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Matthew Ranson, Lauren Morris, and Alex Kats-Rubin

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Matthew Ranson*, Lauren Morris, and Alex Kats-Rubin, Abt Associates

*Corresponding Author:
Environment and Resources Division
Abt Associates Inc.
55 Wheeler Street
Cambridge, MA 02138
617-520-2484
matthew_ranson@abtassoc.com

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Abstract

This paper reviews recent evidence on the potential impacts of climate change on energy demand for space heating in residential and commercial buildings. We cover two main topics. First, we review empirical studies of the historical relationship between temperature and energy use for heating and cooling. These studies show consistent evidence of a U-shaped relationship between temperature and energy demand, in which energy use for heating is greatest at very low temperatures, and energy use for cooling is greatest at very high temperatures. The temperature at which energy use is minimized varies across geography and time periods, but in most studies is between 53°F and 72°F (12°C and 22°C). Second, we review studies that estimate how climate change will affect future energy use for space heating and cooling. Most studies predict that climate change will result in reductions in demand for heating and increases in demand for cooling. Although the sign of the net global effect depends on the time frame and climate change scenario, a very robust conclusion is that there is considerable variation across geographies, with the largest magnitude effects predicted for countries that currently have either very low or very high average temperatures. Overall, the results summarized in this paper will be useful for understanding the potential magnitude of the benefits of climate-related reductions in space heating, and for improving the damage functions used in integrated assessment models of climate change.

Key words: Climate change, space heating, space cooling, energy use, integrated assessment models

JEL Codes: (Q54) Climate/Natural Disasters and Their Management/Global Warming, (Q41) Energy Demand and Supply/Prices

1 Introduction

One of the simplest ways that households and firms will respond to climate change is by adjusting their expenditures on heating and cooling. Because the cost of heating interior building space makes up a substantial part of many households' budgets, the reduction in heating requirements due to climate change could provide a substantial social benefit. Of course, this benefit could be offset by increased expenditures on space cooling (or alternatively, the welfare costs of enduring higher ambient temperatures) during the warmer months.

To understand the potential magnitude of the benefits from climate-related reductions in space heating, and to collect information useful for improving the damage functions used in integrated assessment models (IAMs), this paper reviews economic literature relevant to the relationship between climate change and demand for space heating.[1] We cover two main areas.

We begin by reviewing empirical studies of the relationship between temperature and energy use for heating (and energy use more broadly). These studies use daily, monthly, or yearly variation in temperatures, possibly across different locations, to identify the effect that changes in temperature have on energy use. The results from these studies show consistent evidence of a U-shaped relationship between temperature and energy demand, in which energy use for heating is greatest at very low temperatures, and energy use for cooling is greatest at very high temperatures. For example, the studies we have reviewed suggest that in cold weather (below 50°F/10°C), a one degree Celsius increase in temperature decreases electricity use by 1% to 5%. In warm weather (above 68°F/20°C), the opposite is true: one degree of additional warming increases electricity use by 0% to 8%. The temperature at which energy use is minimized varies across geography and time periods, but in most studies is between 53°F and 72°F (12°C and 22°C).

Second, we review studies that estimate how climate change will affect future energy use for space heating and cooling. Most studies predict that climate change will result in reductions in demand for heating, and increases in demand for cooling. In aggregate, these two effects will partially cancel each other out. Although the sign of the net global effect depends on the time frame and climate change scenario, a very robust conclusion is that there is considerable variation across geographies, with the largest magnitude effects predicted for countries that currently have either very low or very high average temperatures.

The remainder of this paper is organized as follows. To motivate the review, Section 2 presents a simple model of how consumer demand for space heating is affected by changes in climate. Section 3 then summarizes the existing literature on the effect of temperature on space heating energy use. This section considers two main sources of evidence: panel data on how heating expenditures in a given location respond to weather shocks, and cross-sectional data on how average heating expenditures vary across geographic regions with different climates. Next, Section 4 reviews literature on how climate change could affect future space heating demand, and discusses challenges and issues related to making these predictions. Finally, Section 5 concludes.

[1] This review does not cover studies that focus specifically on space cooling, which are discussed elsewhere (see, e.g., Auffhammer and Mansur, 2012). This review also does not cover every study in the large literature on space heating. Instead, we have conducted a high-level survey.

2 Modeling the Welfare Impacts of Changes in Cold Exposure Caused by Climate Change

In order to understand how climate change could affect social welfare via changes in exposure to cold weather, it is useful to consider a representative consumer's space heating choice problem. Suppose that a consumer maximizes a one-period utility function $U(C, X)$, where C is a measure of comfort (e.g., the indoor temperature during a winter month), and X is a composite good (with price normalized to one) that captures all other sources of utility (e.g., food, housing, clothing). The consumer's production function for comfort is given by $C = f(T, E)$, where T is the outdoor temperature and E represents expenditures on space heating. Given a budget constraint, the consumer chooses E and X so that marginal utility from expenditures on space heating and the composite good are equal, conditional on T:

$$\frac{\partial U}{\partial C} \cdot \frac{\partial C}{\partial E} = \frac{\partial U}{\partial X}$$

Now consider the problem of modeling the effects of climate change on consumer welfare. Suppose that global temperatures warm by 1 degree because of climate change. If the consumer's utility function is locally linear, her willingness to pay for this one-degree increase would be approximately equal to the ratio:

$$WTP \equiv \frac{\frac{\partial U}{\partial T}}{\frac{\partial U}{\partial X}}$$

However, based on the results from the utility maximization problem, at the optimum this ratio is equal to:

$$WTP \equiv \frac{\frac{\partial U}{\partial T}}{\frac{\partial U}{\partial X}} = \frac{\frac{\partial U}{\partial C} \cdot \frac{\partial C}{\partial T}}{\frac{\partial U}{\partial X}} = \frac{\frac{\partial C}{\partial T}}{\frac{\partial C}{\partial E}} = \frac{\partial E}{\partial T}$$

This equality shows that the consumer's willingness to pay for climate-change-related reductions in cold exposure can be estimated by observing her marginal change in expenditures on space heating when the outdoor temperature increases by a small amount. This fact is useful because it motivates an empirical approach to estimating what would otherwise be a difficult-to-observe welfare change. For example, if the consumer spends an additional \$20 on space heating when outdoor temperatures cool by one degree, then the consumer's willingness to pay for one degree of climate change would be \$20.

Of course, this simple model neglects several important features of the climate change problem. First, the marginal utility of changes in comfort is not likely to be linear in temperature, particularly for large changes. Second, in the medium term, consumers have the option of switching between different heating technologies and fuels. Third, in the long term, the production function for comfort is not fixed, due to innovation in heating and insulation technology and changes in average interior space per house. Finally, households have the option of migrating to locations with more desirable weather. Nonetheless, despite these and other limitations, the model shows that in order to model the impacts of climate change on space heating demand, an IAM must have an estimate of how consumers' consumption of space heating changes when temperatures increase. The following section of this document reviews literature on this topic.

3 The Impact of Temperature on Space Heating Demand

This section reviews literature on how changes in temperature affect demand for space heating. We begin in Section 3.1 by describing the methodologies used in these studies. Then, in Section 3.2, we summarize the range of empirical results. Finally, in Section 3.3, we discuss some areas of remaining uncertainty in the literature.

3.1 Methodological Approaches

To identify relevant studies, we have relied on a variety of sources, including several existing bibliographies and literature reviews (Baer et al, 2013; Auffhammer and Mansur, 2012; Mideksa and Kallbekken, 2010). As Auffhammer and Mansur (2012) point out, most studies can be grouped into one of two methodological categories.

The first category is studies that use panel data to estimate how space heating energy use in a particular location responds to short-run variation in weather over time (e.g., Eskeland and Mideksa, 2009; De Cian, Lanzi, and Roson, 2013; Auffhammer et al, 2011; Deschenes and Greenstone, 2011; Lee and Chiu, 2011). The basic premise of the panel methodology is that because weather shocks are random, a regression of energy demand on weather will produce unbiased estimates of the causal effect of weather on energy demand. However, the drawback of this approach is that it only estimates the short-run demand response to changes in weather, and does not consider longer-run adaptation possibilities.[2] Thus, the empirical results from studies that use this methodology are likely to be an upper envelope to the long-run responsiveness of demand to changes in climate. The research frontier is currently working to address this challenge: for example, Sue Wing (draft, 2013) uses a dynamic panel data approach to estimate the cumulative long-term lagged effects of weather shocks on space heating demand. However, given that most parts of the world have not yet experienced large secular shifts in climate, it is not yet clear whether a dynamic approach can measure the full potential for long-term adaptation.

The second category is studies that use cross-sectional data to estimate how average space heating energy use depends on geographic variation in climate (e.g., Mansur, Mendelsohn, and Morrison, 2008; Mendelsohn, 2003). These studies run regressions that measure how energy expenditures depend on long-term average temperatures, controlling for other determinants of energy demand that also vary across geographies. The key insight of the cross-sectional approach is that people and businesses adapt to the environmental conditions in the area in which they live (Mendelsohn, Nordhaus, and Shaw, 1994). As a result, the cross-sectional relationship between space heating use and climate takes into account the long-term adaptation possibilities for responding to climate change, given current technologies (Mansur, Mendelsohn, and Morrison, 2008). However, the primary disadvantage of this approach is that it is vulnerable to omitted variable bias. For example, climate might be correlated with some other variable—such as average population age—that also determines demand for space heating.

3.1.1 Methodological Approaches Based on Panel Variation in Weather

We first review the methodologies from studies that use time-series or panel data to measure how space heating energy consumption is affected by weather shocks. These studies typically run regressions that measure how day-to-day, month-to-month, or year-to-year variation in weather affects space heating energy demand. As discussed above, although the use of panel data means that the empirical

[2] In principle, a panel approach could measure long-term adaptation possibilities, but only if the panel dataset included at least some locations where permanent changes in temperature had been observed. In practice, most locations in the United States and elsewhere have probably not yet experienced climatic changes large and salient enough to induce adaptation-related behavior.

relationships estimated by these studies are likely to be unbiased, their results do not capture the full spectrum of long-run adaptation possibilities that could be available for responding to climate change.

The studies we have reviewed use a range of econometric techniques to measure the effects of weather on space heating energy use. At the simplest end of the spectrum, Giannikopolous and Psiloglou (2006) plot daily aggregate residential and commercial electricity consumption against daily temperature, for Athens, Greece, from 1993 to 2001. Although their paper does not provide complete details about their methodology, they appear to have estimated an equation of the general form:

$$Energy_t = \beta_0 + f(Weather_t) + \epsilon_t \tag{1}$$

where the time variable t represents days, the function $f(\cdot)$ is a flexible spline, and ϵ_t is a zero-mean error term. Using this approach, the authors find a highly-significant U-shaped relationship: electricity consumption is highest at cold and hot temperatures, and lowest at approximately 72°F (22°C). Although this approach is straightforward to implement, it neglects seasonal or longer-term influences on energy demand—such as school calendars—that could potentially bias the results.

Other studies use econometric approaches that also control for observable covariates and for time or unit fixed effects (e.g., Auffhammer and Aroonruengsawat, 2012; Petrick et al, 2012; Deschenes and Greenstone, 2011). For example, using a panel of European countries, Eskeland and Mideksa (2009) estimate the effect of annual heating degree days (HDD)[3] and cooling degree days (CDD) on annual national household electricity consumption, controlling for electricity prices, per capita income, and year and country fixed effects. In generic form, their specification can be written as:

$$Energy_{it} = f(Weather_{it}) + \beta_1 Price_{it} + \beta_2 Income_{it} + \theta_i + \tau_t + \epsilon_{it} \tag{2}$$

where i indexes countries, t indexes years, and the coefficients θ_i and τ_t represent the effects of individual country and year dummy variables, respectively. They find that one extra CDD per year increases annual electricity demand by between 0.12% and 0.04%, and that that one extra HDD per year increases electricity demand by between 0.02% and 0.01%. Of course, their approach ignores the fact that electricity prices are not independent of electricity demand. To address this endogeneity, some other studies draw on statistical techniques from the broader literature on energy demand estimation. For example, in a 22-year panel dataset of energy use in OECD countries, Bigano et al (2006) estimate a version of Equation (2) using the Arellano and Bond estimator and lagged energy demand variables. They find that a 1% increase in annual temperature results in a 2.8% increase in annual coal consumption, a 0.6% decrease in electricity consumption, a 1.8% decrease in natural gas consumption, and 3.1% decrease in oil products consumption.

Finally, some studies use a dynamic econometric framework, in which space heating demand depends not only on current-period weather, but on weather in previous periods (e.g., Jorgensen and Joutz, 2012; Paul, Myers, and Palmer, 2009). For example, using a panel of monthly state-level data, Sue Wing (draft, 2013) estimates the long-term response of U.S. electricity demand to temperature shocks based on an autoregressive distributed lag model. A simplified version of his model can be written as:

[3] A "degree day" indicates that the daily average outdoor temperature was one degree higher or lower than some comfortable baseline temperature (in the United States, usually 65 degrees F) on a particular day. For example, if the average temperature on a particular day was 78 F, then that day contributed 13 cooling degree days and 0 heating degree days. If the average outdoor temperature was 34 degrees F, then that day contributed 0 cooling degree days and 31 heating degree days. As a reference, Minneapolis, MN, has about 8,000 HDDs and 700 CDDs per year, and Miami, FL, has 170 HDDs per year and 4,900 CDDs per year.

$$Energy_{it} = \sum_{u=0}^{U} f(Weather_{i,t-u}) + \beta_1 Energy_{i,t-1} + \theta_i + \tau_t + \epsilon_{it} \tag{3}$$

The key feature of the model is that it accounts not only for the contemporaneous effects of weather shocks on space heating use, but also their cumulative lagged effects. The purpose of including these lagged variables is to capture medium-term adaptation possibilities, such as installing new thermostats or switching heating and cooling technologies. Based on the draft results from the paper, the lags appear to be important: the medium-run semi-elasticities are three to four times as large as the single-period semi-elasticities.

As a reference, the first two panels of Table 1 present information about a broader set of studies that use time-series or panel approaches. For each study, the table describes characteristics of the study's dataset, including geography, time period covered, and unit of observation. The table also describes each study's estimation approach, including the dependent energy variable, the independent weather or climate variable, important control variables, specific details of the estimation procedure, and main results.

Note that only a few studies in the table (e.g., Amato et al, 2005; Fung et al, 2006) estimate the effect of temperature on heating as a distinct item, and only by focusing on fuels (e.g., heating oil) that are not used for cooling. The remaining studies consider how temperature affects energy demand more broadly, combining the effects of heating and cooling. As discussed in greater detail below in Section 3.2, many of these studies interpret the left-hand side of the U-shaped relationship between average daily temperature and total daily energy use as representing the effect of temperature on space heating, and the right-hand side as representing the effect of temperature on space cooling. However, since temperatures vary within the course of a day, the same house could potentially be cooled during the day and heated at night. Thus, using even daily data to distinguish the effects of temperature on energy use via the heating and cooling pathways is a challenging econometric exercise.

Due to space limitations, Table 1 provides limited detail about each study. Thus, to supplement the information in the table, Appendix A of this document provides extended descriptions of the methodologies and results from selected studies.

3.1.2 Methodological Approaches Based on Cross-Sectional Variation in Climate

We next review the methodologies from studies that measure how space heating energy consumption is affected by cross-sectional variation in climate. The key insight of the cross-sectional approach is that people and businesses adapt to the environmental conditions in the area in which they live (Mendelsohn, Nordhaus, and Shaw, 1994; Mansur, Mendelsohn, and Morrison, 2008). As a result, the cross-sectional relationship between space heating use and climate takes into account the long-term adaptation possibilities for responding to climate change, conditional on current heating and cooling technologies. Although the theoretical grounds for this approach are compelling, its primary weakness is that long-term climate is likely to be correlated with other determinants of space heating use. For example, if older Americans who prefer warm temperatures are more likely to retire to Florida, then the cross-sectional relationship between space heating use and climate would be biased by the endogenous migration decision.

We have identified only a few studies that use this approach. The most recent is Mansur, Mendelsohn, and Morrison (2008). Using data from representative surveys of households and commercial buildings across the United States, this study estimates a two-stage choice model. In the first stage, households and commercial buildings make a discrete choice of heating fuel type, based on climate and other control variables. Then, conditional on their first-stage decision, they make a second-stage continuous choice of fuel quantity. In the first stage, the authors find that warmer annual temperatures make residential customers less likely to choose oil or gas heat, and more likely to choose electricity only. In the second stage, the authors' estimates imply that households with natural gas or oil heat who live in climates that are 1°C warmer, on average, consume 6% to 15% more electricity annually and 1.5% less natural gas annually (the difference in oil consumption is a statistically-insignificant decrease of 7.1%). However, for customers with electric heat only, a 1°C increase in average annual temperature has no effect on annual electricity use, due to the changes in winter and summer electricity use cancelling out.

As a reference, the third panel of Table 1 presents detailed information about the studies we have found that use a cross-sectional approach. For each study, the table describes characteristics of the study's dataset, including geography, time period covered, and unit of observation. The table also describes characteristics of each study's estimation approach, including the dependent energy variable, the independent weather or climate variable, important control variables, and specific details of the estimation procedure.

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Panel Studies Based on Country-Level Data							
Bigano et al (2006)	3 to 29 OECD and other countries, 1978-2000	Country by year	Residential, commercial, and industrial use of coal, gas, electricity, oil, and oil products (Ktoe)*	Yearly average temperature	GDP, price	Panel regression using Arellano and Bond estimator, with lagged demand and country fixed effects	Elasticities with respect to temperature (in °F) are 2.8 for coal, -0.6 for electricity, -1.8 for natural gas, and -3.1 for oil products.
Bessec and Fouquau (2008)	15 European countries, 1985-2000	Country by month	Combined residential, commercial, and industrial electricity use (gW/hr)	Monthly average temperature	Population, production in total manufacturing, cubic polynomial of time	Panel regression with threshold function approach that allows different functional forms depending on the absolute value of the temperature variable	In the authors' preferred specification, semi-elasticities of electricity use with respect to temperature (in °C) are approximately -2.0 at 0°C, 0 at 15°C, and 0.7 at 25°C.
Eskeland and Mideksa (2009)	31 European countries, 1994-2005	Country by year	Annual household electricity consumption (kWh)	Annual HDD and CDD [base temp is 18°C for HDD and 22°C for CDD]	Electricity prices, per capita income	Panel regression with year and country fixed effects	The semi-elasticity of annual electricity demand with respect to CDDs is between 0.12 and 0.04; the semi-elasticity of annual electricity demand with respect to HDDs is between 0.02 and 0.01.
Lee and Chiu (2011)	24 OECD countries, 1978-2004	Country by year	Electricity consumption per capita (kWh)	Annual average temperature	Income, electricity price	Panel regression allowing non-linear threshold effects of price, income, and temperature, with country fixed effects and lagged explanatory variables	For the specification with temperature as the threshold variable: for countries with yearly average temperatures below 53°F, the elasticity of electricity demand with respect to temperature (in °F) is -0.6 (although not significant), while above 53°F, it is 0.2 and significantly higher.

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
De Cian, Lanzi, and Roson (2013)	31 countries from around the world, 1978-2000	Country by year	Residential gas, electricity, oil products, and coal use (Ktoe)	Temperature (spring, summer, fall, winter)	GDP per capita, fuel price	Panel regression with autoregressive term and country fixed effects, estimated as error correction model, with separate coefficients for hot, mild, and cold countries.	In winter, Fahrenheit temperature semi-elasticities of annual energy use are negative in for every fuel type (-0.9 to -3.5). However, in the spring and summer, some temperature semi-elasticities for electricity are negative and some are positive (-3.3 to 5.4), depending on geography.
Petrick et al (2014)	20 countries (coal), 56 countries (electricity), 36 countries (natural gas), 32 countries (oil), 1970-2002	Country by year, unbalanced	Residential coal, electricity, natural gas, and oil use (per capita toe)	Annual heating degree months (HDM), cooling degree months (CDM)** [base temperature for both HDM and CDM is 18.3°C]	Income, fuel prices	Panel regression with country fixed effects and lagged dependent variables, and quadratic in HDM	The HDM coefficients are positive and generally significant, indicating that fuel use decreases as temperatures rise (for temperatures below the HDM threshold of 18°C/65°F). The elasticity with respect to HDM is 0.45 for coal, 0.03 for electricity, 0.41 for natural gas, and 0.17 for oil. The authors state that none of the CDM coefficients are significantly different from zero, but do not report CDM regression results.
Panel or Time-Series Studies Based on Data from Single Countries or Regions within Single Countries							
Henley and Peirson (1997)	75 U.K. households, 1989-1990	Household by time of day (morning, afternoon, evening, night)	Household electricity demand (kWh)	Hourly temperature	Illumination, weekend, holidays	"Fractional polynomial approach" with household fixed effects	Declining non-linear relationship between electricity consumption and temperature, with consumption flat above approximately 22°C. (See Figure 1 in this literature review for a graphical depiction of the results.)

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Sailor and Munoz (1997)	California, Washington, Texas, Louisiana, Illinois, Ohio, New York, and Florida, 1982-1994	State by month	Combined residential and commercial electricity and natural gas consumption	Model 1: Temperature, humidity, and windspeed; Model 2: HDD, CDD, enthalpy latent days, and windspeed [base temperature for HDD and CDD is 18.3°C, except is 21°C in Florida]	Population	Linear time-series models, estimated separately for each state, with dependent variable normalized by population	Model 1: In the summer, a temperature increase of +1°C increases per capita electricity demand by 6 to 32 kWh/month, depending on the state. In the winter, a temperature increase of +1°C decreases per capita electricity demand by 4 to 16 kWh/month. Model 2: One HDD increases per capita electricity consumption by 0.12 to 0.95 kWh/month. One CDD increases per capita electricity consumption by .44 to 1.5 kWh/month.
Considine (2000)	USA	USA by month	Residential, commercial, industrial, electric utility, and “propane” energy use	Monthly HDD and CDD deviation from 30-year average [base temperature for HDD and CDD is 65°F]	Price, income, output, employment	Linear logit model used to estimate demand systems simultaneously for each sector, with month fixed effects	Residential: the semi-elasticities of monthly energy use with respect to HDDs and CDDs per month are 0.016 and 0.027, respectively. Commercial: the same semi-elasticities are 0.011 and 0.016, respectively.
Valor et al (2001)	Spain, 1983-1999	Spain by day	Combined all-sector electricity consumption	Daily temperature, HDD, CDD [base temperature for HDD and CDD is 18°C]	Seasonality and weekday/ holiday	Spline of daily electricity use as a function of each variable	U-shaped relationship between energy use and temperature, with minima at approximately 64°F (18°C). The effect of hot weather becomes more prominent over time. On average, one additional daily HDD increases daily electricity demand by approximately 1.2%; one additional daily CDD increases daily electricity demand by approximately 1.3%. (See Figure 1 in this literature review for a graphical depiction of the results.)

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Bhattacharya et al (2003)	United States, 1980-1998	Houshold by month (rotating panel)	Expenditures on heating oil, electricity, natural gas, coal, kerosene, and firewood	Monthly temperature	Household income	Log-linear panel regression with year, state, and month fixed effects	A 10°F decrease in average monthly temperature results in a $53 increase in energy expenditures for rich families and a $37 increase in energy expenditures for poor families. (Baseline expenditures are not given in the study.)
Amato et al (2005)	Massachusetts, 1977-2001	State by month	Residential and commercial electricity, natural gas, and heating oil sales (kWh/month)	Monthly HDD and CDD [base temperatures for HDD and CDD are 55°F for commercial electric sector, 60°F for residential electric and commerical fuel sectors, and 65°F for residential fuel sector.]	Population, employment, day length	Linear regression, with dependent energy variable normalized per capita (residential) or per employee (commercial)	Residential: the semi-elasticities of monthly energy use with respect to monthly HDDs and CDDs are 0.047 and 0.038 for electricity use (kWh/person/month). The semi-elasticities with respect to month HDDs are 0.17 for natural gas use (cubic ft/person/month) and 0.13 for heating oil use (gallons/person/month).
Assadoorian et al (2006)	21(?) Chinese provinces, 1995-2000	Province by year	Urban and rural residential and non-residential electricity demand; AC, refrigerator, and TV purchases	Annual, seasonal, and monthly temperature	Electricity price, income	Two-stage choice model, with appliance choice as first stage and electricity consumption as second stage	Residential urban electricity use: elasticities with respect to temperature (in °F) are 2.1 in the summer, -1.9 in the fall, and not significantly different from zero in the winter and spring. Residential rural and non-residential electricity use: almost all of the elasticities are not significant.
Franco and Sanstad (2006)	California, 2004-2005	State by day	Electricity demand (MWh)	Daily average temperature	None	Model electricity demand as cubic function of daily temperature	Strong U-shaped relationship between energy use and temperature, with minimum at 54°F (12°C). (See Figure 1 in this literature review for a graphical depiction of the results).

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Giannikopolous and Psiloglou (2006)	Athens, Greece, 1993-2001	Athens by day and hour	Residential and commercial electricity use (kWh)	Daily and hourly air temperature, daily HDD, daily CDD	None	Spline of raw daily electricity use as a function of each weather variable	Strong U-shaped relationship between energy use and temperature, with minimum at 72°F (22°C). Based on data from 2001, one extra HDD (°C) increases electricity in Athens by 1.14 GWh, and one extra CDD (°C) increases electricity demand by 0.59 GWh. (See Figure 1 in this literature review for a graphical depiction of the results).
Fung et al (2006)	Hong Kong, China, 1990-2004	Hong Kong by month	Residential, commercial, and industrial electricity, natural gas, and oil products	Mean monthly temperature	None	Regress average monthly energy use on quadratic function of average monthly temperature	Residential: Temperature has a U-shaped positive effect on electricity use (with a minimum between 18°C and 20°C), a strictly-declining negative effect on natural gas use, and no effect on oil products use. Commercial and industrial: Electricity use increases linearly with temperature, but natural gas and oil use are not affected by temperature. (See Figure 1 in this literature review for a graphical depiction of the results).
Deschenes and Greenstone (2011)	United States, 1968-2002	State by year	Residential energy use (all fuels, BTU)	Binned daily mean temperature, binned precipitation	Population, GDP	Panel regression with Census division-by-year and state fixed effects	Strong U-shaped relationship between energy use and temperature, with minimum at 55-60°F. (See Figure 1 in this literature review for a graphical depiction of the results).
Auffhammer and Aroonruengsawat (2011)	California (80% of households), 2003-2006	Household by month (billing cycle)	Residential household electricity consumption (kWh), electricity expenditures	Binned daily temperature, quadratic precipitation	Electricity price	Panel regression with household, month, and year fixed effects, estimated separately by climate zone	Strong U-shaped relationship between energy use and temperature, with a minimum at 65°F in most of California's climate zones. (See Figure 1 in this literature review for a graphical depiction of the results).

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Gupta (2012)	Delhi, India, 2000-2009	Delhi by day	Total electricity demand (MkWh)	Daily mean apparent temperature (accounts for humidity and wind), rainfall	Fixed effects for holidays, weekdays, year,	Spline of daily electricity use as a function of temperature	Strong U-shaped relationship that becomes steeper over time (2009 vs 2000). The temperature that minimizes energy use falls from approximately 21°C in 2000 to 19°C in 2009. (See Figure 1 in this literature review for a graphical depiction of the results).
Chikobvu and Sigauke (2013)	South Africa, 2000-2010	Nation by day	Total electricity use for all sectors (MWh)	Daily average temperature, daily HDD and CDD	None	Piecewise linear regression above 22°C and below 18°C	Above 22°C, a 1°C increase causes a 0.55% increase in electricity use. Below 18°C, a 1°C decrease causes a 1.03% increase in electricity use.
Sue Wing (2013)	United States, 1990-2010	State by month	Residential, commercial, and industrial use of electricity (MWh)	Binned daily temperature	Electricity price, natural gas price, income, population, compensation, employment	Autoregressive distributed lag dynamic panel, with state and month fixed effects	Residential: there is a U-shaped relationship between energy use and temperature, with a minimum at 55-60°F. Industrial and commercial: electricity consumption is highest at high temperatures, but levels off below about 45°F. (See Figure 1 in this literature review for a graphical depiction of the results).
Hou et al (2014)	Shanghai, China, 2003-2007	Shanghai by day	Total electricity use for all sectors (million kWh)	Daily average temperature, monthly HDD and CDD	None	Piecewise linear regression	U-shaped relationship between temperature and electricity use, with minimum between 13°C and 20°C. One additional CDD per month increases electricity use by 402,000 kWh (approximately 0.16%). HDDs have no statistically significant effect.
Cross-Sectional Studies of Space Heating Demand and Climate							
Vaage (2000)	2,289 Norwegian households, sampled in 1980	Household	Electricity, oil, and wood expenditures	Dummy variable for five warmest counties	Demographics, building characteristics, fuel prices	Discrete-continuous model of fuel choice and quantity	First stage: households in warmer counties are less likely to use oil or wood (compared to electricity). Second stage: households in warmer counties use 29% less energy.

Table 1: Studies of Energy Demand and Weather

Study	Geography and Time Period	Unit of Obs.	Dependent Variable	Weather/ Climate Variables	Other Key Variables	Methodology	Main Empirical Results
Mendelsohn (2003)	Representative survey of 5,000 households and 5,600 commercial buildings, sampled in clusters from U.S., 1989-1990	Household or building	Energy expenditures	January and July temperature and precipitation	Demographics, building characteristics, fuel prices	Logit choice model of AC use, followed by OLS continuous model of energy expenditures	Residential first stage: higher summer temperatures increase the probability of AC use. Residential second stage: higher winter temperatures reduce energy expenditures; summer energy expenditures are minimized at a temperature of 20°C.
Mansur, Mendelsohn, and Morrison (2008)	Representative survey of 5,000 households and 5,600 commercial buildings, sampled in clusters from U.S., 1989-1990	Household or building	Residential: electricity, natural gas, fuel oil, liquid petroleum gas, and kerosene; Commercial: electricity, natural gas, fuel oil, and district heat	Temperature and precipitation	Demographics, building characteristics, fuel prices,	Multinomial discrete-continuous fuel choice model, with fuel type as first stage regression and fuel quantity as second stage, and with regional fixed effects	First stage: warmer winter temperatures make consumers less likely to choose oil heat, and warmer summer temperatures make consumers more likely to choose oil or electricity only. Second stage: consumers who live in areas that are 1°C warmer in both winter and summer consume 1% more electricity (for households with only electricity; coefficient not significant), 6% more electricity (for households with natural gas heat), and 15% more energy (for households with oil heat).

*Note: To supplement the information in this table, Appendix A of this document provides extended descriptions of the methodologies and results from selected studies. Footnotes: * The abbreviation "toe" refers to tons of oil equivalent. ** Heating and cooling degree months are defined analogously to heating and cooling degree days, but based on whether monthly (not daily) average temperature exceeds some threshold.*

3.2 Summary of Empirical Results

This subsection summarizes the empirical findings from the studies listed in Table 1.

3.2.1 Spatial, Temporal, and Energy Type Coverage

The studies in Table 1 cover a range of geographic areas and time periods. For example, Deschenes and Greenstone (2011) use annual data for U.S. states from the period 1968 to 2002; De Cian, Lanzi, and Roson (2013) use annual data for 31 countries from around the world from the period 1978-2000; and Petrick et al (2014) use annual data for 62 countries from the period from 1970 to 2002. Others cover shorter periods of time and more limited geographies. For example, Auffhammer and Aroonruengsawat (2011) use monthly household level data for almost 80% of households in California, but covering only the period from 2003 to 2006. Most studies focus on the developed world, although a few consider developing countries such as China (Fung et al, 2006; Hou et al, 2014), South Africa (Chikobvu and Sigauke, 2013), and India (Gupta, 2012). It is worth noting that in some areas of the Global South, the climate does not require space heating (Al-Sayer and Al-Ibrahim, 2006; Segal et al, 1992).

Table 1 also highlights the fact that the unit of observation varies considerably across studies. Most of studies use aggregate data, often at the city, state, or national level (e.g., Lee and Chiu, 2011; Bigano et al, 2006). Others, such as Mansur, Mendelsohn, and Morrison (2008) and Auffhammer and Aroonruengsawat (2011), use detailed data on household-level choices.

Finally, the type of energy variables included as dependent variables also varies considerably. One challenge for this literature review is that most studies do not break out impacts on space heating separately, but instead consider combined heating and cooling demand, or energy use more generally. This problem is particularly acute for electricity use, due to the fact that it is difficult to separate electric space heating from other components of electricity demand. Nonetheless, the studies collectively cover demand for a wide variety of space heating energy sources, including coal, electricity, natural gas, and oil, sometimes including a number of fuels within individual studies (e.g., Petrick et al, 2012; De Cian, Lanzi, and Roson, 2013). Some studies also have information on different users or sectors, such as residential and commercial/industrial energy use (e.g., Bigano et al, 2006).

3.2.2 Summary of Empirical Results

The broad finding that emerges from the studies in Table 1 is that weather and climate have a strong effect on space heating use—and more broadly, on energy use. In particular, the empirical evidence strongly suggests that there is a <u>U-shaped relationship</u> between temperature and total energy demand (e.g., Valor et al, 2001; Deschenes and Greenstone, 2011).

To provide some visual intuition for this relationship, Figure 1 presents a selected set of estimates of the relationship between energy use and temperature, drawn from a wide variety of studies. Although the units vary from study to study, all of the plots have temperature on the x-axis and a measure of change in energy consumption on the y-axis. For example, Panel (e) graphs daily electricity consumption and temperature for Athens, Greece, based on Giannikopolous and Psiloglou (2006). The panel shows that electricity use is initially decreasing in temperature, achieves a minimum at approximately 22°C, and then increases sharply. This U-shaped pattern is typical of most of the studies reviewed here, although the location of the minimum and the degree of curvature do vary across studies.

However, as the figure shows, there are at least three cases in which studies do not find a U-shaped relationship between energy use and temperature. First, for fuels that are typically used only for heating, fuel use has a declining relationship with temperature. For example, Panel (d) shows that monthly natural gas sales in Massachusetts are a strictly decreasing function of monthly average temperature, based on Amato et al (2005). Although not shown here, the study finds a similar declining relationship for heating oil, and a U-shape relationship for electricity. Of course, this is completely consistent with an overall U-shaped relationship between total energy demand and temperature, since most space cooling uses electricity, not heating fuel.

Second, there is suggestive evidence that energy consumption in some regions, such as Europe and India, has become more sensitive to high temperatures in more recent years. For example, the Henley and Peirson (1997) results in Panel (a) give no indication that U.K. electricity demand increases when temperatures go above a comfortable temperature, based on data from 1989. Similarly, the Valor et al (2001) results in Panel (c) show only a very modest uptick in Spanish electricity demand on hot days, based on data from 1983. However, Valor et al (2001) find that fifteen years later, using data from 1998, the curvature of the relationship above 17°C is much more pronounced. In disaggregated results not shown here, Bessec and Fouquau (2008) also find that electricity consumption is more sensitive to high temperatures in the 1995-2000 period than in the 1985-1990 period. Furthermore, Panel (e), which shows daily Greek electricity demand based on Giannikopolous and Psiloglou (2006), does suggest that energy consumption increases at high temperatures, based on data covering 1993 through 2001. Finally, in a study of Delhi, India, Gupta (2012) finds that electricity use became more sensitive to temperature between 2000 and 2009.

Third, commercial and industrial energy demand may respond somewhat differently to temperature, compared to residential energy demand. For example, Panel (l) shows results from Sue Wing (2013, draft) for the relationship between commercial electricity use and temperature. The panel shows that this relationship is essentially flat up to 40 or 50°F, and then begins to increase.

To complement these figures, Table 2 summarizes information from selected studies that have estimated the temperature at which energy demand is minimized. The table shows that most estimates indicate that energy use is lowest when daily (or monthly) temperatures are between 50°F and 75°F, with some variation across geographies and studies. The lowest estimates are from Sue Wing (draft, 2013), who finds that electricity use is minimized at average daily temperatures of 25-50°F in the U.S. commercial sector and 35-40°F in the U.S. industrial sector. Even within locations, there may be some variation over time. For example, Gupta (2012) finds that the energy-minimizing temperature declined in Dehli, India, between 2000-2005 and 2006-2009, possibly reflecting increasing air conditioner adoption over that time period. In a survey of available literature on energy demand responses to climate change, Mideksa and Kallbekken (2010) conclude that differences in energy demand responses to temperature across studies reflect, in large part, regional variation. Some factors that determine regional variation include urban structure, technology, household size, wealth, energy efficiency, latitude, variation in regional energy prices due to differing natural resource endowments, and local preferences. And of course, although overall energy demand is U-shaped, demand for space heating is strictly decreasing in temperature. For example, Amato et al (2005) find that the use of natural gas and heating oil—which are primarily used for heating, not cooling—declines as temperatures increase.

Figure 1: Graphical Results from Selected Studies

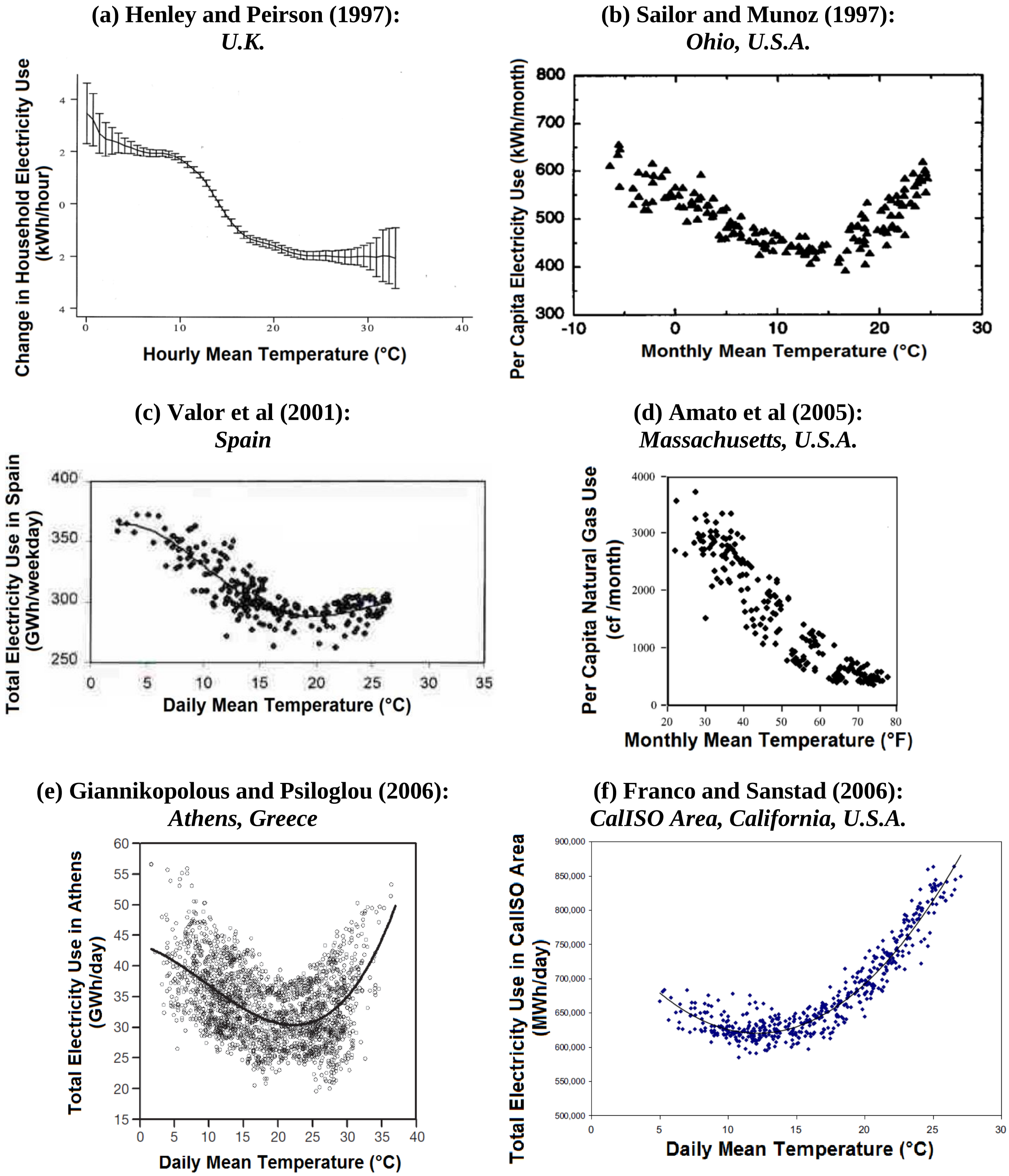
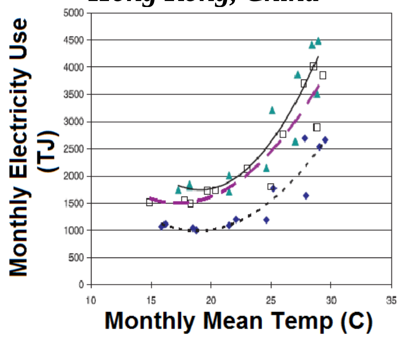
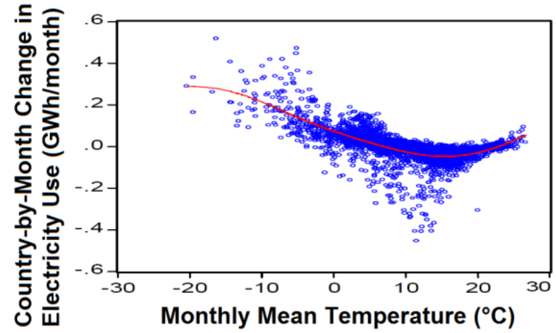


Figure 1: Graphical Results from Selected Studies

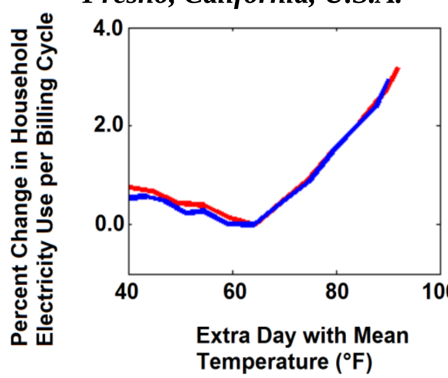
(g) Fung et al (2006):
Hong Kong, China



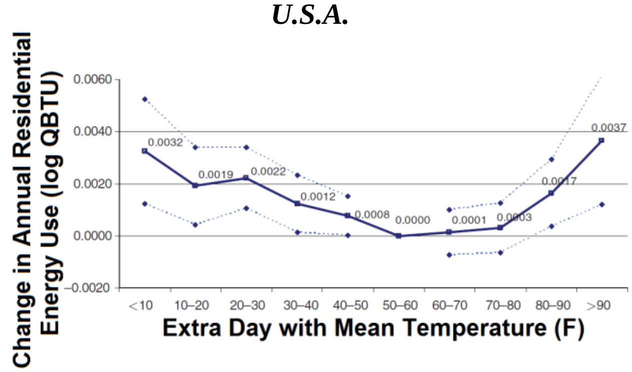
(h) Bessec and Fouquau (2008):
15 E.U. countries



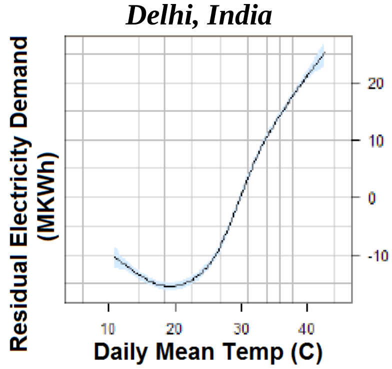
(i) Auffhammer and Aroonruengsawat (2011):
Fresno, California, U.S.A.



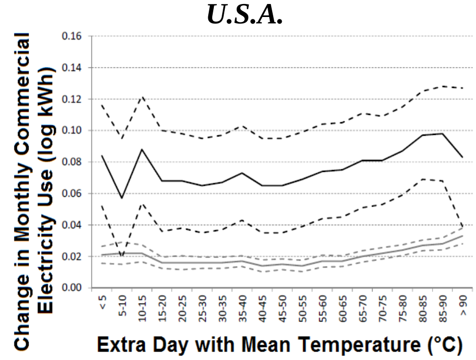
(j) Deschenes and Greenstone (2011):
U.S.A.



(k) Gupta (2012):
Delhi, India



(l) Sue Wing (2013, draft):
U.S.A.



*Sources: **Panel (a):** Figure 3 in Henley and Peirson (1997). It shows hourly electricity use from 4pm and 7pm. **Panel (b):** Figure 2 in Sailor and Munoz (1997). **Panel (c):** Figure 6 in Valor et al (2001). It shows weekday electricity demand in Spain. **Panel (d):** Figure 8 in Amato et al (2005). **Panel (e):** Figure 7 in Giannikopolous and Psiloglou (2006). It shows weekday electricity consumption. **Panel (f)**: Figure 4 in Franco and Sanstad (2006). **Panel (g):** Figure 2 in Fung et al (2006). It shows residential electricity demand. **Panel (h):** Bessec and Fouquau (2008). It shows residuals from a regression of country-by-month electricity consumption on controls. **Panel (i):** Auffhammer and Aroonruengsawat (2011). It shows the impact of an extra day of weather on log electricity use per billing cycle. **Panel (j):** Figure 3 of Deschenes and Greenstone (2011). It shows the effect of an extra day of weather per year on log annual state-level residential energy consumption. **Panel (k)**: Figure 5a of Gupta (2012). It reflects electricity demand in Delhi in 2009. **Panel (l):** Sue Wing (2013, draft). It shows the impact of an extra day of weather on log of state-level monthly commercial electricity use. Gray and black lines are static and lagged dynamic model estimates.*

Table 2: The Temperature at which Energy Use Is Minimized

Study	Geography	Temperature that Minimizes Energy Use	Temperature Definition
Sue Wing (draft, 2013)	United States: *Commercial electricity users* *Industrial electricity users* *Residential electricity users*	 25-50°F 35-40°F 55-60°F	Daily mean temperature
Lee and Chiu (2011)	24 OECD countries	53°F	Annual mean temperature
Franco and Sanstad (2006)	California	54°F (12°C)	Daily mean temperature
Deschenes and Greenstone (2011)	United States	55-60°F	Daily mean temperature
Amato et al (2005)	Massachusetts: *Commercial electricity users* *Residential electricity users* *Natural gas users:* *Heating oil users:*	 55°F 60°F n/a (downward sloping) n/a (downward sloping)	Monthly mean temperature
Bessec and Fouquau (2008)	European Union *4 coldest countries* *All 15 countries* *4 warmest countries*	 58°F (14.7°C) 60°F (16.1°C) 72°F (22.4°C)	Monthly mean temperature
Valor et al (2001)	Spain	64°F (18°C)	Daily mean temperature
Hart and deDear (2004)	Sidney, Australia	64°F (18°C)	Daily mean temperature
Auffhammer and Aroonruengsawat (2011)	California, 16 climate zones *1 of 16 climate zones* *15 of 16 climate zones*	 60°F (16°C) 65°F (18.3°C)	Daily mean temperature
Hou et al (2014)	Shanghai, China	56°F-68°F (13°C-20°C)	Daily mean temperature
Psiloglou et al (2009)	London, UK Athens, Greece	60°F (16°C) 68°F (20°C)	Daily mean temperature
Fung et al (2006)	Hong Kong, China	64°F-68°F (18°C-20°C)	Monthly mean temperature
Sailor and Munoz (1997)	United States, 5 states *Ohio* *California* *Louisiana* *Washington* *Florida*	 57°F (14°C) 63°F (17°C) 64°F (18°C) 68°F (20°C) 70°F (21°C)	Monthly mean temperature
Gupta (2012)	Dehli, India: *2000* *2009*	 70°F (21°C) 66°F (19°C)	Daily mean temperature
Chikobvu and Sigauke (2013)	South Africa	72°F (22°C)	Daily mean temperature
Giannikopolous and Psiloglou (2006)	Athens, Greece	72°F (22°C)	Daily mean temperature
Henley and Peirson (1997)	UK	n/a (downward sloping)	Daily mean temperature

In addition to comparing how the energy-minimizing temperature differs across studies, it is also of interest to compare the slope of the temperature-energy relationship. To make this comparison, Figure 2 presents standardized results from a selected set of studies of the relationship between temperature and residential electricity use. In the figure, the results from each study have been normalized so that total electricity use is set equal to 100 at the energy-minimizing temperature for that study. Panel (a) of the figure presents results similar to those from Figure 1, with estimates from multiple studies superimposed. The panel shows that after normalization, the general U-shaped pattern is quite consistent across studies, although both the energy-minimizing temperature and the energy-temperature slope do vary.

Panel (b) of Figure 2 then uses the same set of studies to calculate the marginal effect of a one degree C change in temperature on residential electricity use, expressed in percentage terms. If temperatures in a particular country were constant across locations and seasons, these results would have a direct interpretation as the predicted effect of climate change on electricity use. For example, at an ambient temperature of 10°C (50°F), one degree of warming causes a decrease in electricity use of between about one and five percent, depending on the study. At 20°C (68°F), the opposite is true: one degree of warming leads to an increase in electricity use of between zero and eight percent. The overall pattern is similar across studies, although again there are differences in the magnitude of the estimated changes.

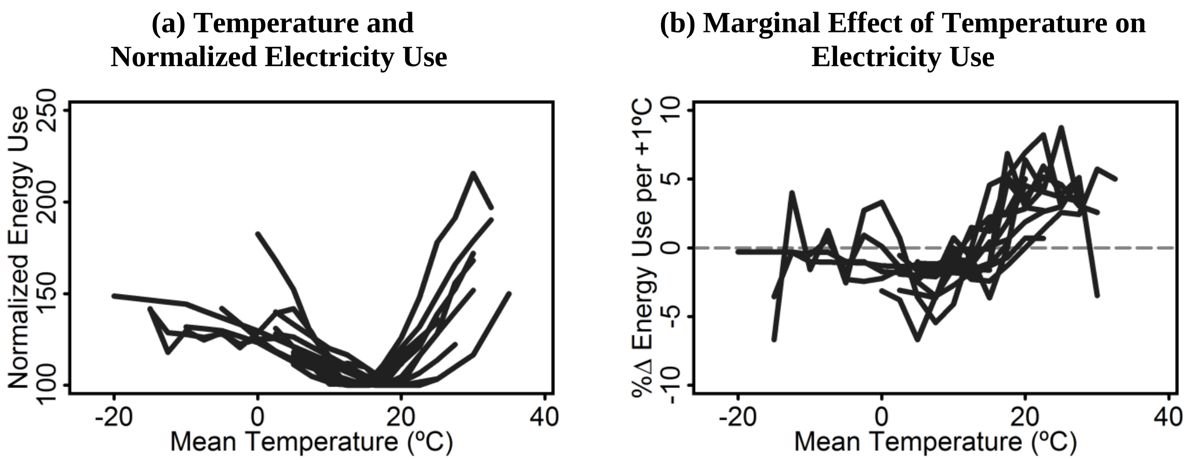
Of course, temperatures do vary across locations and seasons, and so predicting the effects of climate change for a particular country would require using Panel (b) to estimate the marginal change in electricity use at the average temperature for each month of the year at grid points covering the country. The sum of these marginal effects (across all grid points and months, weighted by baseline electricity use) would represent the average effect of one degree of warming on electricity use for that country.

While we do not attempt this calculation for any specific countries, we do consider what Panel (b) implies about how climate change could affect countries with hot and cold climates. For example, Panel (b) suggests that for a very hot country in which temperatures are usually above 20°C, one degree of climate change would produce an unequivocal increase in electricity use, most likely in the range of two to six percent. For a very cold country in which temperatures are usually below 20°C, Panel (b) suggests that one degree of climate change would probably cause a decrease in electricity use, although the magnitude of the decrease would likely be less than five percent and could be close to zero. In general, because most countries experience a range of warm and cool temperatures, country-level aggregate effects of climate change on electricity use are likely to be bounded by these two extreme cases.

To put these estimates in context, it is helpful to compare them to results from studies that estimate temperature-energy use relationships based on country-by-year panel datasets. For comparison, based on a panel of 31 countries for the period from 1978 to 2000, De Cian, Lanzi, and Roson (2013) estimate that a one-degree C increase in summer temperatures would lead to a 5.9% decrease in annual electricity use in cold countries, a 3.8% increase in electricity use in moderate countries, and a 3.2% increase in electricity use in hot countries (-3.3%, +2.1%, and +1.8%, per degree F, respectively). In the winter, the authors estimate that a one degree C increase in temperate reduces annual electricity consumption by 1.6% (+0.9% per degree F) in all countries. Since these semi-elasticities represent the effect of seasonal temperature on annual electricity use, they imply changes in electricity use that are substantially higher than the predictions summarized in Panel (b) of Figure 2.

In a different study using annual panel data for 15 European countries between 1985 and 2000, Bessec and Fouquau (2008) estimate that semi-elasticities of annual electricity use with respect to temperature (in °C) are approximately -2.0 at 0°C, 0 at 15°C, and 0.7 at 25°C. These estimates are generally consistent with the patterns shown in Panel (b) of Figure 2.

Figure 2: The Relationship between Temperature and Residential Electricity Use



Notes: The figure summarizes results from selected studies of the relationship between temperature and residential electricity use (Sailor and Munoz, 1997; Valor et al, 2001; Franco and Sanstad, 2006; Giannikopolous et al, 2006; Bessec and Fouquau, 2008; Auffhammer et al, 2011; Sue Wing, 2013; Hou et al, 2014). Panel (a) presents a separate line for each set of estimates from each study, where each set of results have been scaled so that they take the value 100 at their energy-minimizing temperature. Panel (b) shows the marginal effect of temperature on electricity use, based on each study from Panel (a).

3.3 Areas of Uncertainty in the Literature

Our review of the studies in the previous section and in Table 1 suggests several areas of remaining uncertainty in the literature.

One issue is how to parameterize temperature (Sailor and Munoz, 1997). Studies take several approaches, which can be divided into roughly four groups. Some studies use parametric functions of temperature (e.g., Mendelsohn, 2003). For example, Franco and Sanstad (2006) model electricity demand in California as a cubic function of daily average temperature. While simple to implement, the potential disadvantage of this approach is that it imposes assumptions on the functional form of the temperature-heating demand relationship (Henley and Peirson, 1997). At the other extreme, a few studies use non-parametric approaches (e.g., Valor et al, 2001; Giannikopolous and Psiloglou, 2006). These studies typically plot raw data on temperature versus energy use, possibly with a flexible spline superimposed on top. The disadvantage of this approach is that it does not control for other potential determinants of space heating demand. A third, intermediate approach is to use semi-parametric weather bins that allow for non-linearities (e.g., Auffhammer and Aroonruengsawat, 2011). For example, Deschenes and Greenstone (2011) use a set of variables that represent the number of days per year in which the temperature fell into ten-degree weather bins (<10°F, 10-19°F, …, >90°F). This approach has the strength of avoiding imposing a functional form while still controlling for other covariates. Finally, many studies use parametric functions of HDD and CDD (e.g., Eskeland and Mideksa, 2009). For example, Petrick et al (2014) represent temperature using a nonlinear function of HDM (heating-degree-months). The key issue with this approach is that it relies on the very strong assumption that the true energy-minimizing temperature is equal to the base temperature against which HDD and CDD are defined (Hekkenberg et al, 2009; Giannakopoulous et al., 2009).[4] As Table 2 shows, the energy minimizing temperature can vary substantially across studies and geographies.

A second major area of methodological uncertainty is the time period over which to aggregate weather and heating demand data (e.g., a day, a month, a year). When the unit of observation covers a longer time period, the study will be able to account for any lagged effects that temperatures may have on space heating demand. However, in panel-data studies, aggregating over longer time periods can result in a substantial loss of degrees of freedom. In practice, some studies use daily data (e.g., Valor et al, 2001; Giannikopolous and Psiloglou, 2006; Henley and Peirson, 1997), while others use monthly or yearly data. One study, Sue Wing (draft, 2013), uses a large set of lags of temperature variables that extend the potential effects of weather beyond one year.

A third open question is the extent to which the U-shaped relationship between temperature and space heating varies across geographies. Many studies pool together micro-data from locations with different climates (e.g., Deschenes and Greenstone, 2011; Considine, 2000). These studies implicitly assume that people who live in warm climates respond similarly to people who live in cold climates, when exposed to the same temperature. However, other studies find heterogeneity even within similar locations. For example, Auffhammer and Aroonruengsawat (2011) find considerable differences in the form of the U-shaped relationship within different climate zones in California. Differences between studies are even more pronounced, with the energy-minimizing temperature varying considerably across geographies. These differences could be due to differences in preferences, wealth, heating and cooling technologies, or building design.

A fourth question is how to interpret the average elasticities generated by panel studies based on annual, country-level data. In principle, because of their scale, these parameter estimates could very compatible with an IAM framework. However, the studies in this group suffer from a shared problem: they assume that the elasticity of energy demand is constant across different countries. Given the robust finding from micro-data that the temperature-energy demand relationship is U-shaped, there is no reason to expect that a marginal increase in temperature would have the same effect on two locations with different average temperatures. There is not even any reason to expect that the sign of the effect should be similar across different countries. Thus, while the coefficient from a population-weighted panel regression specification does have a loose interpretation as an approximation of a global response function, it will provide biased results for any specific country. Although a few studies (e.g., De Cian et al, 2014) have begun to try to estimate heterogeneous effects for cold, mild, and hot countries, most studies estimate pooled regressions. Thus, one productive direction for future research would be to estimate country-specific response functions that can address this issue of heterogeneity in responsiveness to marginal temperature changes.

4 Climate Change and Space Heating Demand

The previous section describes the broad literature on how observed space heating demand varies with weather and climate variables. In this section, we discuss how to model how climate change is likely to affect human welfare through changes in future space heating demand. We begin in Section 4.1 by

[4] The base temperature used to calculate heating degree days varies widely. A base temperature of 18°C is commonly used, but numerous other values have been chosen, including 15.5°C in Jordan, 15°C in Turkey, 16.5°C in Europe, 25-28°C in Athens, and 18-21°C in Saudi Arabia (e.g., Jiang et al., 2009; Giannakopoulos and Psiloglou, 2006; Aebischer et al., 2007).

briefly reviewing recent research on climate change and future space heating. Then, in Section 4.2, we discuss methodological considerations and challenges related to predicting future impacts.

4.1 Studies of Climate Change and Space Heating

There are a large number of recent studies that estimate the effects of climate change on space heating demand or energy demand more broadly (e.g., De Cian, Lanzi, and Roson, 2013; Mima, Criqui, and Watkiss, 2011; Dowling, 2013; Isaac and van Vuuren, 2009; Mansur, Mendelsohn, and Morrison, 2005; Aebischer et al, 2007; Hadley et al, 2006; Hamlet et al, 2009). These studies can be divided, roughly, into: (i) those that use behavioral models that predict space heating use under future climatic conditions by extrapolating observed responses of energy use to changes in weather or climate; and (ii) those that use engineering models that calculate the change in energy needed to maintain comfortable indoor temperatures under future climatic conditions, taking into account building structural characteristics.

The first group of studies makes predictions about how climate change will affect space heating energy use based on behavioral models (e.g., Franco and Sanstad, 2006; Giannikopolous and Psiloglou, 2006). These studies rely on econometric estimates of how changes in temperature or climate actually affect space heating use (i.e., results from either the panel or cross-sectional studies discussed in Section 3 of this document). Some studies use simple extrapolation, in which they use their regression equations to predict future heating expenditures under higher values of the temperature variable, with all or most other economic variables *ceteris paribus* (e.g., Deschenes and Greenstone, 2011). Others use the regression results as input parameters for IAMs, and then evaluate much more complicated sets of climatic and economic scenarios (e.g., Sue Wing, draft 2013; Hadley et al, 2006).

The second group of studies are those that use engineering models to consider how climate change is likely to affect temperatures, and what those changes imply for cooling and heating use (e.g., Cline, 1992; Baxter and Calandri, 1992; Rosenthal et al, 1995; Christenson, Manz, and Gyalistras, 2006; Aebischer et al, 2007; Giannakopoulous et al, 2009; Hamlet et al, 2009). These studies typically assume that energy demand has a fixed relationship with HDD and CDD (Diaz and Quayle, 1980), so that if temperatures change, energy demand will respond by the exact amount needed to maintain the same comfortable indoor temperature. For example, Olonschek et al (2011) collect data on the characteristics of the current stock of buildings in Germany, and then calculate how predicted changes in HDD and CDD will affect energy demand for heating and cooling those buildings. Their calculations use engineering equations that model changes in heating energy demand as a function of HDD, transmission loss factors, solar gains, and thermostat setbacks. They also take into consideration predicted growth of the housing stock, renovation of existing buildings, and installation of heating and cooling systems.

Table 3 summarizes the characteristics of selected studies that predict how climate change is likely to affect space heating demand. For each study, the table summarizes the geographic areas analyzed, the climate change scenario and time period modeled, the specific impact pathways considered, the other control variables included in the simulation, and the study's main empirical results. Most studies predict that climate change will lead to higher net expenditures on energy, but there is considerable variation across geographies and studies. For example, Giannikopolous and Psiloglou (2006) predict that under the IPCC's A2 scenario, winter electricity use in Athens, Greece, will decrease by 7.9%, while summer electricity use will increase by 4.1%. Since baseline consumption in the two seasons is similar, the net effect is likely to be a benefit. In contrast, many other studies predict increasing losses. For example, Mansur, Mendelsohn, and Morrison (2008) predict that U.S. residential energy use will increase by 10.3% (under +2.5°C) to 22.4% (under +5.0°C); Deschenes and Greenstone (2011) predict that U.S. residential energy use will increase by 31.9% (under A1FI); and Sue Wing (draft, 2013) predicts that U.S. residential energy consumption will increase by 7.6% (under A2).

Because of differences in the geographies, scenarios, and fuel types covered, it is difficult to compare the results from the behavioral studies and engineering studies. One engineering study that stands out for its broad coverage is Isaac and van Vuuren (2009), which estimates how climate change is likely to affect worldwide energy demand for heating and cooling under a +3.7°C temperature change by 2100. The study predicts that climate change will cause a 34% decrease in energy use for space heating, and 70% increase in energy use for space cooling. The net effect is a small net increase in global energy demand. At the regional level, however, the study predicts very heterogeneous effects. For example, considering both heating and cooling together, the United States will experience a 28% decrease (-4,000 PJ) relative to baseline heating and cooling energy use (the predicted no-climate change baseline is 14,000 PJ in 2100). In contrast, India will experience a substantial increase in energy use, due largely to future air conditioner adoption. Appendix B provides more information about this study and its methodology.

Although many of the studies in Table 3 report only changes in energy use, some do report changes in energy expenditures. As discussed above in Section 2, these changes in expenditures can be interpreted as direct welfare losses. Of course, this interpretation is valid only for small changes in expenditures, to which partial and general equilibrium adjustments do not apply. Nonetheless, regardless of whether the changes are in fact "small", the intuition for the welfare interpretation is still valuable. Because climate change will change the amount of money that households spend on cooling and heating, it will also impact the amount of money that they have available to spend on other welfare-enhancing goods and services.

Table 3: Selected Studies of Climate Change and Space Heating Energy Demand

Study	Geography	Climate Scenarios and Time Periods	Impact Pathways	Other Variables Included in Simulation	Range of Predicted Change in Energy Expenditures or Consumption*
Studies Based on Behavioral Models					
Mendelsohn (2003)	California	+1.5°C & +9%P, +3°C & +18%P, +5°C & +30%P (2100) Hadley, PCM (2020, 2060, 2100)	Residential & commercial energy expenditures	Population, income, building technology, and energy prices	Residential 2100: +3.5% (under +1.5°C) to +18.3% (under +5°C) [2100 baseline energy expenditure is $37 to $62 billion, depending on scenario] Commercial 2100: +2.1% (under +1.5°C) to +36.4% (under +5°C) [2100 baseline energy expenditure is $16 to $24 billion, depending on scenario]
Franco and Sanstad (2006)	California	A2, B1, A1FI (2005-2034, 2035-2064, 2070-2099)	Electricity use	None	2070-2099: +2.9% (under B1) to +17.8 (under A1Fi) [2003 baseline electricity expenditures were $26 billion]
Giannikopolous and Psiloglou (2006)	Athens	A2, B2 (2070-2099)	Residential and commercial electricity use	None	2070-2099 Winter: -5.8% (under B2) to -7.9% (under A2) [the 1961-1990 baseline is 1,667 MWh/day] 2070-2099 Summer: +2.6 (under B2) to +4.1 (under A2) [the 1961-1990 baseline is 1,254 MWh/day]
Deschenes and Greenstone (2011)	United States	A1b, A1FI (2100)	Residential energy consumption and expenditures	Income, energy prices	2100: +31.9% (under A1Fi) [1968-2002 baseline was 16.6 quadrillion BTU]
Mansur, Mendelsohn, and Morrison (2008)	United States	+2.5°C, +5°C (2100)	Residential & commercial heating and cooling energy use	Population, income, building technology, and energy prices	2100: +10.3% (under +2.5°C) to +22.4% (under +5°C) [2100 baseline expenditures on energy are $56.7 billion/year]
De Cian, Lanzi, and Roson (2013)	31 OECD and non-OECD countries	B2 (2085)	Residential electricity, gas, and oil product use	Population, income	2085: Absolute change of +1.8 million Ktoe (under B2) [baseline energy consumption is not reported in study]

Table 3: Selected Studies of Climate Change and Space Heating Energy Demand

Study	Geography	Climate Scenarios and Time Periods	Impact Pathways	Other Variables Included in Simulation	Range of Predicted Change in Energy Expenditures or Consumption*
Sue Wing (draft, 2013)	United States	A2 (2050)	Residential, commercial, and industrial electricity use	Multi-sector inter-regional computable general equilibrium model, with many variables	2050: +7.6% (under A2) [2050 baseline electricity consumption is 6,579 TWh per year]
Studies Based on Engineering Models					
Hadley et al. (2006)	United States (9 regions)	Low (+1.2°C) and high (+3.4°C) climate sensitivity (2003-2025)	Energy use	Housing stock, energy prices, etc (based on National Energy Modeling System)	2003-2025: +$6.1 billion (under (+1.2°C) to +$14.8 billion (under +3.4°C) [baseline expenditures are not reported in study]
Aebischer et al (2007)	Switzerland, Florida, Athens, Murcia, Milan, London, Berlin, Zurich, Copenhagen, Stockholm	+1°C Sept-May and +2°C June-Aug and +5% solar radiation (2030)	Cooling and heating energy use for service sector	Economic growth, energy prices, technological development	2030 Berlin: -8% (+1°C/+2°C) in space heating; +45% (+1°C/+2°C) in space cooling [2030 baselines are 150 and 25 kWh per sq meter of heated and cooled floor area, respectively]
Isaac and van Vuuren (2009)	World (26 regions)	+3.7°C (2100)	Residential cooling and heating energy use	Population, floor space, efficiency, air conditioning penetration, income	2100: -34% in space heating (+3.7°C); +70% in space cooling (+3.7°C) [2100 baseline with no climate change is 47,000 PJ for heating and 29,000 PJ for cooling. For reference, 2000 values 26,000 PJ for heating and 1,000 PJ for cooling]

Table 3: Selected Studies of Climate Change and Space Heating Energy Demand

Study	Geography	Climate Scenarios and Time Periods	Impact Pathways	Other Variables Included in Simulation	Range of Predicted Change in Energy Expenditures or Consumption*
Hamlet et al (2009)	Washington State	A1B and B1 (2010-2039, 2030-2059, 2070-2099)	Energy demand	Population, air conditioning market penetration	2080s: -24% (under B1) to -32% (under A1B) in energy demand for heating relative to baseline heating demand; +370 (under B1) to +745% (under A1B) in energy demand for cooling relative to baseline cooling demand. [2085 baseline heating demand is 7.15 million person-HDD; 2085 baseline cooling demand is 0.077 million person-CDD.]
Olonschek et al (2011)	Germany	+1°C, +2°C, +3°C (2010-2060)	Heating and cooling energy use for all building types	Housing stock growth, renovation of existing buildings, and installation of heating and cooling systems	2031-2060: -44% (under +1°C and low assumptions) to -78% (under +3°C and high assumptions) in energy demand for heating; +25% (under +1°C and low assumptions) to +59% (under +3°C and high assumptions) in energy demand for cooling. [2000 baseline heating use was 850 TWh and baseline cooling use was 0.1 TWh]

*Note: * This column presents the predicted percent change in total energy expenditures or consumption. When these measures are not available, it presents the predicted percent change in heating or cooling expenditures or consumption. Each cell in the column also lists the value and units of the baseline against which the percent changes are calculated.*

4.2 Considerations for Predicting Future Impacts

The studies in Table 3 shows that there are a variety of methodological approaches that can be used predict how climate change is likely to affect future space heating demand. In this subsection, we discuss several issues and challenges related to this process.

4.2.1 Price and Income Elasticities of Space Heating Demand

Developing a credible damage function requires understanding not only how space heating demand responds to changes in climate, but also how it responds to other economic factors, such as changes in income and energy prices. Summarizing the empirical literature on each of these topics (e.g., Considine, 2000; Eskeland and Mideksa, 2009; De Cian, Lanzi, and Roson, 2013; Espey and Espey, 2006; Petrick et al, 2012) is a large task that we have not attempted for this literature review.

4.2.2 Sectoral Realism

As the climate warms, households and businesses will re-optimize their heating technology choices—for example, switching from oil to gas heat, or changing their investments in the energy efficiency of new buildings. Capturing these kinds of technology-switching decisions in a damage function is certainly possible, and we have identified several studies—discussed in Section 3.2—that explicitly model the fuel choice decision (e.g., Mansur, Mendelsohn, and Morrison, 2008; Vaage, 2000). However, an open question is whether the greater level of detail—and associated complexity of representation in a damage function—would be justified by improved accuracy in predicting future impacts.

4.2.3 Technological Change in Space Heating and Insulation Technologies

Because the energy efficiency of new and renovated buildings strongly affects heating energy needs (Olonschek et al., 2011), space heating damage functions need to account for technological change in heating and insulation technologies. For example, in Europe, heating energy demand has been declining by about 0.2% per year, resulting in a predicted reduction by 2035 of 6% compared to a 2005 baseline (Aebischer et al, 2007). In California, stricter building codes and rising electricity prices caused a 16% decrease in residential electricity use from 1960 to 2006, relative to what electricity use would have been otherwise (Costa and Kahn, 2010). One potential source of useful information on this topic is IEA (2011), which provides data and projections on the evolution of space heating and cooling technologies over time for a variety of regions.

4.2.4 Relationship to Space Cooling

Many of the studies covered in this review analyze the relationship between space cooling and climate (e.g., Al-Zayer and Al-Ibrahim, 1996; Christenson, Manz, and Gyalistras, 2006; Eskeland and Mideksa, 2009). While space cooling is not the primary focus of this review, from the standpoint of predicting future impacts of climate change, it is worth making three points.

First, changes in demand for space heating and space cooling may have different side effects on the power grid and on combustion-related pollution. For example, heating and cooling have different patterns of use over the course of a day, implying that they may make different contributions to peak electricity loads (Giannakopoulos and Psiloglou, 2006; Aebischer et al, 2007).

Second, cooling is a less efficient physical process than heating (Hadley et al, 2006). As a result, setting aside behavioral responses, the a priori expectation would be that one additional CDD would increase energy demand by much more than one additional HDD. Empirical studies seem consistent with this finding. For example, in a panel of 31 OECD and non-OECD countries, Eskeland and Mideksa (2009) find that one extra CDD per year raises annual electricity consumption by four times as much as one extra HDD.

Third, as a practical matter, most studies do not separately estimate space heating and cooling curves (e.g., Deschenes and Greenstone, 2011; Lee and Chiu, 2011). Those that do are studies that estimate demand for fuels that clearly are only used for heating (e.g., heating oil).

4.2.5 Other Issues

In addition to the topics discussed above, there are numerous other issues that could affect how to model the effects of climate change on space heating. For example, the distribution of welfare impacts may be mediated by housing markets. In an efficient housing market, regional variation in the quality of life will be reflected in housing prices and wages (Roback, 1982). In the context of climate change, this implies that decreases in space heating expenditures could eventually lead to compensating changes via higher housing prices and rents (Albouy et al, 2010). For homeowners, the distributional consequences would be relatively minor, but for renters and landlords, there could be a non-negligible welfare transfer.

Another potential issue is the possibility of feedback to the climate system. Space heating is a source of greenhouse gases. Thus, if climate change reduces the need for space heating, then overall greenhouse gas emissions will fall, leading to a reduction in climate change, etc. However, this negative feedback loop is likely to be limited in scope, and we have not tried to identify and review studies that consider feedback effects of the reduced energy demand for space heating.

5 Conclusions

There is now a substantial empirical literature on the relationship between temperature and energy expenditures for space heating and cooling. Although the literature is still grappling with several areas of uncertainty, a key stylized result that is consistent across studies is that the energy-temperature relationship is U-shaped.

The modeling literature on how climate change is likely to affect space heating and cooling has also grown substantially in recent years. Due to differences in scope, the results of these studies are difficult to compare. However, the general conclusion that emerges is that the effects of climate change will be heterogeneous, with some cold countries likely to benefit, and some hot countries likely to incur substantial costs.

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Appendix A: Detailed Descriptions of Country-Level Panel Studies

Because IAMs typically require very aggregate data, space heating studies that use national-level data at the yearly-level could be very useful for updating IAM damage functions. Of course, as discussed in Section 3.3, these studies often adopt the very strong assumption that the elasticity of energy demand with respect to temperature is constant across different countries.

In any case, in order to provide the reader with a more detailed sense of their methodologies and results, this appendix describes four of these studies (Eskeland and Mideska, 2009; Lee and Chiu, 2011; Petrick et al, 2012; and De Cian, Lanzi, and Roson, 2013) in extensive detail. Although it is not a country-level study, we also describe Assadorian et al (2007) here, due to its focus on China. The studies are presented by year of publication in the following subsections.

A.1 Asadoorian et al (2007)

This study estimates the impact of changes in temperature on electricity consumption in China. The authors estimate separate specifications for three different types of consumption: urban residential electricity use, rural residential electricity use, and non-residential electricity use (urban and rural combined). Their sample consists of data for approximately twenty-one Chinese provinces, covering 1995 to 2000. Their economic data is taken primarily from the China Energy Databook and the China Statistical Yearbook.

To model how temperature affects residential electricity demand, the authors use a two-stage estimation approach. In the first stage, they model demand for three major types of appliances—AC units, TVs, and refrigerators—as a function of appliance prices, electricity prices, per capita income, a coastal/non-coastal province dummy variable, and temperatures. These regressions use a log-log specification, for example:

$$\begin{aligned} Log(AC\ Unit\ Stock)_{it} &= \alpha_0 + \alpha_1 LogACPrice_{it} + \alpha_2 LogElectricityPrice_{it} + \alpha_3 LogIncome_{it} \\ &+ \alpha_4 Coastal_{it} + \alpha_5 LogWinterTemp_{it} + \alpha_6 LogSpringTemp_{it} \\ &+ \alpha_7 LogSummerTemp_{it} + \alpha_8 LogFallTemp_{it} + \epsilon_{it} \end{aligned}$$

where i represents provinces and t represents years. This equation is estimated using the Prais–Winsten panel corrected standard error estimator (an approach for generating standard errors that are robust to autocorrelation). The regression is estimated separately for urban and rural residential consumers.

Next, in a second stage, the authors estimate how temperatures affect demand for electricity use, conditional on the predicted stock of appliances from the first stage. The variables included in the second-stage log-log regression are similar to those included in the first stage, but exclude appliance prices and include the log of living space, the log of the average number of hours of darkness per month for each of the four seasons, and the predicted stock of appliances. For example:

$$\begin{aligned} Log(ElectricityUse)_{it} &= \beta_0 + \beta_1 LogElectricityPrice_{it} + \beta_2 LogIncome_{it} + \beta_3 Coastal_{it} \\ &+ \beta_4 LogLivingSpace_{it} + \beta_5 LogWinterDarknessHours_{it} \\ &+ \beta_6 LogSpringDarknessHours_{it} + \beta_7 LogSummerDarknessHours_{it} \\ &+ \beta_8 LogFallDarknessHours_{it} + \beta_9 PredictedACStock_{it} + \beta_{10} PredictedTVStock_{it} \\ &+ \beta_{11} PredictedFridgeStock_{it} + \beta_{12} LogWinterTemp_{it} + \beta_{13} LogSpringTemp_{it} \\ &+ \beta_{14} LogSummerTemp_{it} + \beta_{15} LogFallTemp_{it} + \epsilon_{it} \end{aligned}$$

Again, this equation is estimated using panel-corrected standard errors, and is estimated separately for urban and rural residential consumers. In both stages, the authors experiment with different functional forms for temperature, breaking it into twelve monthly average temperature variables, four seasonal average temperature variables, and one annual average temperature variable.

Finally, for non-residential electricity consumption, the authors use a single-stage approach, with a regression specification that is similar to their residential second-stage equation, but without the predicted appliance demand variables. They do not have sufficient data to estimate separate rural and urban non-residential demand functions.

Overall, the authors' regressions produce several findings. In the first stage, they find negative own-price elasticities for appliances and positive elasticities of appliance demand with respect to income. However, their results for temperature are mixed. For example, in both the urban and rural residential models, higher winter temperatures increase demand for all types of appliances, but higher fall temperatures cause lower demand. The coefficients in spring and summer and mixed and mostly not significant.

In the second stage, the authors find that electricity has a positive own-price elasticity and a negative elasticity with respect to income. For urban residential demand, the coefficients on predicted AC stock are positive and significant, and the coefficients on the predicted refrigerator and predicted TV stocks are negative and significant. Table 4 summarizes their estimates of the effect of temperature on electricity demand. The table shows that temperature has a large and significant positive effect on urban residential electricity demand in the summer, a significant negative effect in the fall, and insignificant effects in the winter and spring. In rural residential areas, the temperature coefficients are not significant in any season. Finally, in the single-stage non-residential regression, temperature has a significant (and positive) effect on electricity demand only in the winter.

Table 4: Elasticity of Electricity Use with Respect to Temperature, by Season and Location

	Winter	**Spring**	**Summer**	**Fall**	**Annual**
Residential, Urban	0.215	-0.323	2.054*	-1.928*	0.59*
Residential, Rural	-0.082	-1.688	1.03	0.904	0.758
Non-residential, All	0.243*	-0.212	-0.04	-0.441	0.09

*Note: These numbers are reproduced from the tables on pages 8-9 and 13. The seasonal coefficients are from one set of regressions; the annual coefficients are from another set. * denotes t-statistic greater than 2.*

A.2 Lee and Chiu (2011)

This study estimates the effect of changes in temperature on per capita electricity consumption in a panel of 24 OECD countries, based on yearly country-level data covering the period from 1978 to 2004. The countries included in the dataset are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Luxembourg, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

To estimate how temperatures, income, and electricity prices affect electricity demand, the study uses a "panel smooth transition regression" (PSTR) model. This model allows the relationship between electricity consumption and each of the three independent variables (annual average temperature, income, and electricity price) to be mediated by a threshold variable. In other words, the model allows the effect of temperature on electricity consumption to take different functional forms, depending on the value of the threshold variable.

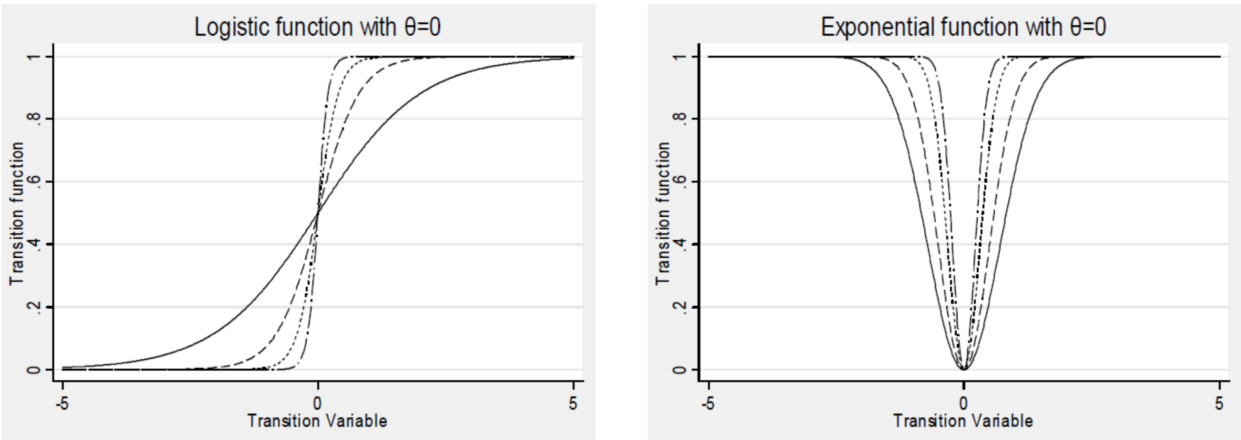
The study explores three different candidates for the threshold variable (these are same three independent variables, logged and lagged by one period). The regression specification can be written as follows:

$$Log(ElectricityUse)_{it} = \phi_i + \beta_1 LogElectricityPrice_{it} + \beta_2 LogGDP_{it} + \beta_3 Temp_{it} + [\alpha_1 LogElectricityPrice_{it} + \alpha_2 LogGDP_{it} + \alpha_3 Temp_{it}] \cdot g(z_{i,t-1}; \theta, \gamma) + \epsilon_{it}$$

where i represents countries, t represents years, ϕ_i are country fixed effects, $z_{i,t-1}$ is the threshold variable, θ is a location parameter, and γ is a curvature parameter. Depending on the values of the threshold variable and the parameters, the function $g(\cdot)$ varies between 0 and 1. When it equals 0, the model is completely in regime 1, and the values of the β terms determine the relationship between electricity consumption and the independent variables. When the function is equal to 0, the model is completely in regime 2, and the values of the α terms (added to the β terms) determine the relationship between electricity consumption and the independent variables. When the function is between 0 and 1, the model is a blend of the two regimes.

The study tests two candidates for the function $g(\cdot)$. The first is a logistic transition function; the second is an exponential transition function. Figure 3 shows examples of both functions, for various values of the curvature parameter γ. The logistic transition function has a low zone that corresponds to regime 1, and a high zone that corresponds to regime 2. Under some values of the curvature parameter, the transition function approaches an indicator function. Under other parameter values, it allows for a smoother transition that blends the two regimes. The exponential transition function has three zones—low, middle, and high—that correspond to regimes 2, 1, and 2, respectively.

Figure 3: Examples of Transition Functions



Notes: The figure is reproduced from Figure 2 of Lee and Chiu (2011).

The authors note the potential for endogeneity bias, since electricity consumption, prices, and GDP are jointly determined. To address this problem, they use lagged values of each variable as instruments.

Table 5 presents the estimated relationship between electricity demand and temperature. The table shows results for the logistic transition function, in which either log GDP per capita or log temperature is used as the threshold variable. In the specification with temperature as the threshold variable, the results are consistent with a U-shaped relationship between electricity use and temperature. Below 53°F, the elasticity of electricity demand with respect to temperature is negative (although not significant), while above 53°F, it is positive and significantly different from the below-53°F elasticity.

Table 5: Temperature Elasticities of Electricity Demand, by Regime and Threshold Variable

		Elasticity of Electricity Demand with respect to Temperature	
Threshold Variable	**Threshold Value**	**Regime 1 (for low values of threshold variable)**	**Regime 2 (for high value of threshold variable)**
Log GDP per capita	$2,497	-3.94*	0.92*
Log Temperature	53°F	-0.61	0.20*

*Note: These results are taken from Table 4 of Lee and Chiu (2011). Note that the Regime 2 elasticities are calculated as the sum of the regime 1 and 2 coefficients. * denotes t-statistic greater than 2.*

A.3 Eskeland and Mideska (2009)

This study estimates the impact of changes in temperature on the residential use of electricity, for 31 European countries. The study uses yearly country-level panel data covering the period from 1994 to 2004.

The regression that the authors estimate is as follows:

$$Log(ElectricityUsePerCapita)_{it} = \phi_i + \tau_t + \alpha_1 LogIncomePerCapita_{it} + \alpha_2 LogElectricityPrice_{it} + \alpha_3 HDD_{it} + \alpha_4 CDD_{it} + \epsilon_{it}$$

where i represents countries, t represents years, ϕ_i are country fixed effects, and τ_t are year fixed effects. Electricity use is measured as annual household electricity consumption (kWh), and HDD and CDD represent the average of the annual degree day totals for the three largest cities in each country.

To address the issues related to the fact that electricity use and price are jointly determined, the paper uses value added tax per kWh as an instrumental variable for electricity price. Additionally, the paper states that in order to address the possibility that income and electricity consumption exhibit reverse causality, the regressions use the "economy's total revenue from value added tax" as an instrumental variable for per capita income.

Table 6 summarizes the estimated coefficients on HDD and CDD, under several alternative specifications. The table shows the coefficients on CDD and HDD are positive and significant in all specifications. Based on the main panel results from column (2), annual household electricity consumption increases 0.038% per each additional CDD per year, and 0.009% per each additional HDD per year.

Table 6: CDD and HDD Coefficients

	Specification				
Variable	**(1) OLS**	**(2) Panel**	**(3) Panel with Price IV**	**(4) Panel with Income IV**	**(5) Panel with Price and Income IV**
Annual CDD	0.00115	0.00038	0.00036	0.00048	0.00040
	(0.00019)	(0.00011)	(0.00015)	(0.00013)	(0.00015)
Annual HDD	0.00020	0.00009	0.00007	0.00010	0.00009
	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00003)

Note: These regression results are reproduced from Table 3 in Eskeland and Mideska (2009). The dependent variable in each regression is the log of annual household electricity consumption (in kWh). The table shows coefficients, with standard errors in parentheses.

By combining these regression results with projections of how annual HDDs and CDDs are likely to be influenced by climate change in Europe, the authors predict future electricity consumption under the IPCC's A1B scenario. They estimate that due to climate change, average per capita electricity use in Europe will decrease from 6,100 kWh in 2000 to 5,950 kWh in 2100. They explain that this small predicted decrease in overall energy use is due to the fact that the benefits of reduced heating outweigh the costs of increased cooling.

A.4 De Cian et al (2013)

This study estimates the impact of changes in temperature on the residential use of gas, electricity, and oil products, for 31 countries from around the world. The study relies on yearly country-level panel data covering the period from 1978 to 2000 (with fewer years for some types of fuel). One of the key features of the study is that it estimates separate electricity results for groups of countries with cold, mild, and warm climates.

The study begins by using a clustering algorithm to separate the 31 countries into three groups, based on their climate characteristics (annual average, maximum, and minimum temperature). The resulting groups are:

- Cold countries: Canada, Finland, Norway, Sweden.
- Mild countries: Austria, Belgium, Denmark, France, Germany, Ireland, Luxembourg, Netherlands, New Zealand, Switzerland, Greece, Hungary, Italy, Japan, South Korea, Portugal, South Africa, Spain, Turkey, United Kingdom, United States
- Hot countries: Australia, India, Indonesia, Mexico, Thailand, Venezuela

To understand how temperatures influence energy demand, the study then estimates an error correction model in which the log of energy use (for each type of fuel) is modeled as an autoregressive process. The model takes the following functional form:

$$
\begin{aligned}
\Delta LogEnergyUse_{it} \\
&= \beta_0 + \beta_1 \Delta LogEnergyUse_{i,t-1} + \beta_2 \Delta EnergyPrice_{it} + \beta_3 \Delta GDPperCapita_{it} \\
&+ \beta_4 \Delta WinterTemp_{it} + \beta_5 \Delta SpringTemp_{it} + \beta_6 \Delta SummerTemp_{it} + \beta_7 \Delta FallTemp_{it} \\
&+ \lambda[\alpha_1 LogEnergyUse_{i,t-1} - \alpha_2 EnergyPrice_{i,t-1} - \alpha_3 GDPperCapita_{i,t-1} \\
&- \alpha_4 WinterTemp_{i,t-1} - \alpha_5 SpringTemp_{i,t-1} - \alpha_6 SummerTemp_{i,t-1} \\
&- \alpha_7 FallTemp_{i,t-1}] + \epsilon_{it}
\end{aligned}
$$

where i represents countries and t represents years. Conceptually, the error correction model has two components: the Δ terms, which capture the short-run response of energy use to changes in the independent variables (including temperature), and the lagged terms in brackets, which capture the long-run equilibrium relationship between energy use and the independent variables. The error correction coefficient λ captures the speed of adjustment towards the long-run equilibrium.

The authors run the regression separately for each type of fuel. For electricity, the study estimates separate coefficients for each of the three groups of countries. Additionally, for electricity, the authors run the regression, drop any temperature variables that don't have significant coefficients, and then run the regressions a second time on the remaining variables.

Table 7 summarizes the study's estimates of the long-term semi-elasticity of energy demand with respect to temperature, for different fuels, seasons of the year, and groups of countries. The results are somewhat mixed. Consistent with intuition, semi-elasticities are negative in the winter, for every fuel type. However, in the spring and summer, some electricity semi-elasticities are negative and some are positive, depending on geography.

Table 7: Long-Run Temperature Semi-Elasticities, by Fuel, Season, and Country Group

	Winter	Spring	Summer	Fall
Electricity				
Cold Countries		5.42	-3.33	
Mild Countries		−0.79	2.08	
Hot Countries		5.42	1.8	
All Countries	-.88			
Gas				
All Countries	-2.60			
Oil				
All Countries	-3.45			-3.36

Note: These semi-elasticities of annual energy use are reproduced from Table 5 in De Cian et al (2013). Because the authors chose not to report results that are not significantly different from zero, many of the cells in the table are missing.

Based on these semi-elasticities, the authors project the absolute change in energy demand in the year 2085 in each country in their sample. For these calculations, they first project energy demand in 2085 without climate change, taking into account growth in population and per capita income. They then use seasonal temperature projections to estimate how climate change would affect future energy demand. Unfortunately, although the study reports the absolute change in future energy demand, it does not include the baseline future energy demand (without climate change), and so it is not possible to normalize the results in terms of a percent impact.

A.5 Petrick et al (2014)

This study estimates the effect of changes in temperature on per capita residential coal, electricity, natural gas, and oil use, for an unbalanced panel of yearly data for 62 countries covering the period from 1970 through 2002. Because fuel prices are available for only a subset of countries, the number of countries actually used in the regressions is much smaller: 20 countries for coal, 56 countries for electricity, 36 countries for natural gas, and 32 countries for oil.

In contrast to other studies in the literature, this study represents temperature using heating degree months (HDM) and cooling degree months (CDM). To calculate these variables, which are defined analogously to HDDs and CDDs, the authors obtain gridded historical monthly average temperature data, for 0.5° degree grid cells. They then calculate the amount by which the average temperature in each grid cell and month exceeds (for CDMs) or falls below (for HDMs) the threshold value of 18.3°C (65°F). They then sum the total over the months within each year to generate CDMs and HDMs for each grid cell in each year, and then calculate the average HDM and CDM across all grid cells in each country, for each year.

The regression that they estimate takes the following functional form:

$$\begin{aligned} Log(EnergyUse)_{it} \\ &= \phi_i + \alpha_1 LogEnergyUse_{i,t-1} + \alpha_2 LogGDPperCapita_{it} + \alpha_3 LogFuelPrice_{it} \\ &+ \alpha_4 LogHDM_{it} + \alpha_5 LogHDM_{it}^2 + \epsilon_{it} \end{aligned}$$

where i represents countries, t represents years, and ϕ_i are country fixed effects. To address the econometric problems created by including both country fixed effects and a lagged dependent variable, the authors use a "corrected least square dummy variable" (LSDVC) estimator.

Table 8 shows the results from the study, for the regressions that use HDM. The coefficients on the log of HDM and the square of the log of HDM are generally positive and significant, indicating that fuel use decreases as temperatures rise (for temperatures below the HDM threshold of 65°F).

Table 8: Temperature Coefficients, by Fuel

	Coal	Electricity	Gas	Oil
Log(HDM)	0.21	0.02*	0.31*	0.12
$[Log(HDM)]^2$	0.05*	0.002	0.02*	0.01*

*Note: These regression results are reproduced from Table 2 in Petrick et al (2014). The dependent variable in each regression is logged. Note that the study does not report any of the CDM specifications, but states that none of the CDM coefficients are significantly different from zero. * denotes significant at p<.05.*

At the average values of the explanatory variables (including HDM), the coefficients imply that the short-run elasticities of fuel use with respect to HDM are 0.45 for coal, 0.03 for electricity, 0.41 for natural gas, and 0.17 for oil.

The authors do not report tables of regressions results from any of the CDM specifications, but do state that none of the CDM coefficients are significantly different from zero. Even in subsamples that include only OECD countries, only warm OECD countries, and only the European Mediterranean, they state that higher temperatures do not lead to additional energy expenditures for any fuel. The only specification in which the CDM coefficients are significantly positive is for a subsample that includes only the United

States. In this specification, the short-run elasticity (presumably of electricity) with respect to CDM is 0.13. The authors conclude that for their sample (which includes 1970 to 2002), air conditioner use was not prevalent enough in most countries to generate a cooling effect.

Appendix B: Detailed Descriptions of Engineering Studies

As a reference, this appendix describes the methodology and results from Isaac and van Vuuren et al (2009). This study uses an engineering-based approach to model how climate change is likely to affect future space heating and cooling. We present this study here as a good example of the many other studies that use engineering-based approaches (see Table 3 for additional examples).

B.1 Isaac and van Vuuren et al (2009)

This study models the effect of climate change on global residential heating and cooling demand, using an engineering-based approach. For each country, the authors draw on parameter estimates from the literature (and from the TIMER and IMAGE 2 models) to predict future changes in temperature, population, living space, income, and heating and cooling technological efficiency. They then use these parameters to predict how energy demand for heating and cooling are likely to change in 26 modeling regions that cover the entire globe, as follows.

First, the authors predict the effects of changes in temperature on annual heating demand for each region, using the following model:

$$HeatingEnergy = Population \cdot Meter^2PerCapita \cdot HDD \cdot \frac{UsefulHeatperMeter^2perHDD}{HeatingEfficiencyOfFuel}$$

In this model, $HeatingEnergy$ is the total amount of heating energy used per year, $Population$ is the total population, $Meter^2PerCapita$ is the average heated floor space per person (in meters squared), HDD is the annual number of population-weighted heating degree days, $UsefulHeatperMeter^2perHDD$ is a measure of the "useful heat energy" needed to warm one square meter of floor space enough to offset the effects of one HDD, and $HeatingEfficiencyOfFuel$ is a measure of the useful heat energy provided per unit of total potential energy contained in the fuel.

Next, to predict the effects of changes in temperature on annual cooling demand for each region, the authors use a different model:

$$CoolingEnergy = Population \cdot Availability \cdot MaxSaturation \cdot CDD \cdot \frac{EnergyPerHHperCDD}{ACCoolingEfficiency}$$

where $CoolingEnergy$ is the total amount of cooling energy used per year, $Population$ is the total population, $Availability$ is the proportion of households that can afford AC units, $MaxSaturation$ is the proportion of households that would own AC units if income were unlimited, CDD is annual population-weighted cooling degree days, $EnergyPerHHperCDD$ is the amount of energy used for cooling per CDD per household (conditional on income), and $ACCoolingEfficiency$ is a parameter that takes into account changes in the energy efficiency of air conditioning technology over time.

The results of the study suggest that under baseline conditions, with socioeconomic growth and technological progress, but no climate change, global energy use for heating will increase from 26,000 PJ in 2000 to 47,000 PJ in 2100. Taking into account climate change (an increase of 3.7°C by 2100), space heating energy use would be approximately 31,000 PJ in 2100 (a 34% decrease relative to baseline 2100 heating energy use).

Over that same period, global baseline energy use for cooling will increase from 1,000 PJ to 29,000 PJ. However, with climate change, cooling energy demand would be substantially higher by the end of the century: 49,000 PJ (a 70% increase relative to baseline 2100 cooling energy use).

The disaggregated results from the model suggest that most regions of the world will experience a net benefit from climate change, due to reductions in space heating energy that outweigh resulting increases from space cooling. However, India, Southeast Asia, and Central and South America are all projected to experience net losses, due to the greater use of energy for air conditioning.