Measuring Climatic Impacts on Energy Consumption: A Review of the Empirical Literature

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Abstract

This paper reviews the literature on the relationship between climate and the energy sector. In particular, we primarily discuss empirical papers published in peer-reviewed economics journals focusing on how climate affects energy expenditures and consumption. Climate will affect energy consumption by changing how consumers respond to short run weather shocks (the intensive margin) as well has how people will adapt in the long run (the extensive margin). Along the intensive margin, further research that uses household and firm-level panel data of energy consumption may help identify how energy consumers around the world respond to weather shocks. Research on technology adoption, e.g. air conditioners, will further our understanding of the extensive margin adjustments and their costs. We also note that most of the literature focuses on the residential sector. Similar studies are urgently needed for the industrial and commercial sectors.

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1 Introduction

This paper reviews the literature on the relationship between climate and the energy sector. The energy climate relationship is interesting as it is a great example of a feedback effect. The causal link from emissions due to the combustion of fossil fuels to deliver energy services to climate change is well established. However, hotter summers and warmer winters will change energy consumption and production patterns. A similar feedback mechanism is hypothesized in land use (Pielke *et al.*, 2002). There are several ways in which climate may affect energy consumption. In the residential, commercial and industrial sectors one would, in a warmer world, expect higher cooling demand, which would lead to increased electricity consumption. On the other hand, fewer cold winter days would result in decreased heating demand, which would drive down natural gas, oil and electricity demand. These are all demand side effects. On the supply side, one would expect increased use of natural gas on hot days, as some power plants become less efficient as well as higher natural gas consumption for generation due to higher electricity demand. During the winter, there might be a decrease in natural gas demand for generation due to lower electricity demand.

In this paper we survey the literature containing empirical papers published in peer-reviewed economics journals focusing on how climate, which is generally defined as a long run average of weather, affects energy expenditures and consumption. Most of the studies we found focus on electricity consumption in the residential sector. The coverage of the commercial and industrial sectors as well as studies on other fuels is most sparse. For example, we could not locate *any* empirical peer-reviewed economics papers on the effect of climate on energy supply.

The empirical estimates of climate sensitivity of the energy sector are typically used to predict the cost of climate change adaptation. Climate models predict a range of changes to temperature, precipitation, and other climate measures. Most models predict a significant increase in global average temperatures by the end of the current century for scenarios close to a business as usual emissions path (IPCC SRES Scenario A1fi) or a slightly more optimistic emissions path (A2). Auffhammer *et al.* (2013) provide a detailed discussion of climate models and their use in the social sciences. Overall one expects that people heat less and cool more. This change in behavior will have both an intensive and extensive margin component.

With regards to the intensive margin, several papers examine the short run response to weather shocks. A common finding in this literature is that usage patterns of existing capital, such as air conditioners, changes in response to climate change. Over time, however, we posit that people will respond to climatic change along extensive margins. They may change purchasing decisions of appliances, switch fuel sources, and even building characteristics. In general, economists know less about these extensive margin adjustments than the intensive ones. While research shows that future generations will likely own more air conditioners, this is due to both price and income effects (Wolfram *et al.*, 2012). There is a nascent literature examining the weather and climate response of air conditioner adoption (e.g. Auffhammer, 2012, 2014).

The questions that researchers will continue to face include: How will climate change affect peoples' energy expenditures, choice of fuel sources, and buildings? How will people adapt to a new and continuously changing climate? What will be the transitional costs of adapting? Much of the uncertainty over the energy costs associated with climate change will inevitably depend on the future income distribution and technologies. Nonetheless, economists have made some progress in studying two complementary issues: first, how energy choices differ among households and firms located in different climates; and second, how a given consumer responds to weather shocks. From a policy perspective, studies of the intensive margin and extensive margin adjustments speak to different, yet relates, policy measures. If one is interested in short run reductions of weather driven energy demand (e.g. peak load) information campaigns, peak pricing and direct load control may be effective ways to achieve reductions in consumption. If one is interested in controlling the extensive margin adjustment, efficiency standards, rebates for efficient appliances and insulation may be more effective. While we do not speak to policy in this paper directly, this is an interesting dichotomy. Below, we review this literature, discuss where the literature could head, and outline the policy implications.

To address this question, the ideal data set would provide information on how a given household consumes energy in randomly assigned climates, all else equal. Unfortunately, this perfect experiment is not feasible as people sort into their preferred climate. One could imagine trying to identify how consumers adapt to climate three different ways. One is to look at how a given household's consumption changes when it relocates to a new climate. For example, how do military families' energy expenditures change when they are relocated to a new climate? This approach raises identification concerns regarding the reason why people move, and why they chose a new housing type. No paper has attempted to explicitly deal with the sorting approach to our knowledge.

A second approach that some economists use is to look at the cross-sectional variation in climate. Namely, if there are two seemingly identical households that are located in different climatic zones, one can then look at how their energy choices differ and ask whether these differences are correlated with climate differences. The main concern with this approach is that estimates are subject to omitted variables bias: unobservable differences in households may be correlated with climate. For example, Albouy *et al.* (2012) find northern households to be less heat-tolerant than southern households. Another issue with looking at cross-sectional data is that we do not get an appreciation of the transition costs of fully adapting to a new climate.

The third approach uses panel (or simply time series) variation to examine how energy consumption responds to weather shocks. Recent studies of this reduced-form, short run response include Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011, 2012b). These estimates could overstate the damages of climatic change since households can adapt to a gradually changing environment in ways that they would not adapt to short-run weather shocks (Deschênes and Greenstone, 2011). On the other hand, these estimates may understate the damages, as individuals may adapt along the extensive margins by purchasing additional capital equipment in the long run, which they might not have done in the time frame of the data.

The paper is structured as follows. Section 2 lays a theoretical foundation to understand the aim of this literature. Section 3 reviews the literature on cross-sectional climatic evidence and panel (or time series) evidence of weather shocks. In Section 4, we discuss the gaps in the literature and where the literature may head. In particular, we examine the need to incorporate the literature on technology adoption in the estimation of the energy effects of climate adaptation. Finally, Section 5 offers concluding remarks on the state of the literature and its policy implications.

2 Theory

Before examining specific papers in this literature, we provide a theoretical foundation to understand why households may change energy expenditures in response to climate change. Define the utility function for a household as follows:

$$U = U(\vec{E}, \vec{D}, Y; F_0(t)), \tag{1}$$

where $\vec{E}$ is a vector of energy sources like electricity, oil, and natural gas. $\vec{D}$ is a vector of durable goods that affect the marginal utility of energy use like refrigerators, air conditioners, and insulation. The other variables are a composite good Y, or numéraire, and the current distribution of (outdoor) temperature $F_0(t)$, or simply F_0. We could broaden the definition of F_0 to include other climate variables that would affect households' purchasing decisions. For example, humidity may affect a household's choice of air conditioning (part of $\vec{D}$), which has implications for its choices of energy sources and other durables.

A household will maximize utility by choosing $\vec{E}$, $\vec{D}$, and Y, subject to income (I), energy prices ($\vec{P}_E$), durables prices ($\vec{P}_D$), the price of the composite good (normalized to one), and its expectation of distribution of temperatures, F_0:

$$\max_{\vec{E},\vec{D},Y} U(.; F_0) \text{ s.t. } \vec{P}_E'\vec{E} + \vec{P}_D'\vec{D} + Y \leq I, \tag{2}$$

where we denote the choices that maximize utility given the current climate as $\vec{E}^*(F_0)$, $\vec{D}^*(F_0)$, and $Y^*(F_0)$.

A household derives utility from $\vec{E}^*(F_0)$ and $\vec{D}^*(F_0)$, in part, because the household can control the interior temperature, t_{in}. The energy needed to attain t_{in} depends on the absolute difference between t_{in} and the exterior temperature t, given the set of durables: $\vec{E} = \vec{E}(|t_{in} - t|; \vec{D})$.

Climate change, by definition, alters the probability $f(t)$ of experiencing temperature t on a given day. As a result, the distribution will change (gradually) from $F_0(t)$ to $F_\tau(t)$, or F_τ. In response, a household may choose to allow the interior temperature to vary with t. However, if it does maintain a constant interior temperature, then the change in expenditures measures the welfare effects of climate change (ΔW):

$$\Delta W = \vec{P}'_E \cdot \left(\vec{E}^*(F_\tau) - \vec{E}^*(F_0)\right) + \vec{P}'_D \left(\vec{D}^*(F_\tau) - \vec{D}^*(F_0)\right). \tag{3}$$

There are several caveats to consider. First, energy and durables prices may respond to climate change. Second, the transition may be costly, especially if unexpected climate change results in suboptimal reversible investments. Third, the transition will occur over time requiring discounting of future costs. Fourth, this measure excludes how climate directly enters the utility function and therefore is only a part of the overall costs. Finally, households may relocate in response to climate change.

We can now compare this measure to what the literature estimates. Papers that use either time series or panel data measure how energy expenditures change with temperature. This measure is conditional on the household's choice of durable goods and the numéraire for the current climate F_0:

$$\frac{\partial W}{\partial t} = \vec{P}'_E \cdot \frac{\partial \vec{E}(F_0)}{\partial t}. \tag{4}$$

This measures the intensive margin. While both time series and panel data are used to estimate this effect, panel data estimates can control for unobserved shocks that are common to all households at a point in time. These unobserved shocks may be correlated with temperature in the time series analysis, thus making the panel estimates preferable. We can use these estimates to measure the welfare effects from climate change (ΔW_{panel}) as follows:

$$\Delta W_{panel} = \int \left[\vec{P}'_E \cdot \left(\frac{\partial \vec{E}(F_0)}{\partial t} \cdot (f_\tau(t) - f_0(t))\right)\right] dt, \tag{5}$$

where we integrate over the probabilities of observing a given temperature in differing climates.

In contrast, papers that use cross sectional data allow all consumption choices (like over durables) to differ with climate. The welfare estimates (ΔW_{cross}) typically are as follows:

$$\Delta W_{cross} = \vec{P}_E' \cdot \left(\vec{E}^*(F_\tau) - \vec{E}^*(F_0) \right). \tag{6}$$

This measures both the extensive and intensive margins. However, these studies do not account for the cost of changing durables, nor do they include the cost of the transition. In addition, these estimates are subject to the omitted variable bias concerns discussed below.

3 Literature

This section discusses notable papers used to measure energy expenditures from climate change. We organize the literature by the type of data used (cross section, time series, and panel), rather than by estimation method. This is because the variation in the data inform what the authors could learn regarding the intensive and extensive margins. They also differ in the type of omitted variables that may bias each approach. After reviewing the existing literature, we discuss how we view the literature moving forward. In the appendix, we discuss two other bodies of literature that could be used to predict changes in energy expenditures from climate change: one estimates electricity demand, while the other uses engineering methods. Here we focus on the direct econometric papers.[1]

3.1 Cross-Sectional Data

One approach to measuring the impact of climate change on energy consumption uses cross-sectional variation in energy expenditures from survey data. One advantage of this approach is that one could argue that each household is in its long run equilibrium. Namely, people's expectation $F(t)$ is consistent with the actual distribution.

[1]For the interested reader, we suggest two additional reviews of energy expenditures and climate change. Mideksa and Kallbekken (2010) discuss papers on electricity use and Schaeffer *et al.* (2012) look at all energy sectors.

Vaage (2000) examines Norwegian residential heating using a discrete-continuous approach developed by Dubin and McFadden (1984). In spring 1980, the Norwegian Central Bureau of Statistics surveyed 2289 households' energy consumption. First, Vaage models households fuel choice–electricity only, wood, oil, or all fuels–as a function of an indicator of warm climate (average historic temperatures above a threshold), as well as fuel price, household demographics, and building characteristics. The continuous fuel choice equations also depend on these variables, in addition to a selection correction calculated from the discrete model. Warmer households are less likely to choose all fuels, and spend 30 percent less on fuel (based on the coefficient from the conditional energy expenditures estimate).

Similarly, Mansur *et al.* (2008) use cross-sectional data and a similar discrete-continuous choice model, where fuel choice is endogenous to climate change. In contrast to Vaage, detailed climate data (i.e., 30-year average monthly temperature and precipitation) from the National Climate Data Center data are matched to household (and firm) Energy Information Administration survey data.[2] These climate variables enter into both the fuel choice and conditional consumption equations. The first step estimates a multinomial logit model where this selection model is identified by the prices of each fuel available to a given consumer. The second equation is of conditional demand, C_{if}, for household i choosing fuel f:

$$C_{if} = x_f \beta_f + \sigma_f f(\theta_{if}) + \varepsilon_{if}, \tag{7}$$

where θ_{if} is the predicted probability of choosing a fuel and x_f is a vector of demand shifters including regional fuel price, household characteristics and climate variables.

In the first stage, Mansur *et al.* (2008) find that global warming will result in fuel switching in the United States: more homes will heat with electricity. Overall, they find that warmer summers result in more electricity and oil consumption, while warmer winters will result in less natural gas consumption for households. Commercial firms are expected to increase electricity consumption and decrease oil consumption as temperatures increase. Overall, American energy expenditures will likely increase.

[2] Several book chapters use these data to address similar questions (Morrison and Mendelsohn, 1999; Mendelsohn, 2001; Mendelsohn, 2006).

There are drawbacks to the cross-sectional approach. One cannot econometrically control for unobservable differences across firms and households, which may be correlated with climate variables. This is the classical omitted variables problem. The implication is that the results are potentially biased. One reason this might arise is that people do not randomly sort into different climate zones. Suppose that households with lower disutility for extreme heat sort into warmer climates. In this case, cross-sectional estimates of the elasticity of air conditioning expenditures with respect to summer temperatures would be biased towards zero if households do not always maintain a constant interior temperature. In addition, interpreting cross-sectional results as indicative of long run equilibrium effects requires that variables, like weather and prices, in the year of the sample are equal to their respective distributional expectations for each market or geographic region. In conclusion, we are hesitant to suggest that this method be used in assessing the effects of climate change until we have a better idea of just how large the bias may be from these omitted variables.

3.2 Univariate Time-Series Data

Several papers exploit weather variation in time-series data. Franco and Sanstad (2008) explain variation in hourly electricity load in the California Independent System Operator during 2004. They regress load on a population-weighted average of daily temperature and find a nonlinear impact of average temperature on electricity load, and a linear impact of maximum temperature on peak demand.

Considine (2000) estimates monthly aggregate energy demand for various fuels and sectors. The elasticities of demand with respect to heating degree days (HDD) exceed the elasticities with respect to cooling degree days (CDD) for nearly all sectors and fuels.[3] Contrary to most other papers, he concludes that the decrease in heating needs (due to warmer temperatures) will more than offset increases in cooling.

For each of eight states, Sailor and Munoz (1997) regress monthly residential and commercial energy consumption (either electricity or natural gas) on temperature. The paper

[3]HDD (CDD) are typically defined as the aggregate degrees below (above) $65°F$ over some time period like a month.

tests whether season-specific linear functions of temperature or functions of HDD and CDD better fit the data. Lam (1998) also uses time-series data for Hong Kong and finds an elasticity of annual electricity demand with respect to cooling degree days of 0.22, though prices are assumed exogenous.

There are a few general concerns with using time series data. First, they only address the short run response to changes in weather and cannot address long run adaptation. Second, aggregate data cannot control for unobserved factors also changing over time. If the income distribution or business composition change over time, data may be used as control variables. However, unobservable factors cannot be taken into account. These omitted variables may cause bias, just like in the case of the cross sectional analysis. In contrast to that literature, time series data cannot only measure the intensive margin. We conclude that this literature is the least likely to be informative on climate damages.

3.3 Panel Data

Panel data allow the econometrician to control for differences in unobservables, both common shocks across time as well as time-invariant differences across households, firms, or counties (whatever is the unit of observation). These data could be used in a matter similar to the cross-sectional studies: use spatial variation in climate variables to estimate long run effects. This would enable the analysis to use multiple years of data on expenditures, fuel prices, weather, and other factors changing over time for a given household. While this addresses some issues, it does not control for the potential omitted variables bias. Therefore, the analysis below includes household (or similar) fixed effects and only examines the short run effects in equation (4). This is also an improvement over the time series papers because time fixed effects can address other omitted variable biases. Therefore, the results are more likely to be consistent estimates of the coefficients on temperature.

Peirson and Henley (1994), and Henley and Peirson (1997, 1998) wrote some of the earliest published papers using panel data to examine explicitly the relationship between temperature and energy consumption. The authors use residential electricity panel data from England's

Electricity Management Unit Demonstration Project pricing experiment from April 1989 to March 1990. Not only do extreme temperatures increase consumption, they also note that price elasticities change with temperature: moving away from $50°F$ results in less own- and cross-price elastic demand. The reverse is also the case: higher prices reduce consumers' temperature elasticities. Both effects are important for climate change and are not frequently mentioned.

In addition to these micro data studies, there have been some studies using panel data where demand is aggregated across consumers by Chinese province (Asadoorian *et al.*, 2008) or nation (Eskeland and Mideksa, 2010, and De Cian *et al.*, 2007). Asadoorian *et al.* (2008) model both the extensive margin (appliance choice for AC, fans, refrigerators, and TVs), as well as the intensive margin (electricity consumption) in the short run.[4] Eskeland and Mideksa (2010) study European countries' annual electricity demand. With aggregate data they recognize that electricity prices and income are endogenous and use the per-kWh value added tax rate and the total value added taxes in the economy as instruments. They find extremely small effects of temperature on consumption.[5] De Cian *et al.* (2007) use the Arellano-Bond (1991) estimator to study European countries' annual energy use. Studies using aggregate data introduce a similar critique as the literature of the two previous sub-sections: omitted variables may be correlated with changes over time within a province or country. Without fixed effects at the level of the consumer, we cannot be confident that these results are unbiased even with instrumental variables.

Deschênes and Greenstone (2011) explain variation in state-level annual panel data of residential energy consumption using flexible functional forms of daily mean temperatures. The energy data, measured in BTUs, are from the Energy Information Administration's State Energy Data System. The weather data, specifically the average of daily maximum

[4] They find electricity demand elasticities with respect temperature of for urban residential, rural residential, and non-residential of 0.59, 0.76, and 0.06, respectively. While these estimates are for models without provincial fixed effects, the authors note that the results are similar when these were included.

[5] The coefficients are 0.00050 and 0.00010 for CDD and HDD, respectively. A one standard deviation increase in the 2005 levels of each variable (24.3 and 201) results in an annual increase of less than 0.3 kWh per capita (where the average kWh use per capita is 3587 kWh).

and minimum temperature, are from the National Climatic Data Center Summary of the Day Data (File TD-3200). The identification strategy behind their paper relies on random fluctuations in weather to identify climate effects on residential energy consumption (C_{st}). The model includes state fixed effects (α_s), census division by year fixed effects (γ_{dt}), and flexible functions of precipitation, population and income, $f(X_{st}; \beta)$. The mean daily temperature data ($TMEAN_{stj}$) enter the model as the number of days in bin j for state s and year t, where j is one of several pre-determined temperature intervals. For idiosyncratic shock ε_{st}, they model log consumption as:

$$\ln(C_{st}) = \sum_j \theta_j^{TMEAN} TMEAN_{stj} + f(X_{st}; \beta) + \alpha_s + \gamma_{dt} + \varepsilon_{st}. \tag{8}$$

The authors find a U-shaped response function where electricity consumption is higher on very cold and hot days (see Figure 2). They conclude that "business-as-usual" climatic predictions for 2099 will increase residential energy consumption by 11 percent. Their are two concerns with this study that were also mentioned for several other papers above. First, responses to weather shocks only estimate the intensive margin. Second, aggregate data mask changes in composition of households and industry that more detailed-level data could address.

In contrast, Auffhammer and Aroonruengsawat (2011, 2012b) use household-level panel data on electricity billing to examine the impact of climate change on residential electricity consumption. Weather data are the Cooperative Station Dataset published by National Oceanic and Atmospheric Administration's National Climate Data Center. The electricity data are from California's three largest investor-owned utilities for the years 2003– 2006. One concern with these data is that the authors only observe a household's monthly consumption, electricity price, and location at the five-digit ZIP code level. Auffhammer and Aroonruengsawat (2011, 2012b) use variation in the start dates and lengths of billing periods across households to identify the effect of temperature on electricity consumption while controlling for household (α_i), month (ϕ_m), and year (γ_y) fixed effects. For household i and billing period t, they estimate the following equation:

$$\ln C_{it} = \sum_j \theta_j^{TMEAN} TMEAN_{itj} + f(X_{it};\beta) + \alpha_i + \phi_m + \gamma_y + \varepsilon_{it}, \tag{9}$$

where $f(X_{it};\beta)$ is a flexible function of precipitation and (in some specifications) household average monthly prices. Importantly, they estimate this model separately for each climate zone (see Figure 3). Unfortunately, these data are only for California and may not be representative of other US regions or other industrialized countries.

We conclude that using panel data is the most promising method for estimating the effect of weather on energy expenditures. The first caveat raised with temperature still remains: the papers only address the short run response to changes in weather and cannot address long run adaptation. Nonetheless, the omitted variables issue that was raised for both the cross section and time series data is less likely to be an issue in this work.

4 Moving the Literature Forward

We see this literature progressing on two related fronts. On the intensive margin, economists can continue to refine the panel data estimates of how consumption and expenditures respond to weather shocks. In particular, building on Auffhammer and Aroonruengsawat (2011, 2012b), the literature could ask how these response functions differ by climate zone. Detailed, high-frequency micro data on households' and firms' energy expenditures over large geographic areas would provide substantial variation that would allow for the greatest understanding of how people respond to weather. Furthermore, understanding the likelihood of relevant weather events in a given climate zone is important in thinking about how these estimates apply to scenarios with climatic change. On the extensive margin, there is much to be learned. In particular, economists can work to improve our understanding of how building characteristics - like air conditioning, fuel choice, and insulation and other energy-efficiency technologies - vary with climate. The only well-developed literature on the extensive margin responses looks at the adoption of air conditioners. There is a significant opening for studies looking at investments in other building characteristics. Due to this literature constraint, we now turn to describing what has been written on air conditioning adoption as we see this as a significant part of how research on climate adaptation and energy use can proceed.

4.1 Air Conditioner Adoption and the Extensive Margin

Most empirical papers on air conditioner adoption–largely due to data availability concerns–estimate models based on cross sections or repeated cross sections. Data collection efforts enabling panel data methods will add a meaningful dimension to this literature. The literature examining the adoption of air conditioners in response to *changes* in climate is essentially non-existent. There is a much longer literature looking at empirical models of durable goods adoption as a function of incomes, fixed and variable costs. Surveying these approaches taken to better understand the impact of income and prices on adoption provides a useful overview of the methods employed in this literature nonetheless. We review the literature for the United States, Europe, and in developing countries.

4.2 Air Conditioning Adoption in the United States

In the early 1950s in the United States, air conditioners were mainly found in movie theaters, supermarkets, and other public spaces (Biddle, 2008). Less than two percent of households owned air conditioners in 1955. By 1980, the residential penetration rate rose to 50 percent, with half of these households having installed central air conditioning units. There was significant heterogeneity in the penetration, where half of the residences in the Northeast were air-conditioned and some urban areas in Texas and Florida had penetration rates in excess of 90 percent. What is relevant to the discussion in this paper is the relative importance of weather/climate over changes in policy, population movements, income, prices or air conditioners and electricity in the adoption decision.

There was much movement in all of these confounders since the 1950s. On the policy front in 1957 "the Federal Housing Authority announced that the cost of air conditioning could be rolled into approved mortgage packages, which led to a jump in installations." Biddle (2008) also addresses the concern raised above about the importance of sorting and population movements. He provides an interesting back-of-the-envelope calculation suggesting that the extensive population shifts during this period can only account for a fraction of the changes in penetration over time. He also documents significant changes in prices, by showing that after adjusting for efficiency gains and inflation, the price of air conditioners dropped by 25 percent during the 1970s and another 20 percent during the 1980s. While AC prices fell, electricity prices were volatile: they dropped significantly during the 1950s and 1960s and then rose again during the 1970s. During this entire period incomes rose substantially, which suggests that the falling costs of installation and operation combined with rising incomes drove the adoption of air conditioners during this period.

In order to determine the relative importance of these factors, Biddle (2008) matches the air conditioning indicators with the corresponding socioeconomic characteristics from three Census cross sections for 1960, 1970 and 1980 to electricity rates in the Standard Metropolitan Statistical Area (SMSA), incomes and detailed climate variables (e.g. Cooling and Heating Degree Days, wind speed, relative humidity). He uses a reduced form econometric model, which accounts for changes in incomes, prices and weather in order to explain the heterogeneity in penetration.

Biddle shows that differences in climate across SMSAs explain 75-95 percent as much of the variation in penetration in the cross section relative to the models, which also control for prices and socioeconomic factors. He also shows that the home characteristics relevant to retrofitting played a significant role.

Sailor and Pavlova (2003) use data on air conditioning penetration for 39 US cities to parameterize a relationship between cooling degree days and market saturation. They take issue with existing estimates that electricity consumption rises by two to four percent for each degree Celsius in warming as these estimates only account for intensive margin adjustments (more frequent operation of existing air conditioning equipment). A hotter future will result in extensive margin adjustments, namely higher saturation levels. They use penetration data from the American housing survey for 39 cities for the year 1994-1996 for both central and window units. They show that a significant number of cities have air conditioning penetration below 80 percent suggesting that there is room for two temperature driven margins of adjustment under climate change: Increased adoption of air conditioners and increased usage. Ignoring the adoption decision would lead to an underestimation of future electricity consumption. They estimate a relationship between saturation and cooling degree days for the combined saturation plot. They estimate an equation between what they call saturation (which is the recent penetration from the 1994-1996 American Housing Survey) and cooling degree days of the form:

$$S_o = 0.944 - 1.17 \exp(-0.00298 \cdot CDD) \tag{10}$$

This simple relationship does not control for any other observables (such as income) or other climate factors. Further, no standard errors are provided so it is not clear whether the relationship is statistically significant. To model consumption, the authors explain variation in state per capita electricity consumption as a proxy for city level per capita consumption using CDDs, HDDs and wind speed. It is shown that higher CDDs lead to increased adoption of air conditioners and higher use. Adding the extensive margin adjustment results in increases that are significant and matter when making forecasts. Sailor and Pavlova (2003) note that "Based on these results, Los Angeles' per capita residential electricity consumption is projected to increase by eight percent in July for a 20 percent increase in CDD. If the market saturation were assumed to remain constant, however, the projection would be for only a five percent increase."

Rapson (2011) estimates a state of the art discrete-time, infinite horizon dynamic consumer optimization problem. In his structural model, consumers in each period decide between buying a maximum of one unit of a durable good and the amount of household production. An interesting and important feature of his model is that households operate in an environment of uncertainty, where they do not know the efficiency of a durable bought in a future period and may therefore wait to purchase until technological progress has happened. In a "first stage", he estimates derived demand for electricity from central and room air conditioners. He uses five cross sections of the Energy Information Administration's Residential Electricity Consumer Survey (RECS), which he matches to air conditioner prices and efficiencies. His first stage derived demand elasticities are consistent with more general estimated of electricity demand. For central air conditioners the estimates price elasticity of derived demand is -0.170 for the whole sample and drops to -0.068 if one drops California. The income elasticities for both samples are 0.21. The cooling degree elasticities are near unity (0.989 for the whole sample and 0.961 once he drops California from the sample). For room air conditioners, the price elasticity for both samples is higher (-0.34 for both samples) The cooling degree elasticities are also higher at 1.07 for all states and 1.092 for the sample dropping California. The income elasticities are 0.114 and 0.126 respectively. These estimation results for derived electricity demand are precisely estimated and consistent with the prior literature.

Rapson (2011) then goes on to estimate unit demand elasticities with respect to electricity price, unit efficiency and purchase price of the units. His estimates suggest significant responsiveness in the adoption of room and central air conditioners with respect to efficiency. The elasticities for central AC range from 0.7 to 1 and for room AC range from 0.2 to 0.3. The estimated elasticities with respect to purchase price are lower. For central air conditioning they are clustered around -0.241 and for room units they range from -0.12 to -0.13. The elasticities with respect to electricity prices are small for and not statistically significant for central unit adoption (-0.024) and bigger and significant for room unit adoption (-0.220; -0.35). This is an innovative structural paper, which exploits the time dimension of the repeated cross sections and arrives at credible and precisely estimated coefficients for both intensive and extensive margin adjustments.

While the data for the 2011 RECS survey have not been fully released at the writing of this paper, the Energy Information Administration (EIA, 2011) shows a preview of the data which displays further growth in air conditioner penetration on the US. Time series show little slowdown in the growth of air conditioner penetration. 87 percent of US households had air conditioning in 2009, which is the latest year of data. The EIA (2011) notes that "wider use has coincided with much improved energy efficiency standards for AC equipment, a population shift to hotter and more humid regions, and a housing boom during which average housing sizes increased." However, the continued growth of air conditioner penetration puts in question using a cross section of current penetration levels as "saturation" proxies for other regions with similar climate characteristics based on the equation by Sailor and Perova (2003) above. As we will see in the next sections, cross sectional US data are used to parameterize relationships which determine climate dependent saturation levels in other countries.

EIA (2011) also shows that there is little variation in usage over the summer. This is when the percentage of households using AC during the summer is between 30 and 40 percent, except in the South, where 67 percent of households run their air conditioners all summer. Further, newer homes are most likely to have central AC, whereas older homes are more likely to have no air conditioning or window units as retrofitting with central AC has non-trivial transactions costs. EIA (2011) further notes that there is significant heterogeneity in the penetration and type of AC units installed across the income spectrum, which is not surprising given the high cost of installing central air.

4.3 Air Conditioning Adoption in Europe

In Europe, data on air conditioner usage and adoption are scarce and the literature we could gain access to is thin as a result. Much of the literature on changing energy demand in Europe as a consequence of climate change focuses on decreasing demand for heating instead of the increased demand for cooling. What is even more surprising was the apparent lack of publicly available data and studies at member country level. Given the predicted shifts in climate for EU member countries and the relatively high incomes, a better understanding of intra-European adoption patterns is very important to better project future electricity demand in the European Union.

The maybe most informative report is a study by the Directorate-General for Mobility and Transport (European Commission) published in 2003, which provides an overview of the penetration of central air conditioners (CACs) and their efficiencies across EU member states. Central air conditioners here are defined as air conditioning systems with more than

12 kW of cooling capacity, which does not include smaller room type air conditioners. The report indicates that the area cooled per inhabitant is expected to rise rapidly from 3m^2 per inhabitant in 2000 to 5m^2 per inhabitant by 2010. Recent data indicate almost a quintupling in CAC area in the EU over the past 20 year period. The rapid growth is driven by expansion of cooled floor area in Italy and Spain, which now are responsible for more than 50 percent of the cooled floor area. If one normalizes cooled area by population, the distribution of cooled square meters per person is highly correlated with summer temperatures. This report only discusses the cross sectional variation, when in fact how these measures have developed over time would enable us to better understand the drivers of these series–especially the relative roles of rising incomes versus changing temperatures.

Aebischer *et al.* (2007) provide another study predicting energy demand for Europe under climate change. The paper is not very clear on how predictions are calculated and focuses much on the trade-off between heating and cooling demand thereafter. Given the climate heterogeneity in Europe and predicted warming throughout the continent combined with the member countries relatively high incomes, further studies of changing air conditioner penetration and collection of data could provide important insights into the future of European energy demand.

A concerted effort, if not already underway, to collect and analyze data for Europe similar to what Rapson (2011) or Biddle (2008) did for the US would be insightful, given the tremendous degree of heterogeneity in weather, electricity prices and incomes across the European Union member states. While the penetration of air conditioners in central and northern Europe is very small, under climate change these rates can potentially grow rapidly with significant impacts on electricity consumption and the load profile. Given a shift away from nuclear power for base load in *e.g.* Germany, these shifts could have significant impacts on load profiles and the ability of generators to meet peak demand.

4.4 Air Conditioning Adoption in Developing Countries

McNeil and Letschert (2010) provide a model of adoption of air conditioners and appliances using cross-country data. They incorporate the fact that saturation levels are climate dependent, which is the idea raised in Sailor and Pavlova (2003). They have collected appliance penetration levels across countries from a number of micro level surveys–most of which are in the LSMS database of the WorldBank for various years (mostly late 1990s and early 2000s). McNeil and Letschert (2008) discuss these data in more detail. In a first step, they estimate a relationship between saturation (which they call "Climate Maximum") and cooling degree days for 39 US cities. They then use this estimated relationship to estimate a predicted saturation level based on cooling degree days for a given location. For developing country locations in their sample air conditioner saturation is assumed to approach this frontier, but never exceed it. They then model diffusion of air conditioners as a function of income, conditional on a location's Climate Maximum, which is a function of CDD. The diffusion equation for air conditioners is given by:

$$\log\left(\frac{\text{Climate Maximum}_i}{\text{Diff}_i} - 1\right) = \log\gamma + \beta_{inc}\text{Inc}_i \tag{11}$$

What is different in this equation is that Climate Maximum is the cooling degree dependent saturation level based on the cross section of US cities discussed above. For other appliances, such as refrigerators, a common value (e.g. 1 per household) is used. If the climate maximum for a given country is one and the saturation is one, penetration is therefore 100 percent. If the climate maximum is 0.1 and the saturation is 0.1, penetration is also 100 percent. Their regression is based on 24 observations.

They explain 70 percent of the variation in the transformed dependent variable, which means that their model fits the cross sectional data fairly well. What is noteworthy about the estimated adoption curve is that the penetration rates are very low and clustered around zero for a number of countries. At income levels of $25,000 the adoption rates seem to rise drastically. While the modeling approach here is appealing and the data collection effort is impressive, this is essentially a cross sectional regression which cannot meaningfully control for confounding factors. Using repeated cross sections or panel data on this model would allow one to separate out unobservables via a two-way fixed or random effects strategy.

Isaac and van Vuuren (2009) build on the model by McNeil and Letschert (2010) but in addition endogenize the unit energy consumption (UEC) as a function of income, which allows for income dependent energy efficiency of air conditioners. They then predict penetration rates based on CDD and income, which allows them to build regional predictions. They show that their model can predict US penetration very well, but is off by 30 percent for Japan.

Akpinar-Ferrand and Singh (2010) look at air conditioning demand for India. The authors used a combination of AC ownership data from the NSS 55 survey (2001) and obtained sales data from industry sources. They follow the same approach as Isaac and van Vuuren (2009) described above. The combination of rapidly rising incomes and a hot and in many cases humid climate has led to very fast growth in sales in urban areas with a relatively reliable electricity supply. Rural area adoption has lagged as only 44 percent of rural households have access to electricity. The authors predict a rapid rise in the penetration rates of air conditioners over the next century.

What would be of great interest are studies, which project future air conditioner penetration by country by 2100 under different climate, income and price scenarios. Unfortunately our understanding of air conditioner penetration by country is very limited, which makes issuing these projections a challenging yet important task.

5 Conclusion

This paper reviews the literature on the relationship between climate and the energy sector. In particular, we primarily discuss empirical papers published in peer-reviewed economics journals focusing on how climate affects energy expenditures. Climate will affect energy consumption by changing how consumers respond to short run weather shocks (the intensive margin) as well has how people will adapt in the long run by changing durable goods (the extensive margins).

Along the intensive margin, we conclude that much of the existing literature has been limited to time series variation or aggregated panel data. Both raise concerns of omitted variables bias. Until recently, few studies used household-level panel data and even those are informative of only a small part of the world. Further research that uses household-level panel data of energy consumption may help identify how consumers around the world respond to weather shocks. Research on technology adoption, like air conditioning use, will further our understanding of the extensive margin.

The current literature has made some progress in these dimensions. The coefficient estimates from papers like Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011, 2012b) offer some of the best evidence we have on the intensive margin. We have not identified any paper that identify the extensive margin using panel data. As such, the implications for policy makers are muted. What we would like to be able to identify for policy makers and integrated assessment modelers is a reduced-form, long run response coefficient. It is not clear to us how this can be credibly estimated.

Finally, we recognize that there is great uncertainty about the future. If we are to learn about the extensive margin, it is important to keep in mind that these capital investments are being made in the context of a continuously changing and uncertain climate. One factor that we are uncertain over is technology. We do know, however, that changing the climate will induce technological change. Some technologies that are not economic today may become so in the future. For example, at some price even hydrogen fuel cells, which could end the positive feedback loop between climate and energy use, would become viable. These futures possibilities are not measured in the empirical literature we discussed in this paper, but are important to consider in a broader context.

Appendix on Related Literatures

Economists have written extensively on the estimation of electricity demand. In estimating price elasticity, many papers recognize the importance of controlling for weather shocks (*e.g.*, Lee and Chiu 2011). Some early studies even focused explicitly on the relationship between weather and electricity sales: Engle *et al.* (1986) estimate electricity demand response to temperature for four US utilities. Rather than imposing linearity in HDD and CDD, the authors allow for flexible temperature responses using cubic and piecewise linear splines (see Figure 1). In contrast to current papers focusing on climate change, their motivation for understanding this relationship was because weather-adjusted sales are used in regulatory rate hearings. For this reason we do not include them in the body of the paper. Nonetheless, the findings from these types of studies could be used in evaluating the impacts climate on energy demand.

An alternative to the econometric methods discussed in Section 3 would be to use engineering methods to map temperature into expenditures. For example, Rosenthal and Gruenspecht (1995) take climate model predictions of changes in heating and cooling degree days and calculate the resulting changes in US energy expenditures. In contrast to the majority of studies mentioned, they predict a *reduction* in expenditures due to a temperature increase. This approach, however, is based on technology, not on human behavior.

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Tables and Figures

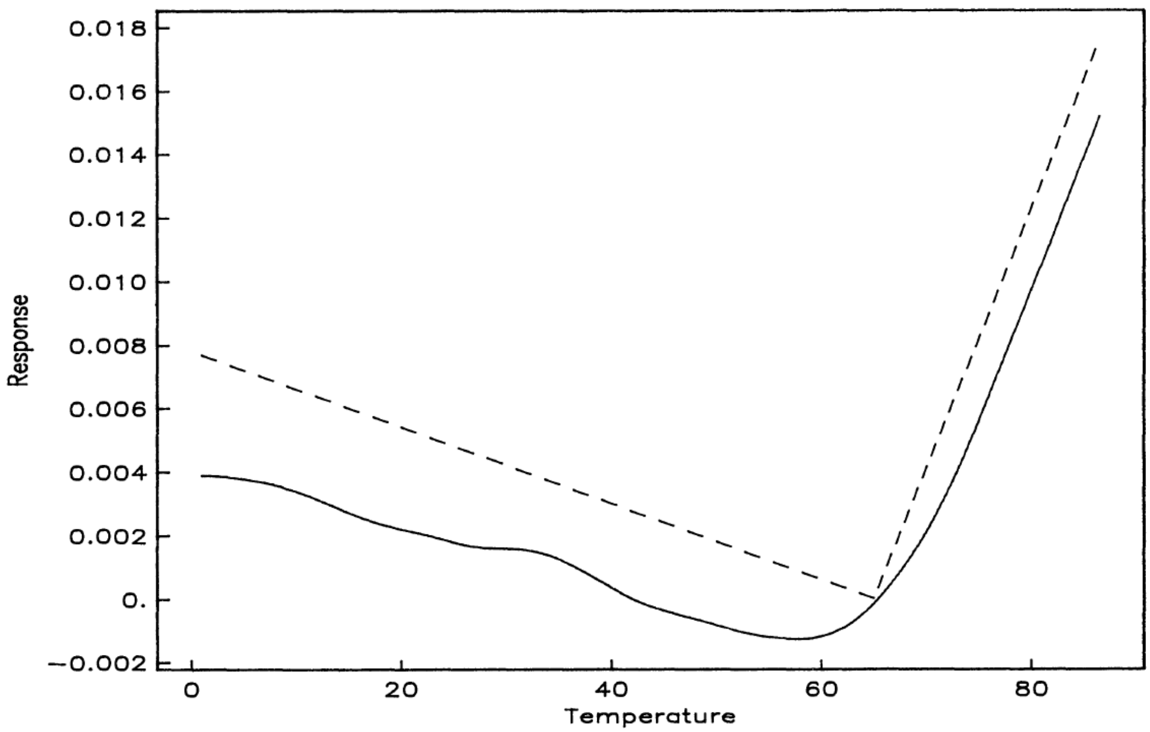

Figure 1. Replication of Figure 4 from Engle et al. (1986): Temperature Response Functions for Northeast Utilities where The Solid Curve is the Nonparametric Estimate and the Dashed Curve is the Parametric Estimate.

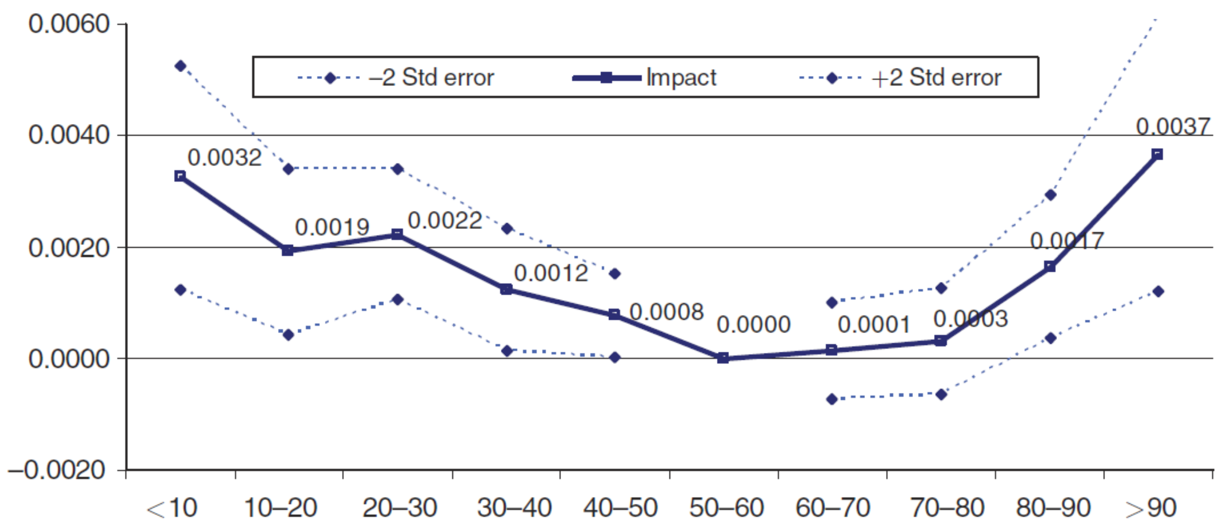

Figure 2. Replication of Figure 3 in Deschênes and Greenstone (2011): The Estimated Relative Impact of a Single Day in a given mean temperature (°F) bin (Relative to a Day in the 50-60°F Bin) on Log Annual Residential Energy Consumption.

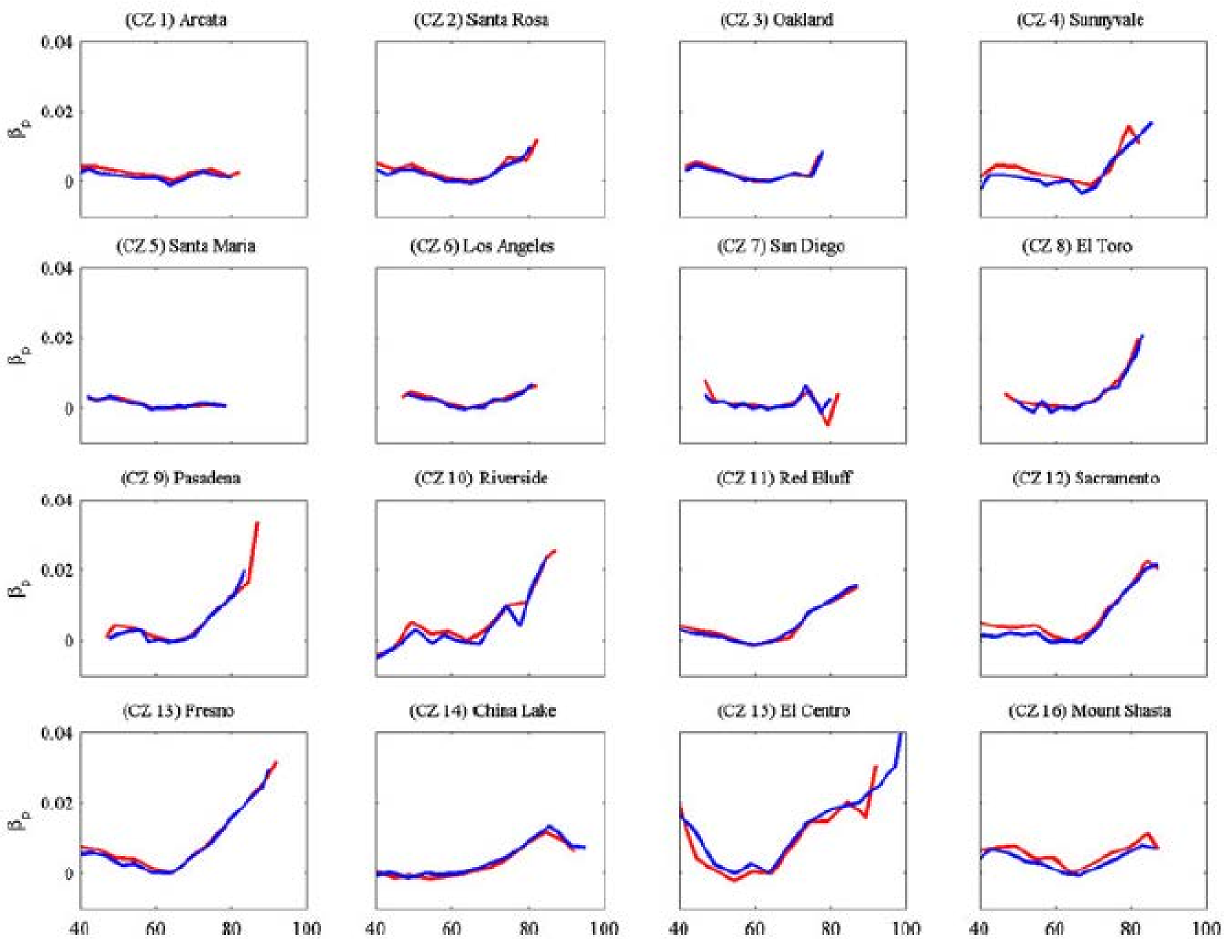

Figure 3. Replication of Figure 3 in Auffhammer and Aroonruengsawat (forthcoming): The figure displays the estimated temperature slope coefficients for each of the fourteen percentile bins (blue) and the equidistant bins (red) against the midpoint of each bin. The plots were normalized using the coefficient estimate for the 60–65 temperature bin. The title of each panel displays the name of a representative city for that climate zone.