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Climate change adaptation: A study of fuel choice and consumption in the US energy sector

Erin T. Mansur[a,*], Robert Mendelsohn[b], Wendy Morrison[c]

[a] Yale School of Management and NBER, 135 Prospect Street, P.O. Box 208200, New Haven, CT 06520 8200, USA
[b] Yale School of Forestry and Environmental Studies, 230 Prospect Street, New Haven, CT 06511, USA
[c] Texas A&M, El Paso Agricultural Research Center, USA

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Abstract

Using cross-sectional data, this paper estimates a national energy model of fuel choice by both households and firms. Consumers in warmer locations rely relatively more heavily on electricity rather than natural gas, oil, and other fuels. They also use more energy. Climate change will likely increase electricity consumption on cooling but reduce the use of other fuels for heating. On net, American energy expenditures will likely increase, resulting in welfare damages that increase as temperatures rise. For example, if the US warms by 5 °C by 2100, we predict annual welfare losses of $57 billion.
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1. Introduction

While many researchers have studied the effects of energy consumption on global warming, few have examined how changing the climate (long-term weather) is likely to impact the demand for energy [1]. Most of the studies that do consider the impacts of climate on the energy sector rely mainly on expert opinion [2], engineering models [3], time series variation of aggregate data [4], or case studies of electricity [5]. The few empirical studies that consider the entire energy sector use an aggregate expenditure model that examines all fuels without distinction [6,7].

This paper contributes to this literature by estimating a fuel choice model of energy demand using a multinomial discrete-continuous choice framework. We estimate the parameters of this model using a cross section of US residential and commercial energy consumers. We find that both the choice of fuel and the conditional demand for energy by fuel type are sensitive to climate and especially temperature. We then use the results of this model to predict the implications of future climate scenarios. By estimating this

*Corresponding author. Fax: +1 203 432 6974.
E-mail addresses: erin.mansur@yale.edu (E.T. Mansur), robert.mendelsohn@yale.edu (R. Mendelsohn), mmorrison@elp.rr.com (W. Morrison).

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discrete-continuous model of energy demand, we are able not only to estimate the welfare effects of climate change on the energy sector but also to discuss how consumers may adapt as climate changes.

Models that explicitly consider the discrete and continuous components of consumer choice have been used to examine a wide range of topics including housing [8], food and drink [9], transportation [10,11], and water [12,13]. Demand is evaluated as a discrete choice over limited alternatives with a corresponding continuous component conditional on that choice. The approach has also been used in the energy literature [14–18]. Baughman and Joskow [14] develop a model of fuel choice and energy consumption for electricity, natural gas, and oil in the commercial and residential sectors of the United States. Their study, however, does not account for potential interactions between fuel choice and consumption decisions. If the decisions are not independent, then the estimates will suffer from a selection bias [19].

We rely on a basic econometric model developed by Dubin and McFadden [16] (hereafter, DM) to address this bias in the context of a polychotomous-continuous choice. DM apply their method to electricity demand and the choice of appliance holdings. As they note, the dynamic investment decisions of households can only be reasonably measured with cross-sectional data if there are static expectations regarding operating costs. Ideally, one might be interested in a dynamic model and panel data to better evaluate consumers' choices, but climate change occurs very slowly and panel data do not exist for energy use. We argue that the relationship between energy consumption and climate measures reflected in cross-sectional data captures "long term" adaptation because households can adjust not only their immediate energy use but also their capital stock.[1] In contrast, the relationship between annual or daily weather and energy consumption would measure short run adjustments because presumably capital stocks would be held fixed.

2. Theory

In response to climate change, households and firms may alter: (1) fuel choice, (2) the quantity of fuel, (3) expenditures on building characteristics, and/or (4) interior comfort levels. For households, a measure of the welfare impacts of climate change on energy can be described as the change in income necessary to keep utility constant given climate change:

$$\left.\frac{\partial Y}{\partial C}\right| U*(T*, R*), \tag{1}$$

where Y is income, C is climate, U is utility, T is interior temperature, and R is an index of all other goods. Interior temperature is assumed to be a function of climate, energy use (Q_f conditional on fuel choice f among F alternatives), and building characteristics (Z): $T = T(C,Q_f,Z)$, where C is exogenous and Q_f and Z are purchased inputs. In aggregate, energy consumption may have a feedback effect on climate. However, climate remains exogenous to an individual household's behavior.

To measure the welfare effects of climate change, we make the following three assumptions:

Assumption A1. Households do not vary interior temperatures: $\partial T/\partial C = 0$.

As mentioned above, one possible adaptation to climate is to vary the interior temperature.[2] However, if people (and firms) maintain a preferred interior temperature regardless of outdoor climate, there will be no loss of interior comfort from climate change.[3] The only welfare effect of climate change will be the cost of maintaining the desired interior temperature. In this case, increases (decreases) in energy and building expenditures will measure the welfare loss (gain) from climate change.

[1]This paper relies on cross-sectional data to measure how households and businesses use energy in different climates. The economy constantly receives shocks and many markets are unlikely to be in long run equilibria. Nonetheless, we argue that cross-sectional data are more informative, relative to time series data, of how adaptation to gradual climatic change may happen.

[2]To the extent that comfort levels fall or rise with warming, our measures of the impacts of climate change will be attenuated. This is likely to be the case especially for low-income households [20,21]. However, if climate change induces adoption of central air conditioning, people may become more comfortable. Thus, the welfare effects of interior temperature changes are theoretically ambiguous.

[3]An EIA survey of US households revealed that households currently maintain the same interior temperatures in the winter, but not in the summer, regardless of climate ("Household Energy Consumption and Expenditures 1990," Data and accompanying documentation and reports: DOE/EIA-0321/1(90). February 1993).

Assumption A2. Energy supply is perfectly elastic.

We assume that energy prices do not change as a result of climate change. The long-run supply of electricity is expected to be elastic because it can use many fuels. Although end users shift away from heating fuels, most of these heating fuels will then be used to generate electricity. Consequently, the aggregate demand for the fuels will not change much. We test the sensitivity of our results with respect to this assumption in Section 6.

Assumption A3. The capital expenditures from changing building characteristics in response to climatic change are relatively small.

The correct welfare measure would account for changes in building expenditures, as well as changes in energy expenditures. However, this study has data only on energy expenditures and building characteristics. The installation of central cooling, for example, will lead to both capital costs and increased demand for electricity.[4] The capital costs of cooling are not reflected in our welfare calculations; so our estimates understate the costs of climate change. In contrast, with reduced demand for heating, the reduced capital costs associated with heating will cause our energy-only estimates to overstate the costs of warming. The net effect is ambiguous and beyond the scope of this study.

Given Assumptions (A1)–(A3), the change in welfare (ΔW), measured as the compensating variation, equals:

$$\begin{aligned}\Delta W &= \int_{C_1}^{C_0} \frac{\partial Y}{\partial C}\, dC = \sum_{f=1}^{F} P_f Q_{f(C_0)} - \sum_{f=1}^{F} P_f Q_{f(C_1)} + P_z Z_0 - P_z Z_1 \\ &\cong \sum_{f=1}^{F} P_f Q_{f(C_0)} - \sum_{f=1}^{F} P_f Q_{f(C_1)}, \end{aligned} \tag{2}$$

where P_f and P_z are vectors of the prices of fuel f and building attributes, respectively. The subscripts 0 and 1 represent the baseline case (i.e., current climate) and climate change scenario, respectively. Assumption (A3) implies that the last term in (2) is approximately zero.

The probability that a particular fuel portfolio, $f \in F$, is chosen is defined as θ_f. In the discrete-continuous situation, the measure of the expected change in welfare, (2), is:

$$\begin{aligned}E[\Delta W] &\cong \sum_{f=1}^{F} P_f E[Q_{f(C_0)}] - \sum_{f=1}^{F} P_f E[Q_{f(C_1)}] \\ &= \sum_{f=1}^{F} [P_f \theta_{f(C_0)} Q_{f(C_0)} - P_f \theta_{f(C_1)} Q_{f(C_1)}], \end{aligned} \tag{3}$$

where $E[\cdot]$ identifies the expected value. Therefore, expenditures over all alternatives are defined as the sum of prices P_f times the conditional quantities Q_f, weighted by the choice probabilities θ_f. The link between the model components determining θ_f and Q_f is further described below.

3. Empirical model

We model fuel choice and fuel consumption using a discrete-continuous model based on the DM two-step estimation method. A multinomial logit model of fuel choice is estimated in the first stage. We examine all of the major fuels (e.g., electricity, natural gas, and oil) that are available to each consumer. The second stage estimates the amount of fuel demanded given the fuel chosen. The second stage is estimated using ordinary least squares (OLS) with selection correction terms, as defined below, from the first stage to control for the correlation of errors between the two decisions. There are two main approaches to estimating a polychotomous choice two-step model suggested in the literature: one can include the selection correction

[4] Air conditioning penetration is highly correlated with the number of cooling degree days [22] and temperature [23]. Warming will result in greater saturation of the air conditioning market.

term of the own choice [24] or the selection correction terms of the alternative choices [16].[5] One cannot include both sets of selection correction terms, as the sum of all the choice probabilities must be equal to one. Both the DM and the Lee [24] models are widely used, including in estimating energy models [17,18].

The Lee model places substantial restrictions on the covariance between the continuous demand and selection indices [28]. Monte Carlo studies have shown the Lee model to be significantly biased when this assumption is violated [25,28]. Both of these studies find the DM model to be more robust to various data generating processes. Further, the advantage of including the alternative choices is that one can explore cross fuel effects. For example, one can see whether the natural gas consumption of consumers is different depending on whether the fuel choice model predicted that the consumer would have chosen oil versus electricity only.

3.1. The Dubin–Mcfadden model

Consumers maximize utility by choosing the type of fuel used (f) as well as the quantity of the fuel consumed (Q_f).[6] An agent choosing option f, among a set of F available choices, will have the latent conditional indirect utility (V_f^*):

$$V_f^* = z_f\gamma_f + \eta_f, \quad f = 1 \ldots F, \tag{4}$$

where z_f denotes the observable, exogenous factors influencing this conditional indirect utility function and η_f is the unobservable, idiosyncratic shock. However, the only observable action to the econometrician is whether a fuel is chosen: V_f is 1 if fuel f is chosen and 0 otherwise.

For the chosen fuel, the conditional demand function is:

$$Q_f = x_f\beta_f + u_f, \tag{5}$$

where x_f denotes those exogenous variables affecting the conditional demand function. Energy consumption, Q_f, will be positive only when fuel f is chosen ($V_f = 1$). The idiosyncratic term, u_f, has the properties: $E(u_f|x,z) = 0$ and $V(u_f|x,z) = \sigma_f^2$. In this paper, we allow for the possible correlation of the idiosyncratic terms u_f and η_f.[7]

A consumer will choose fuel f based on the following fuel choice process:

$$V_f^* > \max_{j \neq f} (V_j^*). \tag{6}$$

Condition (6) is equivalent to $z_f\gamma_f > \varepsilon_f$ where

$$\varepsilon_f = \max_{j \neq f} (V_j^* - \eta_f).$$

Following McFadden [29], we assume the unobservable term of the latent variable model, η_f, is distributed extreme value type I.[8] This specification implies that the probability of choosing fuel f (θ_f) will be

$$\theta_f \equiv Pr(z_f\gamma_f > \varepsilon_f) = \frac{\exp(z_f\gamma_f)}{\sum_{j=1}^{F} \exp(z_j\gamma_j)}. \tag{7}$$

The parameters of the latent variable model, γ_f, can be estimated by maximum likelihood. However, the estimation of β_f requires further assumptions. DM assume an important linearity condition

$$E(u_f|\eta_1 \ldots \eta_F) = \sigma_f \sum_{j \neq f}^{F} r_j(\eta_j - E(\eta_j)), \tag{8}$$

where, by construction, the correlations between u_f and η_f sum to zero: $\sum_{j=1}^{F} r_j = 0$.

[5]Other less common models include [25–27].

[6]This section outlines the DM model using the notation of [25].

[7]If these unobservables were correlated, then OLS estimates of β_f would be inconsistent.

[8]A widely noted property of the multinomial logit model is the independence from irrelevant alternatives (IIA) assumption, which we test in Section 5.

DM propose three estimation strategies for estimating β_f. In this paper, we focus on a commonly cited method but reach qualitatively similar conclusions using all three methods. The DM method that we use adds what we will refer to as ''selection correction terms'' to each fuel's conditional demand function (5). The selection correction terms in this model are similar to the selection correction terms in the Heckman two-stage decision model [19]. In the Heckman model there is only one choice; so there is only one correction term. In this model, there are several choices so that there are several correction terms, one for each alternative choice. The correction terms provide some insight into observations that the choice model predicted would pick the alternative fuel but did not. For example, the correction term for oil in the natural gas equation indicates whether consumers that the fuel choice model predicted would pick oil consume more or less natural gas. By including the selection correction terms, we remove sample selection biases. Assuming (8), DM note that OLS estimates of β_f from the following equation will be consistent:

$$Q_f = x_f \beta_f + \sigma_f \sum_{j \neq f}^{F} r_j \left(\frac{\theta_j \ln(\theta_j)}{1 - \theta_j} + \ln(\theta_f) \right) + w_f, \tag{9}$$

where w_f is an independent error term. We use this approach to estimate our model.

4. Data

The data come from earlier studies conducted of climate change and energy expenditures [6,7]. These studies relied on two surveys conducted by the Energy Information Administration (EIA).[9] These surveys provide detailed data on energy expenditures and consumption as well as demographics and building characteristics. The data include several thousand buildings distributed in random clusters across the continental US that are weighted to represent the true population of buildings. Data are available for the five major residential fuels: electricity, natural gas, fuel oil, liquid petroleum gas (LPG), and kerosene, as well as the four major commercial fuels: electricity, natural gas, fuel oil, and district heat. The data sets do not disaggregate energy uses. Although space-conditioning energy is expected to be more sensitive to climate, other commercial and residential energy uses may also be affected. Hence, the model is estimated for fuel portfolio choice and consumption across all energy uses.

The original EIA data sets measured only degree-days as a proxy for climate. However, degree-days are defined relative to an arbitrary standard temperature. Further, it is not clear that i degrees for j days is equivalent to j degrees for i days. To analyze climate sensitivity with these data, the EIA merged the energy data with monthly climate (30 year average) data on temperature and precipitation [7].

Because warming reduces heating costs but increases cooling costs, we expect that energy has a nonlinear relationship with climate. In very cold places, the heating effects will dominate and, in hot places, the cooling effects will dominate. Somewhere between is a temperate climate that minimizes both heating and cooling. Climate, of course, is not unidimensional. In addition to annual mean temperatures, the distribution of temperatures across seasons may also be important (contrast San Francisco and Chicago). In this study, we will distinguish between winter and summer temperatures. We also explore the less important but still potentially significant role of precipitation. Precipitation affects relative humidity, which in turn affects comfort. It is relatively easier to endure high and low temperatures with lower relative humidity, for example.[10]

A number of explanatory variables are expected to influence fuel choice and consumption. The variables used to predict residential and commercial fuel choice and consumption are described in Table A.I. (Tables A.I–A.V can be found in an appendix available online through JEEM's archive for supplementary

[9]The surveys are the Commercial Buildings Energy Consumption and Expenditures 1989 (Department of Energy DOE/EIA-0318(89), April 1992) and the Household Energy Consumption and Expenditures 1990 (Department of Energy DOE/EIA-0321/1(90), February 1993).

[10]For the above reasons, we include a quadratic term of our temperature and precipitation variables. The relationship between choice (or quantity demanded) and climate could be modeled with additional variables that account for higher order terms of climate and interaction terms of climate variables with other covariates. However, our relatively small sample size limits our ability to explore these more detailed models.

material accessible at http://www.aere.org/journal/index.html). In general, explanatory variables include climate, demographic and firm-specific information, and building characteristics. We know household and firm location at a regional level (there are nine EIA regions). We employ regional fixed effects to control for building and other unmeasured characteristics that may vary by climate zone. Of course, the regional fixed effects also eliminate some of the interregional differences in climate.

The initial EIA surveys included information on annual expenditures and annual consumption, by fuel type, as reported by consumers. We compute the average fuel price of each customer as the ratio of expenditures over consumption. These average prices may differ from the marginal social costs of each fuel.[11] Each household and commercial firm chooses only one fuel in our sample. For those fuels not chosen, the EIA constructed proxy prices by calculating the average expenditures on that fuel in each customer's region. We only use the full set of prices in the first stage to estimate fuel choice. For identification of the discrete-continuous estimation, we restrict the conditional demand functions to depend only on the own price of each fuel. This is the same restriction imposed by [16].

The building characteristics are divided into climate-sensitive and non-sensitive categories. Non-sensitive building characteristics such as building size, type of occupancy, and building age are used to control for exogenous non-climatic factors that affect energy consumption. Climate-sensitive characteristics affecting thermal efficiency include building materials, conservation capital, the choice of heating and cooling equipment, and some aspects of the household structure [31]. There are (at least) two possible estimation strategies for modeling these climate-sensitive variables. One would be to develop additional choice equations for the decision of whether to invest in each of these capital expenses. However, this would require additional data beyond what are available, and would add considerable complexity to our model. An alternative option is to exclude those climate-sensitive variables for which we have data. This "reduced form," or indirect, approach will result in the climate variables capturing the variation in expenditures associated with air conditioning units, insulation, etc.[12]

Our residential results suggest there is another important distinction to make in energy demand. We find that households that have access to natural gas (pipeable) and households that do not have access (non-pipeable) make different consumption choices. We consequently analyze residential fuel choice and conditional demand separately for pipeable and non-pipeable households. It is not clear whether the additional choice of natural gas alone is the source of this distinction or whether there is an unmeasured characteristic that makes pipeable and non-pipeable households different. For example, these households are more likely to be in a metropolitan area. However, they do not differ with respect to climate.[13]

There are three categories of customers, and each faces a different choice set. (1) When natural gas is available, households can choose: (a) electricity only; (b) natural gas and electricity ("gas"); or (c) fuel oil and electricity ("oil"). Of the 3747 pipeable residential consumers, 82% opt for gas, 9% pick oil, and the rest choose electricity only.[14] (2) When gas is not available, residential customers can choose: (a) electricity only; (b) fuel oil and electricity; or (c) other fuels (like LPG and kerosene) and electricity ("other"). Of the 1283 non-pipeable residential consumers, 44% choose electricity only, 26% pick oil, and the rest opt for kerosene or LPG. (3) We do not have information about whether commercial customers have access to natural gas so they can choose: (a) electricity only; (b) gas; (c) oil; or (d) other fuels (i.e., district heat) and electricity ("other"). Of the 5605 firms, 55% opt for natural gas, 27% pick electricity only, 10% choose oil, and the rest use district heat.

[11] Given data limitations, we use average prices as a proxy for the social marginal value. These proxies ignore environmental externalities, include fixed costs (administrative and capital), and fail to account for nonlinear pricing. Using a log–log specification, the price elasticity estimates will be consistent [30]; only the constant term will be biased.

[12] This estimation method may cause an omitted variables bias. The estimates will be consistent if the omitted climate-sensitive building characteristics are uncorrelated with our other covariates, like the house size or fuel prices. While some of these restrictions appear unlikely, previous analyses found that the energy expenditures did not change dramatically according to whether one controlled for climate-sensitive building characteristics [6,7]. These results imply that the bias from omitting these building characteristics is small.

[13] An OLS regression of gas availability on an MSA indicator, January temperatures, and July temperatures suggests a positive (conditional) correlation between availability and MSA but no significant (conditional) correlation between availability and climate. The unconditional correlations between availability and climate are also insignificant.

[14] Very few households choose kerosene or LPG when gas is available. We do not include those in the sample, as there are fewer observations than independent variables.

Based on our sample, \$181 billion was spent in 1990 on residential and commercial energy (Table A.II reports the actual expenditures for each customer class). Overall, 70% is for electricity. Furthermore, of the overall expenditures on electricity, 75% is by customers who use other fuels as well. Thus, even though a large portion of the sample is labeled "natural gas" consumers, most of the expenditures are on electricity. The share of total energy expenditures for electricity and natural gas is 90%.

5. Empirical results

The estimation results are reported separately in four sections: the residential discrete choice models; the residential conditional demand models; the commercial discrete choice model; and the commercial conditional demand models. The last section summarizes the expected marginal climate impacts. Results are estimated using the selmlog command [25] in Stata 9.

5.1. Residential fuel choice results

We begin by summarizing the results of the multinomial logit fuel choice model of the residential sector. To test the importance of the IIA assumption, we perform Hausman tests by excluding each of the choices from the consumers' choice set and re-estimating the parameters. The IIA assumption is rejected for one case in each of the three customer classes.[15] Some fuel choices are more prevalent in specific regions of the country. Customers may have regional preferences that indicate different choice parameters. We test whether the differences in preferences are restricted to the non-climate variables by testing a simplified multinomial logit model with only climate variables. The IIA assumptions are supported in every case with this simplified model yet the climate coefficients are statistically indistinguishable from those presented in the paper.[16] We present the full model to investigate how consumers might respond to other non-climatic variables of interest given their initial choice set.

Table 1 reports the γ_f coefficients from estimating the latent variable model (4). For both pipeable and non-pipeable groups, "electricity alone" is the base category where the normalization $\gamma_1 = 0$ is imposed. The models fit the data relatively well. The pseudo-R^2 is 0.41 for the pipeable households and is 0.43 for the others. We do not report the regional fixed effects for any of our results; however, they were jointly significant at the five percent level in most (12 of 19) of our models.

Temperature and precipitation variables suggest that households' choice of fuel is sensitive to climate. Households in warmer regions more often rely on electricity alone. On the cooling side, electricity is virtually the only option. On the heating side, it has a high marginal cost but a low fixed cost, making it desirable in places with moderate winters. In relatively warmer locations, more households use electricity.

Table 2 reports the marginal impacts from the coefficients in Table 1 for temperature and precipitation for January, July, and overall.[17] For the pipeable households, customers in places with warmer January temperatures are less likely to choose oil (relative to the other options). Households in places with warmer July temperatures are less likely to choose natural gas and more likely to choose oil. These offsetting effects for oil selection are consistent with oil being the cheapest fuel, per BTU, and therefore the best choice in regions with the largest temperature swings. In aggregate, households in places with warmer annual temperatures are more likely to choose electricity only. Households with more precipitation are less likely to select natural gas and

[15]For the pipeable residential customers, χ^2 tests show that dropping oil does not significantly change the natural gas parameters ($\chi^2_{\mathrm{DF}(26)} = 5$). However, dropping natural gas does change the oil parameters ($\chi^2 = 418$). For the non-pipeable residential customers, dropping "other fuel" does not significantly change the oil parameters ($\chi^2_{\mathrm{DF}(27)} < 1$) but dropping oil from the choice set does change the coefficients of "other fuel" ($\chi^2 = 66$). For commercial customers, we drop each of the choices (relative to electricity only) one at a time. Dropping either oil or "other fuel" does not significantly change the parameters (($\chi^2_{\mathrm{DF}(65)} = 4$ and 3, respectively). However, dropping natural gas from the choice set does have a significant impact ($\chi^2 = 200$).

[16]Note that with a non-linear model, the marginal effects of the variables may differ even when their coefficients estimates are similar.

[17]The marginal effects are calculated in the following manner: $\partial P_j/\partial C_j = P_j[\gamma_j - \sum_{k \neq j}\gamma_k]$ [32]. We calculate the marginal effects for each observation in the sample and report the median. To compute standard errors, we bootstrap these median marginal effects 1000 times and report the median of these results, as well as whether or not the 90th, 95th, and 99th percent confidence intervals span zero. By reporting the median draws, probabilities may not sum to one over fuels or in climatic effects over time. A marginal increase in temperature is an increase of 1 °C and a marginal increase in precipitation is an increase of 1 mm/month.

Table 1
Selection model for residential customers

	Natural gas is available		Natural gas is not available	
	Gas	Oil	Oil	Other
Temperature				
January	0.0011	−0.3525***	−0.0697	−0.0250
January^2	−0.0034*	−0.0102**	−0.0057	−0.0040*
July	−0.1185*	0.1161	−0.5679***	−0.1542*
July^2	−0.0077	−0.0041	−0.0752***	0.0090
Precipitation				
January	−0.1771***	0.1728*	−0.1955	−0.0944
January^2	0.0032*	0.0007	0.0014	0.0035
July	0.0668	−0.0711	0.1711*	0.1163*
July^2	−0.0087**	0.0479***	−0.0112	−0.0128**
Log elec. price	3.96***	2.12***	3.53***	4.24***
Log n. gas price	−1.76***	6.04***		
Log fuel oil price	−1.18	−5.76***	−0.98	−3.10
Log LPG price			1.98***	−2.63***
Log kero. price			−0.90	−3.85**
Log building age	0.80***	2.09***	1.37***	0.54***
Log no. floors	−0.31**	0.44*	−0.30	−1.47*
Log age of head	0.54***	0.83***	0.62*	0.25
Log home area	0.44***	0.51**	0.98***	−0.0065
Log income	−0.0069	−0.099	−0.11	−0.40***
Log family size	0.66***	0.87***	0.29	0.60***
Mobile home	1.35***	−0.12	0.68	1.24***
Multi unit	−0.46**	−1.20***	−0.74*	−1.96***
Metropolitan	−0.14	−0.76***	0.15	−0.43
Burn wood	−0.70***	−0.41	−1.45	−0.56***

Note: Regressions have left out electricity only as a choice. The model on the left-hand side examines residences with access to natural gas and the model on the right-hand side examines residences without access to natural gas. Very few residences choose an alternative fuel when natural gas is available. The significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. Regional fixed effects not shown.

more likely to opt for oil or electricity only. Presumably, for some households, the higher relative humidity encourages the purchase of combined heating and cooling systems in moister locations.

Non-pipeable households are more temperature-sensitive than pipeable households. Those households with relatively hot summers are more likely to choose electricity (over oil). Again, this may simply be a result of not having a choice of piped natural gas or it may reflect other unmeasured characteristics of the two groups. Another difference between the two groups is that non-pipeable households are not sensitive to variation in precipitation.

Table 1 also reports the coefficient estimates for other factors that affect fuel choice including fuel prices and demographic and structural characteristics. The price variables significantly influence the choice probabilities. The own-price effects are negative while the cross-price effects are positive, suggesting that the other options are substitutes. The coefficients on the other covariates are consistent with expectations. For example, owners of multiunit buildings are more likely to pick electricity because usage is easier to apportion to each unit. Owners of larger homes are more likely to pick fuels with increasing returns, like oil and natural gas.

5.2. Residential conditional consumption results

Given the results of the selection model, we then estimate the conditional demand for each fuel shown in Eq. (9). The results of the detailed regressions are available in Tables A.III (pipeable residences) and A.IV

Table 2
Marginal effects of selection model for residential customers

	Electricity (%)	Gas (%)	Oil (%)
Panel A: Natural gas is available			
Temperature			
January	0.05	0.19	−0.17***
July	0.21	−1.10***	0.17**
Annual	0.29***	−0.16	−0.02
Precipitation			
January	0.37***	−1.46***	0.23***
July	−0.13	0.32**	−0.02
Annual	0.16*	−0.70***	0.06**
	Electricity (%)	**Oil (%)**	**Other (%)**
Panel B: Natural gas is not available			
Temperature			
January	0.52	−0.19	−0.09
July	2.15*	−0.93**	−0.39
Annual	2.97***	−1.06***	−0.68*
Precipitation			
January	1.31**	−0.78*	−0.14
July	−1.09*	0.47	0.11
Annual	0.10	−0.12	0.10

The marginal effects of the sample median were calculated for 1000 bootstrap draws. This table reports median of these draws. Significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. A marginal increase in temperature is an increase of 1 °C. A marginal increase in precipitation is an increase of 1 cm per month.

(non-pipeable residences). In general, energy consumption is increasing in home size, income, and age of head of household.

Many (40%) of the coefficients on the selection correction terms are at least weakly significant at the 10% level, suggesting that households simultaneously determine fuel choice and energy consumption. Many of these coefficients are easily interpreted. For example, households who unexpectedly chose natural gas instead of oil (i.e., they have a high probability of choosing oil) tend to consume more natural gas. Households with greater heating needs tend to use the relatively low cost oil.

Table 3 presents the marginal impacts of the climate and price variables on residential fuel consumption. We report the median marginal impact of temperature and precipitation across the sample again using bootstrapping. The temperature variables behave as expected–customers who face warmer summers or cooler winters consume more energy.

The magnitude of the climate sensitivity varies substantially across customers in our sample. On the one hand, for pipeable households only using electricity, the amount of energy consumed does not vary with the climate. However, the electricity consumption by pipeable households consuming gas or oil is quite sensitive: those households with milder winters (i.e., 1 °C warmer in January) and hotter summers (i.e., 1 °C warmer in July) consume about 6% and 15% more electricity than others, respectively. This is not surprising as these customers primarily use electricity for cooling whereas the electricity-only customers also use it for heating. As expected, households facing colder winters use more natural gas. In contrast, the quantity of oil consumed by pipeable customers appears to be insensitive to climate.

Non-pipeable customers who only use electricity consume more in warmer areas. The amount of electricity used by non-pipeable households with oil heat is also climate-sensitive: households in areas with 1 °C warmer temperatures in January and July use about 13% more electricity. The only non-pipeable customers who are not climate sensitive are the ones who choose "other fuels". The choice of "other fuels" is correlated with low incomes hinting that poorer people may choose to be less comfortable in warmer summers rather than increase their expenditures. By only measuring changes in energy consumption and expenditures, we do not value this

Table 3
Marginal climate effects and price elasticity estimates of the conditional demand models for residential customers

	Electricity consumption			Other fuels	
	Only	Gas	Oil	Gas	Oil
Panel A: *Natural gas is available*					
Temperature					
January	−0.0231	0.0092***	−0.0076	−0.0185***	−0.0180
July	0.0135	0.0463***	0.1600**	0.0038	−0.0579
Annual	−0.0093	0.0557***	0.1542***	−0.0153***	−0.0707
Precipitation					
January	−0.0092	0.0236***	0.0632	0.0005	0.0140
July	0.0095	−0.0095**	−0.0282	−0.0011	−0.0431
Annual	0.0032	0.0140***	0.0355	−0.0009	−0.0245
Log elec. price	0.3312	−0.7202	−1.0669***		
Log n. gas price				−0.7717***	
Log fuel oil price					0.4670*
	Electricity consumption			Other fuels	
	Only	Oil	Other	Oil	Other
Panel B: *Natural gas is not available*					
Temperature					
January	−0.0051	0.0122	−0.0032	−0.0342	−0.0305
July	0.0504***	0.1081*	0.0101	0.1439**	−0.0023
Annual	0.0444***	0.1272**	0.0092	0.1197**	−0.0341
Precipitation					
January	0.0179	0.0161	0.0207	0.0433	−0.0103
July	0.0053	0.0114	0.0157	0.0101	−0.0476
Annual	0.0226	0.0256	0.0371*	0.0547	−0.0590
Log elec. price	−0.3900***	−1.2620***	−0.9376***		
Log fuel oil price				0.5945*	
Log LPG price					−1.0424***
Log kero. price					1.2215

Notes: Consumption in ln(kWh) for electricity, ln(therms) for natural gas, and ln(gallons) for oil and other fuels. We report the median marginal climate effects using bootstrapping. Significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. A marginal increase in temperature is an increase of 1 °C. A marginal increase in precipitation is an increase of 1 cm per month. See Tables A.III and A.IV for regressions.

additional discomfort and therefore underestimate the welfare losses. An interesting finding is that households with warmer summers consume *more* oil. Households who enjoy warmer annual temperatures may choose to keep their homes warmer in the winter. Homes in warm areas may also have less insulation so that it takes more heat to keep them warm in winter. The overall impact of precipitation is insignificant for all consumers.

The own-price elasticities in the conditional equations for electricity consumption are very inelastic for households only using electricity and roughly unit elastic (between −0.7 and −1.3) for households that use other fuels as well. The own-price elasticities are −0.8 for natural gas consumption and −1.0 for "other fuels" based on the LPG price.[18] The only problem with the price results concerns the price elasticities for oil, which are +0.5 and +0.6, but are only weakly significant at the 10% level. These positive oil price elasticities may

[18]Our results are similar to other estimates of own-price elasticities. The price elasticity of residential electricity demand is around unity [30,33]. Carol Dahl wrote an unpublished survey of energy demand elasticities (DOE contract DE-AP01-93EI23499, 1993) that reports average long-run elasticities of −0.9 (residential) and −0.8 (commercial) for electricity demand, and for natural gas, −0.7 and −1,

Table 4
Selection model for commercial customers

	Gas	Oil	Other
Temperature			
January	−0.0470**	−0.0908***	−0.0354
January^2	−0.0018	0.0025	−0.0040*
July	−0.0181	−0.2187***	−0.0882
July^2	−0.0061	−0.0377***	−0.0116
Precipitation			
January	0.0018	0.0990*	−0.0034
January^2	−0.0034***	−0.0050**	−0.0033*
July	0.0239	0.1119**	0.1245***
July^2	−0.0024	−0.0113*	−0.0091*
Log elec. price	0.43***	0.20	−0.78***
Log n. gas price	−3.96***	0.099	−0.68***
Log fuel oil price	1.50**	0.150	2.09**
Log dist. heat price	−0.038	−0.41	−1.53***
Alt. fuel used	−2.40***	−1.95***	−3.37***
Log building age	0.38***	0.52***	1.02***
Log no. floors	0.02	0.43***	1.10***
Log square feet	0.18***	0.16***	0.41***
Multi-bldg facility	−0.60***	−0.81***	1.85***
Metropolitan	0.41***	−0.08	0.81***
Months open/year	0.11***	0.14***	0.031
No. establishments	−0.0092**	−0.022***	−0.019***
% Assembly	0.0002	0.0006	−0.0010
% Educational activities	0.0014	0.0099***	0.0034
% Food service activities	0.0099***	0.0041	0.0013
% In-door parking	−0.031***	−0.023***	−0.039***
% Warehouse/vacant	−0.012***	−0.011***	−0.017***
% Office	−0.0055***	−0.0077***	−0.0050**

Note: Significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. The excluded percentage of space is for retail or service. Regional fixed effects not shown.

reflect problems in collecting price data for oil. It is possible that there are serious misreporting errors for oil because deliveries are intermittent. It is also possible that supplies within a region are price inelastic and somewhat independent so that cities with more demand also face higher prices, relative to the rest of the region.

5.3. *Commercial fuel choice results*

Table 4 presents the results of the multinomial logit fuel choice model for the commercial sector. We cannot distinguish between firms with or without access to natural gas, so there is only one model. Electricity alone is the base category relative to selecting gas, oil, or other fuel (in this case, district heat). The pseudo-R^2 is 0.37.

Many of the climate coefficients are statistically significant, particularly for the choice of oil. Table 5 reports the median marginal effects of the temperature variables (see footnote 17). Firms with relatively warmer summers are more likely to use electricity only and less likely to use oil. Firms in wetter places are more likely to select oil but not natural gas or electricity only. Generally, greater precipitation makes a given temperature less comfortable. Regions with more precipitation, especially in winter, will have greater demand for heating. This may lead firms to choose oil because it is cheaper per BTU than electricity or gas.

(*footnote continued*)
respectively. Estimated elasticities vary depending on research method and data source. More recent studies have also displayed a similar range of estimates [34].

Table 5
Marginal effects of selection model for commercial customers

	Electricity (%)	Gas (%)	Oil (%)	Other (%)
Temperature				
January	0.58***	−0.30*	−0.12*	0.00
July	0.36*	0.24	−0.36***	−0.06
Annual	0.97***	0.00	−0.58***	−0.04
Precipitation				
January	−0.06	−0.27	0.27*	−0.01
July	−0.32	−0.20	0.18*	0.11**
Annual	−0.36*	−0.55**	0.46***	0.07

The marginal effects of the sample median were calculated for 1000 bootstrap draws. This table reports median of these draws. Significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. A marginal increase in temperature is an increase of 1 °C. A marginal increase in precipitation is an increase of 1 cm per month.

From Table 4, we note that the own-price effects of gas and district heat are negative while the own price effect of oil selection is insignificant. Most of the cross-price effects are positive. The table also reports many coefficients on the control variables that are consistent with economic theory. For example, district heat has economies to scale so that many large facilities, such as hospitals and universities, use district heat. Buildings with more establishments tend to select electricity-only probably because it is easier to meter each establishment for their share.

5.4. *Commercial conditional consumption results*

The commercial conditional consumption analysis employs a system of regressions as shown in Eq. (9). Table 6 presents just the marginal climate and price effects (The quantitative results are presented in Table A.V.). As expected, firms that experience relatively warmer winters use less of gas and oil. Firms that experience relatively warmer summers use more electricity and (as with the residential customers) *more* oil. On net, firms in warmer areas use more electricity and less gas. As with non-pipeable households, firms' energy demand is not sensitive to precipitation.

Overall, firms are relatively sensitive to the prices of the fuels they consume. For electricity consumption, the own-price elasticities range from −1.1 to −2.1. The own-price elasticities are relatively large in magnitude for natural gas, −2.0, and for oil, −3.8. In contrast, district heat consumption is inelastic, −0.3. District heat is characteristically used in multi-building non-profit institutions.[19] One possible explanation for the low price elasticity is that non-profits are poor managers and fail to respond to prices by encouraging conservation. Most of the coefficients on the firm characteristics are consistent with expectations. For example, larger buildings and buildings that are open for more months use more energy. It is interesting to note that newer buildings use more energy. Although it is likely that new buildings are more energy efficient, they have more energy using operations than older buildings and so demand more energy.

5.5. *Expected marginal climate sensitivity*

Given the multitude of effects on energy expenditures discussed above, we calculate the marginal effects of temperature and precipitation for the entire model. This climate sensitivity calculation takes into account the expected switching of fuels and changes in conditional consumption. For each pipeable and non-pipeable residential customer and each commercial firm, we predict the fuel choice and conditional demand for the current climate and then we predict the new fuel choice and new conditional demand for a 1 °C increase in temperature with a 7% increase in precipitation. This is a relatively small change in climate compared to the range of climate across the sample. The energy system is not particularly sensitive to precipitation so that most

[19] Of the commercial buildings that consume district heat, 83% are multi-complex facilities and 93% are in designated "urban" areas.

Table 6
Marginal climate effects and price elasticity estimates of the conditional demand models for commercial customers

	Only	Gas	Oil	Other
Panel A: Electricity consumption				
Temperature				
January	−0.0036	0.0475***	−0.0213	0.0454
July	0.0570**	−0.0047	0.3056***	−0.0063
Annual	0.0530**	0.0438***	0.2800***	0.0378
Precipitation				
January	0.0226	0.0014	0.0375	−0.0096
July	−0.0224	−0.0103	−0.0438	−0.0126
Annual	−0.0007	−0.0082	−0.0005	−0.0217
Log elec. price	−2.1293***	−1.8361***	−1.7523***	−1.1082***

	Gas	Oil	Other
Panel B: Consumption of other fuels			
Temperature			
January	−0.0314***	−0.1044***	0.0104
July	−0.0072	0.2251***	−0.0043
Annual	−0.0377**	0.1129	0.0064
Precipitation			
January	−0.0015	−0.0111	−0.0213
July	0.0015	−0.0405	0.0074
Annual	0.0004	−0.0578	−0.0159
Log n. gas price	−1.9790***		
Log fuel oil price		−3.8133***	
Log dist. heat price			−0.2842***

Notes: Consumption in ln(kWh) for electricity, ln(therms) for natural gas, ln(gallons) for oil, and ln(pounds of steam) for district heat. For the climate variables, we bootstrap the marginal effects and report the median. Significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. A marginal increase in temperature is an increase of 1 °C. A marginal increase in precipitation is an increase of 1 cm per month. See Table A.V for regressions.

of the change is due to temperature. This allows us to determine the overall marginal sensitivity of each customer to climate.

Given the complexity of the linkages between the variance–covariance matrices of the climate coefficient estimates in both stages, we measure the uncertainty of our predictions using a bootstrapping method. We create 1000 data sets by drawing, with replacement, from the original data. As with our estimation procedure, we treat each observation as independent. In other words, we use the sample weights to calculate aggregate effects, but not in estimating the coefficients. For each sample drawn, we estimate the discrete-continuous DM model and use the estimated coefficients to measure the changes in expenditures associated with a marginal change in climate.

In Table 7, we report the median, 5%, and 95% of the draws. With these last two measures, we construct the 90% confidence interval. In addition, we report whether the 90th, 95th, and 99th percent confidence intervals span zero. All annual expenditures are represented in $1990.

With this small change in climate, overall annual residential expenditures increase $3.2 billion with a 90% confidence interval between $1.7 and $16.8 billion. This is about a 3% change, suggesting a relatively small elasticity with respect to temperature of approximately 0.34. All of the increase is due to increased electricity expenditures (an average increase of $4.3 billion per year for all residential customers). This is partially offset by less consumption of oil and natural gas. Commercial customers added another $2.9 billion annually which is about a 4% increase. The 90% confidence interval for commercial impacts is between $1.8 and $4.0 billion per year. Increases in annual electricity expenditures explain this result as well.

Table 7
Sensitivity of energy expenditures to climate variables (in billions of $1990)

	Residential gas available	Residential gas not available	Commercial total	Total
Electricity only	0.7** [0.2, 1.5] 12%	1.7*** [1.2,2.3] 12%	1.6*** [1.1,2.2] 13%	4.0*** [2.5,5.9] 12%
Electricity others	2.3*** [1.6,3.6] 6%	−0.4 [−1, 1.8] −4%	1.6** [0.7, 2.5] 4%	3.4*** [1.4,7.8] 4%
Natural gas	−0.6*** [−0.9, −0.4] −2%	N/a	−0.2* [−0.3, 0] −2%	−0.8*** [−1.3, −0.4] −2%
Oil	−0.3 [−0.6, 0.1] −8%	−0.2 [−0.5, 0.8] −4%	0.0 [−0.1, 0.2] 2%	−0.4 [−1.2, 1.1] −4%
Other*	N/a	−0.2 [−0.7, 0] −4%	−0.1 [−0.3, 0.1] −3%	−0.3 [−1, 0.1] −4%
Total	2.1*** [1.3, 3.5] 3%	1.0* [0.1, 11.6] 3%	2.9*** [1.8, 4] 4%	5.9*** [3.2, 19.1] 3%

Notes: The table reports the impact of a 1 °C increase in all temperatures and a 7% increase in precipitation. We report the median of the bootstrap results and the 90 percent confidence intervals in brackets. The significance is marked *** at the 1% level, ** at the 5% level, and * at the 10% level. "Other" is LPG and kerosene for residential and district heat for commercial.

Throughout the analysis, we note several interesting patterns. We consistently observe that consumers spend more on electricity because of greater needs for cooling but they spend less on other fuels that are primarily used for heating. Another consistent result is that residences and firms in warmer climates have higher energy expenditures. The additional cooling costs exceed the reduction in heating expenditures.

6. Simulations of the welfare effects of climate change

Next, we use these cross-sectional estimates to simulate the intertemporal impacts of various future climate scenarios on energy expenditures. We are assuming that the responses of customers from place to place will be similar to the long run responses of customers over time. Note that we are not modeling the consequences of changes in year to year weather but rather gradual decadal changes in climate. We are thus anticipating that customers will have time over these multiple decades to adjust their capital stock and behavior to the new climates they face.

The early climate impact literature focused on how climate might affect the current economy as shown in the marginal exercise above. The energy sector is likely to be quite different by the time that forecasted climate scenarios come to pass. For example, the Intergovernmental Panel on Climate Change (IPCC) estimates that temperatures will warm between 1.4 and 5.8 °C by 2100 [35]. We propose a possible base case scenario for 2100. We then explore how a 2.5 °C and a 5.0 °C warming scenario (with a 15% increase in precipitation) would impact this future economy.

Of course, no one knows exactly what will happen in the future not only to climate but to many other key variables as well. In addition to our base case scenario, we therefore explore alternative baseline assumptions in order to give a sense of the importance of alternative assumptions regarding energy prices (including endogeneity), population growth, and economic growth.

The population in the United States is projected to grow annually by approximately 0.3% [35]. Based on historical averages, we assume income per capita will grow at 2% per year. We assume that these changes are

Table 8
Welfare loss of each climate change scenario (in billions of $1990/year)

Scenarios	Residential	Commercial	Total	Percent (%)
Base case	35.1**	21.6***	56.7**	22.4
	[20, 4108]	[13, 41]	[43, 4126]	
2.5 °C warming	16.2***	9.9***	26.0***	10.3
	[10, 749]	[6, 16]	[20, 878]	
Endogenous prices	35.7**	22.8**	58.5**	23.1
	[36, 3102]	[5, 29]	[48, 3123]	
Expensive electricity	45.0**	17.8***	62.8**	24.7
	[30, 5039]	[11, 34]	[47, 6095]	
No oil	29.3**	34.7***	64.0**	27.6
	[17, 53]	[20, 65]	[46, 107]	
Higher population growth	47.3***	28.5***	75.8***	22.4
	[29, 3610]	[18, 53]	[56, 3649]	
Higher income growth	44.0**	25.9***	69.9***	22.3
	[23, 4882]	[16, 50]	[50, 4969]	
Current economy	16.8**	17.9***	34.7**	23.1
	[10, 1456]	[12, 32]	[27, 1541]	

Notes: In this table, we simulate the impacts of climate change in the year 2100. For the base case, we assume that electricity prices will increase 25%, other fuel prices will increase 50%, population will grow at 0.3%/year and income per capita at 2%/year. The commercial sector will increase proportionally with the residential sector. Building ages will remain constant. We assume a 5 °C warming and a 15% increase in precipitation across the board. The remaining scenarios test alternative assumptions in 2100. We test a warming of only 2.5 °C degrees. We test the importance of making prices endogenous. We test our assumption about the cost of future electricity. We test what would happen if oil or a close substitute of oil were no longer available. We test alternative assumptions about population growth (0.6%) and income growth (4%). We also test what would happen with the current economy. The reported results are the median of 1000 bootstrap runs. The 90% simulated confidence interval is shown in brackets. The significance is noted by *** at the 1% level, ** at the 5% level, and * at the 10% level.

proportional across the country. We assume that the age distribution of the building stock will not change (new buildings will replace old ones) and that the building technology (but for the modeled fuel choice) will not change. We assume commercial energy demand will grow proportionally with residential demand.[20]

We predict that fuel prices will increase over the next century. These changes are likely to occur due to expected reductions in remaining fossil fuel reserves [36]. In our base case scenario, we assume that oil, natural gas, and other fuel prices increase 50% by 2100. We assume that electricity prices will increase only 25% because of the presence of relatively plentiful coal and nuclear power. As oil and gas prices rise, we assume that synthetic gases and oils will be made from coal. This backstop technology is expensive but likely abundant. All of these changes will affect the baseline fuel choice, conditional consumption, and energy expenditures in our forecasts for 2100.

Given the baseline assumptions, we simulate how climate change may impact the 2100 economy. The scenarios test the change in energy expenditure with and without the climate changing. Both climate change scenarios assume uniform climate change across the US. Although individual climate models predict that changes in climate are likely to vary across regions within the US, there is no agreement across models regarding how that variation will occur. The uniform change scenarios are a reasonable approximation to the expected climate effects for a country [37] and they are easy to interpret.

Table 8 reports our findings for the future climate scenarios, focusing on the total residential, commercial, and aggregate changes in expenditures again using bootstrapping. In our base case future scenario, a 5 °C warming increases energy expenditures by $57 billion per year. The impact is split 38% to the commercial sector and 62% to the residential sector. The low climate warming scenario (a uniform increase of 2.5 °C) predicts that total expenditures will increase by $26 billion annually. Again, the effects are borne

[20]Namely, commercial buildings grow at the same rate as the population grows. We also allow the number of buildings to increase with income. The growth rate was determined so that the ratio of the ''base case'' and ''income growth'' case were the same for residential and commercial.

primarily by residential customers. Note that doubling the temperature change more than doubles the expected damages.[21]

Our sensitivity analysis reveals there are important interactions between assumptions about the base case for the energy sector and the impact of climate change on annual energy expenditures. Using just the 5 °C warming scenario, Table 8 reports the results of several alternative assumptions about the future energy sector. The first sensitivity analysis explores what difference it makes if energy prices are endogenous. See the appendix for a discussion of the endogenous price scenario. The analysis suggests that average electricity prices will increase by 1.3¢ kWh. The price increase will lead to a reduction in consumption of residential electricity of 89 billion kWh compared to our base case, implying a larger welfare loss of $0.6 billion. For commercial customers, consumption decreases 185 billion kWh compared to the base case leading to a reduction in the welfare loss of $1.2 billion. The predicted welfare loss with endogenous prices is $58.5 billion annually. In the remaining scenarios, we find that the larger the energy sector in 2100, the larger the climate impacts. For example, we explore what would happen if all energy prices uniformly increase by 50%, including electricity prices. In this scenario, the higher energy prices imply higher energy expenditures (especially electricity) with current climate. Climate change, then, causes energy expenditures to increase by $63 billion per year which is $6 billion more than the base case. The third sensitivity analysis assumes that oil supplies and synthetic oil substitutes are exhausted. Without oil, consumers must set their shares of oil consumption to zero. The multinomial logit model suggests that in the absence of a choice of oil, consumers will allow the other fuel shares to increase proportionally. Expenditures increase $64 billion annually as a result of climate change.

We then test the sensitivity of our results to a doubling of the assumed population growth rate. The change in annual expenditures is $76 billion, a 37% increase over the base case. In our simulations, we assume that the population distribution will not be affected by climate change.[22] The next row doubles the income per capita for residential customers relative to the base case. Welfare falls by $70 billion per year as a result of climate change. In the last row, we see that what would happen to today's economy. The change in expenditures would be only $35 billion a year, about half of the effect seen in the base case.

In general, the welfare effects are increasing in baseline energy expenditures. Under current climate conditions, our base case expenditures are $253 billion annually while the baseline expenditures when assuming greater population growth increase to $339 billion. For a 5 °C warming, Table 8 shows similar percent change in expenditures across simulations.

Overall, we conclude that the impacts of climate change on energy expenditures are quite sensitive to assumptions about future energy. Our base case simulation of the annual welfare loss associated with a 5 °C increase in temperature for 2100 is approximately $57 billion. In contrast, our predictions that allow for different assumptions regarding changes in climate, prices, population growth, and income growth range from $26 to $76 billion a year.

7. Conclusions

This paper develops a discrete-continuous model of fuel choice and energy consumption. The model is estimated using cross-sectional data from surveys of households and firms across the US. Capturing fuel choice provides valuable insights regarding the nature of adjustments to climate in the US energy sector. This is the first study to explicitly consider how climate change may impact fuel choice in both residential and commercial energy markets. The estimated model suggests that the fuel choice component may be an important aspect of adjustment to climate change. In warmer climates, both firms and households tend to choose electricity to heat and cool. When heating demand is low (less BTU's), consumers may find the low capital cost but high marginal cost of electricity relatively more attractive. It is important to note that this is an adaptation by residents and firms to warmer parts of the US. Electricity is more attractive than combining electricity with other heating fuels in areas where heating is less important.

[21]This suggests that if regional changes were greatest in currently warm (cool) areas, the damages would be greater (smaller).

[22]If climate change induces people to move to cooler regions, our results provide an upper bound of the welfare effects.

We also examine the combined effect of fuel switching and conditional fuel consumption. Consumers who face slightly warmer temperatures than others use more electricity and less of the other fuels, especially oil. Consumers facing warmer winter temperatures consume less heating fuel while those facing warmer summers purchase dramatically more electricity. On net, energy expenditures are greater in places with slightly higher temperatures. This implies that a marginal uniform warming would lead to net damages in the US energy sector.

Lastly, we explore future climate scenarios. All scenarios measure annual damages (flows), not stock effects. Given our best guess of the US energy sector in 2100, a 2.5 °C warming would cause damages of approximately $26 billion per year. With a 5 °C warming, annual residential energy damages might rise to $35 billion with another $22 billion of damages in the commercial side. These estimates are sensitive to assumptions about price changes, population growth, and economic growth. With the current economy, the damages would be about 60% of the effects reported above. On the other hand, doubling population growth or income growth could increase the damages by a quarter to a third. That is, the larger the energy sector in 2100, the greater will be the likely impacts of climate change.

Our estimated impacts exceed those predicted by previous studies. Partly, our overall welfare impacts are more severe because our fuel-specific model predicts large swings in fuel choice towards electricity as a result of warming. This change in fuel choice increases the relative expenditures on fuel and thus damages from warming. Previous studies that have treated fuel choice as exogenous have consequently underestimated the damages from global warming on the energy sector [3]. Note that this is contrary to other examples of adaptation where, for example, ignoring how farmers adapt in choosing crops overstates damages [38]. In the US energy sector, warming causes customers to install more cooling capacity, raising both capital and energy consumption. It is still true that allowing capital to adjust reduces the damages from warming but cooling capital and energy are complements not substitutes.

The other major reason why our damage estimates are higher than the earlier literature is because we are projecting climate change impacts on a 2100 economy. Some studies focused on a 1990 economy [2,3]. Other studies projected a future economy but only until 2060 [6,7]. As our sensitivity analysis reveals, the size of the future energy sector has a big impact on the magnitude of the damages. The impacts of climate change are much larger if one accounts for possible future growth in energy prices, population, and income.

This study advances the analysis of climate change energy impacts but there is further work needed. The study did not consider other possible technological changes besides just fuel switching. For example, changes in the fuel efficiency of devices, changes in interior space, and new energy consuming devices may all change future energy demand and climate sensitivity. Since climate change is a global phenomenon, impact estimates are needed around the world. Both the pattern and type of energy use vary significantly across countries. An important next step is to study the nature of impacts in other countries in order to develop an aggregate estimate of world energy impacts. In addition, other studies of costs and benefits need to be considered in developing optimal regulation of greenhouse gases.

The approach in this paper could be used to test whether climate change in the form of overall global warming causes a positive feedback effect on greenhouse gases and other air emissions by increasing energy demand. In principle, one could do such an analysis. However, our study only captures the fuel choices and the energy demand of final users. We do not model what fuels electrical generators are using. For example, it would make a great difference whether future electricity generation came from coal (where there could be large amounts of greenhouse gas and other pollutants) or a relatively clean energy source such as natural gas, nuclear, renewable, or other technology (with little greenhouse gas or traditional air emissions).

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Appendix A. Supporting Information

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References

[1] J. McCarthy, O. Canziani, N. Leary, D. Dokken, K. White (Eds.), Climate Change 2001: Impacts, Adaptation, and Vulnerability, Cambridge University Press, Cambridge, 2001.
[2] W. Nordhaus, To slow or not to slow: the economics of the greenhouse effect, Econ J. 101 (1991) 920–937.
[3] D. Rosenthal, H. Gruenspecht, E. Moran, Effects of global warming on energy use for space heating and cooling in the United States, Energy J. 16 (1995) 77–96.
[4] T. Considine, The impacts of weather variations on energy demand and carbon emissions, Resource Energy Econ. 22 (2000) 295–314.
[5] T. Crocker, Electricity demand in all-electric commercial buildings: the effect of climate, in: T. Ferrar (Ed.), The Urban Costs of Climate Modification, Wiley, New York, 1976.
[6] R. Mendelsohn, Energy: cross-sectional analysis, in: R. Mendelsohn (Ed.), Global Warming and the American Economy: A Regional Assessment of Climate Change Impacts, Edward Elgar Publishing, Northampton, MA, 2001.
[7] W. Morrison, R. Mendelsohn, The impact of global warming on US energy expenditures, in: R. Mendelsohn, J. Neumann (Eds.), The Impact of Climate Change on the United States Economy, Cambridge University Press, Cambridge, UK, 1999.
[8] L. Lee, R. Trost, Estimation of some limited dependent variable models with application to housing demand, J. Econometrics 8 (1978) 357–382.
[9] P. Haines, D. Guilkey, B. Popkin, Modeling food consumption decisions as a two-step process, Amer. J. Agr. Econ. 70 (1988) 543–552.
[10] P. Goldberg, The regulation of fuel economy and the demand for 'light trucks', J. Ind. Econ. 46 (1998) 1–33.
[11] S. West, Distributional effects of alternative vehicle pollution control policies, J. Public Econ. 88 (2004) 735–757.
[12] J. Hewitt, W. Hanemann, A discrete/continuous choice approach to residential water demand under block rate pricing, Land Econ. 71 (1995) 173–192.
[13] S. Olmstead, W. Hanemann, R. Stavins, Water demand under alternative price structures, J. Environ. Econ. Manage. 54 (2007) 181–198.
[14] M. Baughman, P. Joskow, Energy consumption and fuel choice by residential and commercial consumers in the United States, Energy Systems Pol. 1 (1976) 305–323.
[15] T. Cameron, A nested logit model of energy conservation activity by owners of existing single family dwelling, Rev. Econ. Statist. 67 (1985) 205–211.
[16] J. Dubin, D. McFadden, An econometric analysis of residential electric appliance holdings and consumption, Econometrica 52 (1984) 345–362.
[17] H. Liao, T.F. Chang, Space-heating and water-heating energy demands of the aged in the US, Energy Econ. 24 (2002) 267–284.
[18] K. Vaage, Heating technology and energy use: a discrete/continuous choice approach to Norwegian household energy demand, Energy Econ. 22 (2000) 649–666.
[19] J. Heckman, Sample selection bias as a specification error, Econometrica 47 (1979) 153–161.
[20] S. Berg, C. Taylor, Electricity consumption in manufactured housing, Energy Econ. 16 (1994) 54–62.
[21] P. Schwarz, T. Taylor, Cold hands, warm hearth? Climate, net takeback, and household comfort, Energy J. 16 (1995) 41–54.
[22] D. Sailor, A. Pavlova, Air conditioning market saturation and long-term response of residential cooling energy demand to climate change, Energy 28 (2003) 941–951.
[23] R. Mendelsohn, Energy impacts, in: J. Smith, R. Mendelsohn (Eds.), The Impact of Climate Change on Regional Systems: A Comprehensive Analysis of California, Edward Elgar Publishing, Northampton, MA, 2006.
[24] L. Lee, Generalized econometric models with selectivity, Econometrica 51 (1983) 507–512.
[25] F. Bourguignon, M. Fournier, M. Gurgand, Selection bias corrections based on the multinomial logit model: Monte-Carlo comparisons, J. Econ. Surveys 21 (2007) 174–205.
[26] G. Dahl, Mobility and the returns to education: testing a roy model with multiple markets, Econometrica 70 (2002) 2367–2420.
[27] W. Hanemann, Discrete/continuous models of consumer demand, Econometrica 52 (1984) 541–561.
[28] C. Schmertmann, Selectivity bias correction methods in polychotomous sample selection models, J. Econometrics 60 (1994) 101–132.
[29] D. McFadden, Conditional logit analysis of qualitative choice behavior, in: P. Zarembka (Ed.), Frontiers in Econometrics, Academic Press, New York, 1973.
[30] R. Halvorsen, Residential demand for electric energy, Rev. Econ. Statist. 57 (1975) 13–18.
[31] F. Wirl, The Economics of Conservation Programs, Kluwer Academic Publishers, Boston, 1997.
[32] W. Greene, Econometric Analysis, Macmillan Publishing Company, New York, 1993.
[33] D. Kamerschen, D.V. Porter, The demand for residential, industrial and total electricity, 1973–1998, Energy Econ. 26 (2004) 87–100.

[34] L. Garcia-Cerrutti, Estimating elasticities of residential energy demand from panel county data using dynamic random variables models with heteroskedastic and correlated error terms, Resource Energy Econ. 22 (2000) 355–366.
[35] J. Houghton, Y. Ding, D. Griggs, M. Noguer, P. van der Linden, X. Dui, K. Maskell, C. Johnson (Eds.), Climate Change 2001: The Scientific Basis, Cambridge University Press, Cambridge, 2001.
[36] H. Hotelling, The economics of exhaustible resources, J. Polit. Economy 39 (1931) 137–175.
[37] L. Williams, D. Shaw, R. Mendelsohn, Evaluating GCM output with impact models, Climatic Change 39 (1998) 111–133.
[38] R. Mendelsohn, W. Nordhaus, D. Shaw, Measuring the impact of global warming on agriculture, Amer. Econ. Rev. 84 (1994) 753–771.