-based model for the 21 states in the north U.S. region

Figure B-2 shows that month-specific effects have a negative sign in spring and autumn under both specifications, implying that climatic metrics tend to

[17] The joint significance test for annual dummies under the Hum_{int} model is $\chi(15)=85.68^{***}$

overestimate the effect of weather variation on per capita residential electricity use during those seasons. During the winter season, addition of the new modelling features under the Hum_{int} specification reduces the reliance of model predictions on monthly dummy variables, as shown by their decreased size in February and December. Addition of the new modelling features through Hum_{int}[18] also reduces reliance of model predictions on August's dummy variable. On the other hand, model predictions for June's and July's residential electricity use levels depend less on month-specific effects under the $Base_0$ model.

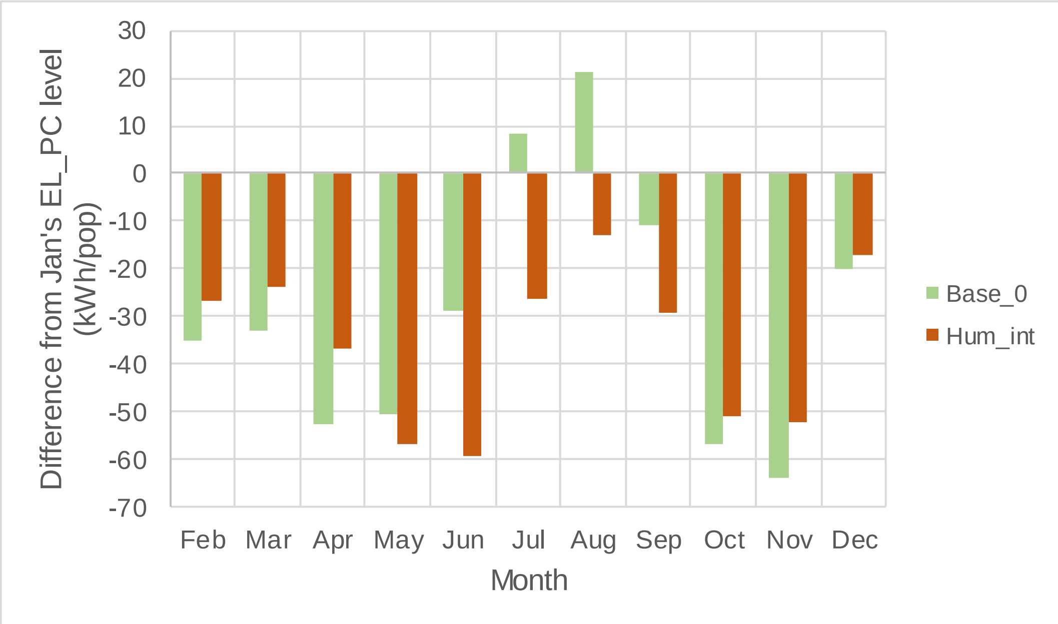

Figure B-2 Variation of month-specific effects under the reference and humidity-based model for the 21 states in the north U.S. region

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18 The joint significance test for monthly dummies under the Hum_{int} model is $\chi(11)=319.85^{***}$