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A Discrete-Continuous Choice Model of Climate Change Impacts on Energy

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Abstract

This paper estimates a discrete- continuous fuel choice model in order to explore climate impacts on the energy sector. The model is estimated on a national data set of firms and households. The results reveals that actors switch from oil in cold climates to electricity and natural gas in warm climates and that fuel-specific expenditures follow a U-shaped relationship with respect to temperature. The model implies that warming will increase American energy expenditures, reflecting a sizable welfare damage.

Introduction

This paper applies a discrete-continuous choice model to the joint decisions about fuel choice and energy expenditures. Although discrete-continuous modeling has been used to model numerous consumption decisions, it has received little attention in the energy literature. In this paper, we apply this model to specifically examine the interface between climate and energy demand. Climate change is expected to affect the demand for space conditioning energy by reducing heating needs and increasing cooling needs. In this paper, we explore how climate currently affects both fuel choice and energy expenditures. The estimated model is then used to predict the American energy impacts from alternative future climate change scenarios.

Despite the widespread interest in global warming, few studies have calibrated the impact of climate on energy demand. Most energy-climate studies have focused on measuring energy as a source of greenhouse gases, not as a victim of climate change (IPCC, 1996). The studies that do consider the impacts of climate on the energy sector rely mainly on expert opinion (Nordhaus 1991b, Cline 1992), engineering models (Rosenthal et al. 1995) or business-industry studies (Smith and Tirpak 1989). The few empirical studies that have been done focus solely on electricity (Crocker 1976, Linder et al. 1987, Smith and Tirpak 1989). This study is unique in its reliance on empirical methods, its inclusion of all major fuels, and its coverage of both the national residential and commercial sectors.

The discrete-continuous model is briefly presented in section 1. Section 2 presents the theory describing the welfare measurement of climate impacts on energy. The impact model should accommodate adjustments people make to climate including changing fuels, changing expenditures on fuel, altering buildings, and changing their comfort levels. Because we do not have building expenditure data, we explore both short run and long run changes in energy expenditures to approximate welfare effects. The data and empirical methodology are presented in section 3. Section 4 presents the results of the empirical modeling on fuel choice and expenditures. The estimated model is then used, in section 5, to project what energy impacts might be for future climate scenarios. The paper concludes with a discussion of the implications of climate change for the energy sector and a comparison to previous study results.

1. Modeling Discrete-Continuous Choice

Modeling techniques that explicitly consider the discrete and continuous components of consumer choice are found widely in the literature. For many consumer choices, total demand or expenditures can be broken down into a discrete component involving choice over alternatives and a corresponding continuous component describing demand or expenditures conditional on that choice. For example, discrete-continuous choice is used to study demand for transport (Abdelwahab and Sargious 1992, Mannering and Winston 1985, Hensher and Milthorpe 1987), housing (Lee and Trost 1978, King 1980), food and drink (Pompelli and Heien 1991, Haines, Guilkey and Popkin 1988), and shopping (Barnard and Hensher 1992).

While energy demand includes a discrete fuel choice and a continuous choice of consumption level, this approach has received little attention in the extensive literature. Baugham and Joskow (1976) 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, the model will suffer from selection bias (Heckman, 1979). For many consumer choice occasions, the error term in the choice equation is correlated with the error term in the continuous equation, requiring a two-step estimation method (Heckman, 1979). Dubin and McFadden (1984) apply this method to energy, but focus only on electricity demand conditional on the choice of appliance holdings. In this paper, a variant of the Heckman technique suggested by Lee (1983) is used to perform a comprehensive analysis of fuel choice and energy expenditures in the commercial and residential energy sectors in the United States. The model specifically explores the interactions between climate change and the energy sector since changes in climate are expected to affect both fuel choice and the level of energy expenditures.

2. Welfare Impacts Of Climate Change

Ideal Welfare Measure

In response to climate change, households and firms may alter: 1) fuel choice, 2) expenditures on energy, 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:

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

where Y is income, C climate, U is utility, T is interior temperature and R is an index of all other goods. Interior temperature, T, is assumed to be a function of climate, C, energy use, Q (conditional on fuel choice f) and building characteristics, Z where C is exogenous and Q and Z are purchased inputs.

If people maintain optimal interior temperatures regardless of climate, there will be no loss of comfort from climate change. A survey of interior temperatures conducted across households in the winter revealed that households in all regions of the country maintained the same winter temperatures[1]. If, with increased air conditioning penetration in the future, the same result holds for the summer, future households and firms will not alter their interior comfort in response to

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[1] Energy Information Administration (1993).

climate change. The welfare effect from climate chnage will simply be the change in expenditure required to maintain these desired temperatures[2]. Increases (decreases) in energy and building expenditures will measure the welfare loss (gain) from climate change:

$$2) \qquad CV = \int_{C_0}^{C_1} \frac{\partial Y}{\partial C} \cong P_q \cdot Q_1 | f_1 + P_z \cdot Z_1 - P_q \cdot Q_0 | f_0 - P_z \cdot Z_0$$

where P_q and P_z are the prices of energy and building attributes, respectively and subscripts 0 and 1 represent the baseline case and climate change scenario, respectively. As long as firms hold interior temperatures constant as well, (2) applies to them as well.

Feasible Welfare Measure

Although changes in both energy and building expenditures provide the desired measure of welfare change, only energy expenditure data and detailed data about building characteristics are available. We propose to use short and long run estimates of fuel choice and energy expenditures to gauge the importance of unobserved building expenditures and predict the magnitude of climate change impacts based on energy expenditures alone. In the short run, individuals and firms can only adjust energy expenditures. A model of energy expenditures, holding fuel choice and building characteristics constant, should reflect these short run adjustments. In the long run, individuals and firms can adapt buildings to the warmer climate. Hence, fuel choice as well as energy and building expenditures can be adjusted. In order to allow building characteristics to adjust, they are assumed endogenous in the long run model. While this allows for flexibility of building characteristics, the actual estimate does not include building expenditures. The difference between the short run and long run measures provides an indication of how important building adjustments are likely to be. If short run and long run measures are similar, building adjustments

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[2] To the extent that comfort levels fall or rise with warming, the impacts of climate change will be underestimated.

are likely to be small. In this case, the absence of building expenditure data should not induce significant bias to the climate impact estimate. If the disparity between short and long run adjustments using energy expenditures alone is large, however, the bias from omitting the building adjustments are likely to be important.

The bias from omitting building adjustments is expected to be different for heating versus cooling dominated buildings. With heating dominated buildings, the primary building adjustment is to change insulation which is a substitute for energy. As warming occurs, heating dominated buildings reduce energy in the short run as illustrated in Figure 1 for a building moving from climate A to a warmer A*. In the long run, insulation will also be reduced causing long run energy reductions to be less than short run reductions. Because the building expenditures are not included, the short run measure is closer to the correct welfare measurement. With cooling dominated buildings, the primary adjustment is to increase cooling capacity, which is a complement to energy expenditures. With warming from B to B*, cooling dominated buildings will increase energy expenditures in the short run as illustrated in Figure 2. However, as cooling capacity is increased, long run energy expenditures will increase even more. In this case, long run energy expenditures are a better welfare approximation. However, in both cases, the change in energy expenditures underestimates the magnitude of the welfare impact.

Because warming reduces heating costs but increases cooling costs, we expect that energy has a quadratic 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 which minimizes both heating and cooling

FIG. 1. Climate Elasticities of Long and Short Run Heating Expenditures

Energy and Capital: Substitutes

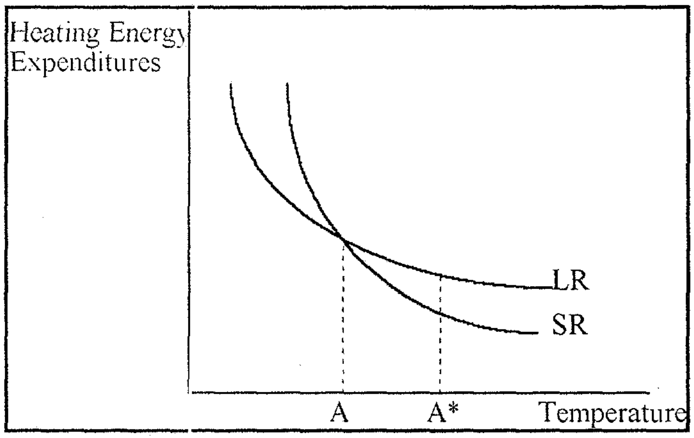
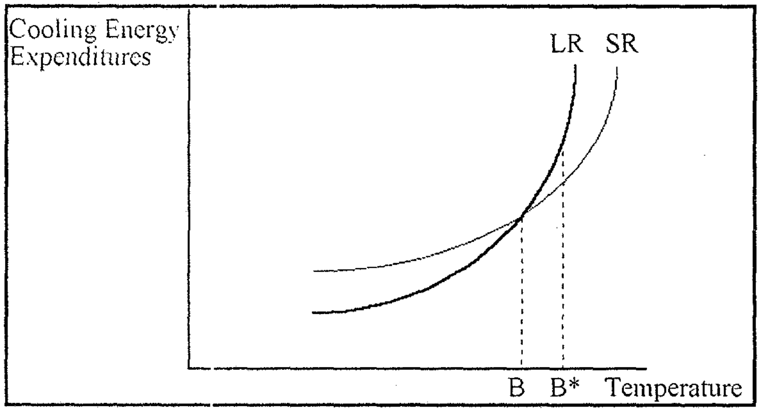


FIG. 2. Climate Elasticities of Long and Short Run Cooling Expenditures

Energy and Capital: Complements



Modeling Discrete-Continuous Components of Welfare Impacts

In the discrete continuous model, welfare impacts are defined as the change in the expected value of energy expenditures. The probability that a particular fuel portfolio, $f \in F$, is chosen is defined as θ_f and in turn, expenditures conditional on that portfolio choice are defined as W_f. In this discrete-continuous situation, the estimate of compensating variation corresponding to equations (2) is:

$$\begin{aligned} CV &= \mathrm{E}[W(C_0)] - \mathrm{E}[W(C_1)] \\ &= \sum_{f \in F} \left[\theta_f(C_0) \cdot W_f(C_0) - \theta_f(C_1) \cdot W_f(C_1)\right] \end{aligned} \quad 3)$$

where E identifies the expected value. Therefore, marginal expenditures over all alternatives are defined as the weighted average of conditional expenditures where the choice probabilities, θ_f, are the weights. The link between the model components determining θ_f and W_f is further described in the empirical section.

3. Discrete-Continuous Empirical Methodology

A variant of the Heckman two-step method proposed by Lee (1983) is employed to estimate fuel choice and energy expenditures In the first stage of the analysis, fuel choice is estimated. Since it is likely that the level of energy expenditures is correlated with fuel choice, we rely on a sample selection correction method instead. Poirier and Ruud (1981), point out that a model that does not correct for sample selection bias is only appropriate if the researcher is seeking to predict actual demand (in this case expenditures) for the people currently choosing that alternative. In this case, however, we are interested in the potential demand of individuals not originally assigned to this alternative. The sample selection specification must be utilized to avoid bias (Hensher and Milthorpe 1987).

Following Lee (1983)[3], a model of polychotomous fuel choice and conditional energy expenditures is developed. The discrete-continuous choice model can be written as:

4) $I_f^* = \alpha_f' Z + \eta_f \qquad (f = 1,2,\ldots,F)$

5) $W_f = \beta_f' X + \mu_f \qquad (f = 1,2,\ldots,F)$

where W is energy expenditures conditional on fuel choice f, X and Z are vectors of exogenous explanatory variables, β and α are parameter vectors, and μ and η are error terms. There are F alternative fuel choices. Equation (4) identifies an index function, I*, that takes values 1 to F where I=f if and only if the fth fuel portfolio is chosen. Equation (5) is the continuous expenditure equation that is estimated on the subsample of households and firms that consume each fuel portfolio, f. The potential correlation between μ_f and η_f is the reason for using a two-step sample selection method for estimation.

In the first stage, fuel choice is estimated. A particular fuel portfolio is assumed to be chosen only if the index of satisfaction derived from that alternative is greater than that derived from all other alternatives:

6) $I = f \;\text{ iff }\; I_f^* > \max\; I_j^* \;\Rightarrow I = f \;\text{ iff }\; \alpha_f' Z > \max\; I_j^* - \eta_f \quad (j = 1,\ldots,F,\ j \neq f)$.

Setting $\varepsilon_f = \max\; I_j^* - \eta_f \;\; (j = 1,\ldots,F,\ j \neq f)$, implies that $I = f$ iff $\varepsilon_f < \alpha_f' Z$. Assuming that the errors are independently and identically distributed with a Type I Extreme Value distribution, yields a multinomial logit-OLS stage estimator with choice probabilities of the following form:

7) $\text{Prob}(\varepsilon_f < \alpha_f' z) = \text{Prob}(I = f) = \theta_f = \dfrac{\exp(\alpha_f' Z)}{\sum_f \exp(\alpha_f' Z)}$.

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[3] This methodology is also described in detail in Maddala (1983, 275-278).

In the second stage, expenditures conditional on fuel choice are estimated. The two model components are linked through the inclusion of a sample selection correction variable in the second stage regression. One key requirement in unifying the two model components is that they have the same error distributions. Lee's (1983) methodology allows for a multinomial logit specification of the choice model that only requires a one step transformation to ensure that the sample selection variable is compatible with the ordinary least squares component.[4] The full second stage regression, including the sample selection correction term is:

$$8)\quad \begin{aligned} W_f &= \beta_f{}'X + (\rho_f \sigma_f)\left[\frac{\phi\left(\Phi^{-1}(\theta_f)\right)}{\theta_f}\right] + \eta_f \\ &= \beta_f{}'X + \delta_f \lambda_f + \eta_f \end{aligned}$$

where the functions $\phi(\cdot)$ and $\Phi(\cdot)$ are the PDF and CDF, respectively, of the standard normal distribution, σ is the standard error of the continuous choice estimate and ρ is the correlation between the error terms of the discrete and continuous choice. The sample selection correction variable is calculated as a function of the fuel choice probabilities. The inclusion of this variable in the second stage regression accounts for the presence of selection bias. The coefficient on λ represents the impact of the conditional mean of μ on the expenditure equation results and allows for consistent estimation of β using OLS (Pompelli and Heien 1991, 123). A test of the statistical significance of the coefficient on the selection correction variable will determine whether the null hypothesis that the two model components are independent can be rejected.[5]

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[4] Hensher and Milthorpe (1987) perform a comparison of selection correction methodologies, comparing the method utilized in this study (Lee, 1983) to two commonly used alternatives and determine that there is no predictive gain from one specification versus the other.

[5] Hensher and Milthorpe (1987) in their comparison of selection methodologies show that even if the selectivity variable is insignificant, its inclusion in the model is necessary to account for the magnitude of selection bias on individual parameters (p. 145).

Some researchers have jointly estimated the model system using full information maximum likelihood rather than two stage techniques. However, joint estimation is difficult with a large number of choices and is generally utilized for the binary choice model. Other researchers also suggest the Tobit model for this type of analysis. A Tobit model would estimate conditional expenditures directly, accounting for truncation. However, researchers have shown that in a number of cases the choice dimension and continuous choice do not have the same parameters (Haines et al. 1988). Since it is likely that the policy variables of interest, including temperature and precipitation, may differentially affect fuel choice and the level of expenditures, a two-stage model is selected. It should be noted that because the models are estimated sequentially the standard errors are downward biased and the t-statistics are upward biased. The unadjusted standard errors are, however, correct for the null hypothesis of no correlation between the two equations.

Fuel Choice Model

A multinomial logit specification, equation (8), is used to predict fuel choice. Although approximately 10% of the sample in both sectors consume more than two fuels, there are generally one or two primary fuel selections. This study focuses on choice over these primary fuel alternatives. All households and firms in the data sets consume electricity (at least for lighting), so all fuel portfolios contain this alternative. On the residential side there are five different fuel portfolios, electricity alone, electricity & natural gas, electricity & fuel oil, electricity & LPG and electricity & kerosene. There are four commercial options including electricity alone, electricity & natural gas, electricity & fuel oil and electricity & district heat (steam or hot water). While a number of the explanatory variables are logged, the climate variables are in a quadratic form to reflect the hypothesized climate-expenditure relationship.[6]

Only a long run fuel choice model is estimated, since fuel choice is assumed to remain constant in the short run. Baseline fuel choices are used to predict short run expected expenditures corresponding to equation (3). In the long run, fuel choice is allowed to vary with changes in climate.

The choice of a multinomial logit model as distinguished from the conditional logit and nested multinomial logit specifications deserves comment. Although there is some discrepancy in the literature, the multinomial logit specification generally assumes that the choice probabilities are a function of individual characteristics. The conditional logit, on the other hand, assumes the choice probabilities are a function of the attributes of the alternatives. Maddala (1983, p.42-43) notes that the multinomial logit is useful for determining which choice a new or specific individual will make given characteristics about that individual, whereas the conditional logit is useful for estimating the probability that a new alternative will be chosen, given characteristics of that alternative. Hartman (1982) asserts that the conditional logit is an inappropriate model for estimating fuel choice due to the importance of individual characteristics in the decision and recommends the multinomial logit and more general specifications. We rely upon the multinomial logit, because this study seeks to estimate the probability that individuals and firms will select each of the existing fuels when their climates change. The conditional logit would be more appropriate if one were interested in modeling the probability that a new fuel would be selected based on its characteristics. The primary difference is that the key policy variable in this study is a characteristic of the individual and not the alternative.

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[6] The climate variables are also demeaned for interpretive purposes.

The multinomial logit model makes a further assumption regarding the independence of irrelevant alternatives (IIA). The multinomial logit is by far the least computationally burdensome method for modeling polychotomous choice. The IIA assumption, however, is somewhat restrictive. Frequently the nested logit model is used because it allows a simple form of correlation amongst the error terms of subsets (or nests) of alternatives. Researchers have noted that it is not necessarily the multinomial logit specification that leads to the assumption of independence, but the requirement that the set of explanatory variables depend only on attributes of the relevant alternative and not other alternatives or individual characteristics (McFadden 1984, p. 1415). McFadden (1984) shows that models that incorporate characteristics of all choices and individuals appear to do a better job at circumventing the independence restriction. A broadly specified multinomial logit model is selected for this analysis because it is expected to most accurately reflect the climate sensitivity of fuel choice for individuals and firms

I think I lost part of this.

. ENERGY EXPENDITURE MODEL

Expenditure models are estimated for each fuel portfolio. In this case, the dependent variable and most continuous explanatory variables are logged to fit the proportional relationship that is expected to hold. The climate variables are included in linear and quadratic form since a quadratic relationship between climate and expenditures is hypothesized to exist.[7] Tests of various combinations of climate variables indicate that including only the January and July temperature provides a better fit than including all four seasons. Since these regressions are conditional on the selection of a particular fuel portfolio, only the relevant prices are included in each analysis. The individual expenditure equations will identify the effect that a change in the explanatory variable has on energy expenditures given that a particular fuel portfolio is chosen. By correcting for selection bias the correct regression equation for the observed samples can be derived.

Data

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[7] These climate variables are also demeaned for interpretive purposes. The coefficient represents the marginal effect on expenditures at the mean climate.

The data come from the Department of Energy's Commercial Buildings Energy Consumption Survey (EIA 1992) and Residential Energy Consumption Survey (EIA 1993). These surveys provide detailed data on energy expenditures and consumption as well as demographics, building characteristics and climate. The data include several thousand buildings distributed in random clusters across the continental US and 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 and kerosene, as well as the four major commercial fuels: electricity, natural gas, fuel oil and district heat. The original data do not disaggregate energy uses. Although space conditioning energy is expected to be most sensitive to climate change, other commercial and residential energy uses may be affected. Hence, the model is estimated for fuel portfolio choice and expenditures across all energy uses.

The DOE data sets did not originally include seasonal climate data. These data were added to the commercial and residential data sets in order to allow for a more detailed analysis. The climate data include average monthly temperature and precipitation for January, April, July and October. The climate data were originally collected from the National Climatic Data Center as 30 year averages for 5,511 meteorological stations in the US. The data by meteorological station were interpolated to US counties using weighted regressions of all weather stations within 500 miles of each county (see Mendelsohn et al. 1994).

A number of explanatory variables are expected to influence fuel choice and expenditures. The variables used to predict residential and commercial fuel choice and expenditures are described in the Appendix. In general, explanatory variables include climate, demographic and firmographic information and building characteristics. The building characteristics are divided into climate sensitive and non-sensitive categories. Non-climate sensitive building characteristics such as building size, type of occupancy, and building age are included in all model runs to control for exogenous non-climatic factors that affect energy consumption. Climate sensitive characteristics affecting thermal efficiency such as building material, conservation, the choice of heating and cooling equipment and some aspects of the household structure are included in the short run models but not the long run models since they are assumed endogenous in the long run.

4. Results

Residential Sector Results

The results of the multinomial logit fuel choice estimation for the residential sector are shown in Table 1 (t-statistics are in parentheses). The electricity alone portfolio is the base category where the normalization $\alpha_0=0$ is imposed. The coefficients in the fuel choice model represent the change in the probability of choosing an alternative (relative to the base category) with respect to a change in the relevant explanatory variable. The percent correctly predicted is relatively high at 82%. This implies that in 82% of the cases, the portfolio with the highest predicted probability is the one that the individual was observed to select.

All explanatory variables have a statistically significant impact on at least one choice probability and in some cases all choice probabilities. January temperature is a significant predictor of the choice between electricity & fuel oil and electricity & kerosene versus electricity only but does not significantly impact the remaining choices. These results reflect the fact that fuel oil and kerosene are primarily cold weather fuels. July temperature significantly influences the choice of electricity & natural gas and electricity & LPG versus electricity only but not the alternative choices. The July effects reflect the importance of cooling in the summer. Other important factors include electricity and own prices and a number of demographic and structural characteristics.

The parameter estimates in Table 1, however, do not represent the marginal effect of a change in the relevant explanatory variable on the choice probabilities. These marginal effects must be calculated from the coefficient estimates and are summarized in Table 2.[8] The majority of researchers do not report these marginal effects, yet they provide important information about

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[8] The marginal effects are calculated in the following manner: $\frac{\partial P_j}{\partial x_i} = P_j [\beta_j - \Sigma_k \beta_k]$ (Green 1993, 666).

TABLE 1. Coefficient Estimates for Residential Fuel Choice Model

Climate and Price Variables

Variable	Electricity & Natural Gas	Electricity & Fuel Oil	Electricity & LPG	Electricity & Kerosene

constant	6.8e+2	1.1e+3	6.9e+2	6.0e+2
	(6.98)	(14.29)	(8.14)	(5.00)
Jan. temp	2.4e-2	-0.18	2.5e-2	-0.13
	(1.34)	(-5.93)	(0.97)	(-2.92)
Jan. precip	-0.16	0.13	8.5e-2	0.29
	(-3.69)	(1.82)	(1.41)	(3.14)
July temp	-9.8e-2	5.4e-3	-0.17	-6.4e-2
	(-2.35)	(0.08)	(-2.90)	(-0.61)
July precip	-0.12	-2.5e-2	-0.11	0.30
	(-2.18)	(-0.31)	(-1.58)	(2.53)
log elec. price	3.64	2.67	4.15	1.69
	(12.89)	(8.71)	(10.19)	(3.19)
log nat. gas price	-2.75	3.19	-0.95	0.94
	(-8.76)	(8.43)	(-1.88)	(1.45)
log fuel oil price	2.18	-2.65	-2.46	-3.62
	(1.73)	(-2.30)	(-1.41)	(-1.77)
log lpg price	-0.56	0.55	-3.36	-3.4e-2
	(-1.57)	(1.44)	(-8.02)	(-5.5e-2)
log kero. price	-0.52	-2.00	-0.81	-6.02
	(-0.81)	(-2.21)	(-1.03)	(-3.82)
metropolitan	-0.11	-0.47	-1.08	0.20
	(-0.77)	(-2.44)	(-3.85)	(0.65)
log income	1.7e-2	-0.08	-0.37	-0.26
	(0.20)	(-0.82)	(-3.12)	(-1.56)
log sq ft	0.60	0.76	-9.9e-2	-0.38
	(4.21)	(4.53)	(-0.50)	(-1.32)
log year built	-91.85	-1.4e+2	-89.44	-77.55
	(-10.28)	(-14.27)	(-7.97)	(-4.89)
log family size	0.61	0.58	0.64	0.74
	(4.89)	(3.80)	(3.63)	(3.10)
log age of head	0.49	0.65	0.54	-0.66
	(2.82)	(2.91)	(2.10)	(-1.94)
more than 1 unit	-0.52	-0.92	-2.01	-2.78
	(-2.77)	(-3.85)	(-5.45)	(-4.97)
burn wood	-0.78	-0.45	-0.20	-0.61
	(-4.91)	(-2.57)	(-1.06)	(-2.20)
nat. gas avail.	16.95	0.64	-1.23	-0.58
	(0.24)	(3.56)	(-5.49)	(-2.00)
mobile home	1.11	0.63	1.48	1.51
	(3.28)	(1.55)	(4.92)	(4.10)
log likelihood				*-2572*
percent correctly predicted				*82*
Observations				*5029*

* (t-statistics in parentheses)

the effect the policy variables have on fuel choice. From Table 2 the influence of climate on each fuel choice at the margin can be identified. An increase in January temperature redcues the probability that households will choose electricity & fuel oil and electricity & kerosene, thus incresaing the probability that other fuels will be used. An increase in July temperature makes it more likely that individuals will choose electricity alone reflecting the fact that electricity is the primary cooling fuel. An increase in January precipitation decreases the probability that electricity alone and electricity & natural gas will be chosen. July precipitation positively influences the choice of electricity alone, illustrating the growing importance of cooling in places where humidity is high.

The remaining explanatory variables identify other important influences on fuel choice in the residential sector. The price variables strongly influence the choice probabilities with own-price effects being negative as expected. The presence of more than one housing unit has a strong positive influence on the choice of electricity alone. This may reflect the popularity of using a single fuel portfolio in places like apartment buildings where multiple fuels can lead to undesirable billing complexity. The year the home was built has a positive influence on the choice of electricity reflecting the increasing prevalence of this fuel in new homes. Metropolitan location also has a positive effect on the choice of electricity alone and a negative effect on electricity & fuel oil as well as electricity & LPG The use of LPG for supplemental and room heating purposes in lower income households is evident in the income coefficient which shows that the probability of choosing this fuel decreases as incomes rise.

TABLE 2. Marginal Effects for Residential Fuel Choice Model

Variable	Electricity	Electricity & Natural Gas	Electricity & Fuel Oil	Electricity & LPG	Electricity & Kerosene
constant	-260.150	29.738	141.300	17.683	2.092
Jan. temp	0.020	0.008	-0.035	0.007	-0.002
Jan. precip	-0.004	-0.024	0.029	0.008	0.007
July temp	0.021	-0.009	0.011	-0.013	-0.001
July precip	0.019	-0.012	0.003	-0.007	0.009
log elec. price	-1.007	0.260	0.160	0.221	-0.008
log nat. gas price	-0.017	-0.393	0.770	-0.102	0.024
log fuel oil price	0.232	0.367	-0.534	-0.207	-0.083
log lpg price	0.175	-0.035	0.219	-0.311	0.008
log kero. price	0.428	0.035	-0.279	0.005	-0.135
metropolitan	0.124	0.016	-0.054	-0.086	0.012
log income	0.031	0.010	-0.006	-0.032	-0.005
log home area	-0.155	0.045	0.109	-0.042	-0.018
log year built	34.402	-4.138	-18.581	-2.135	-0.229
log family size	-0.189	0.039	0.050	0.028	0.009
log age of head	-0.157	0.029	0.081	0.023	-0.026
more than 1 unit	0.315	0.006	-0.070	-0.142	-0.056
burn wood	0.168	-0.068	-0.027	0.015	-0.007
nat. gas available	-2.074	1.870	-0.855	-0.556	-0.124
mobile home	-0.309	0.079	0.004	0.089	0.023

TABLE 3. Coefficient Estimates for Commercial Fuel Choice Model

Climate and Price Variables

Variable	Electricity & Natural Gas	Electricity & Fuel Oil	Electricity & District Heat
constant	2.5e+2	2.4e+2	4.3e+2
	(8.77)	(6.77)	(10.87)
Jan. temp	2.0e-2	-0.11	-6.3e-2
	(2.36)	(-7.33)	(-4.02)
Jan. precip.	-6.5e-2	1.1e-2	-9.3e-2
	(-2.47)	(0.25)	(-1.95)
July temp.	-7.2e-2	-0.17	-7.5e-2
	(-3.97)	(-4.37)	(-2.14)
July precip.	-9.5e-2	0.19	-3.6e-2
	(-3.96)	(3.82)	(-0.76)
log elec. price	0.51	0.60	-0.42
	(4.56)	(4.13)	(-2.20)
log nat. gas price	-3.39	0.63	-0.46
	(-25.95)	(4.79)	(-2.73)
log fuel oil price	1.53	-1.431	4.18
	(2.03)	(-1.87)	(3.94)
log dist. heat price	0.86	1.66	-0.67
	(2.47)	(3.33)	(-2.09)

* (t-statistics in parentheses)

metropolitan	0.66	0.29	1.11
	(6.53)	(2.08)	(4.95)
log sqft	0.21	0.18	0.42
	(6.33)	(3.59)	(7.21)
log # floors	-3.1e-2	0.44	0.89
	(0.40)	(3.80)	(7.40)
log year built	-33.49	-32.76	-57.75
	(-8.88)	(-6.93)	(-10.99)
multi-bldg facility	-0.53	-0.68	1.72
	(-6.48)	(-5.47)	(10.52)
months open/ year	0.12	0.15	4.8e-2
	(6.77)	(4.92)	(1.50)
# establishments	-7.7e-3	-2.4e-2	-9.7e-3
	(-2.22)	(-3.66)	(-2.00)
% educational	2.9e-3	1.0e-2	4.2e-4
	(1.61)	(4.12)	(0.18)
% food service	1.0e-2	4.9e-3	-6.2e-3
	(3.43)	(1.18)	(-0.85)
% assembly	4.7e-4	1.6e-3	-6.5e-3
	(0.27)	(0.66)	(-2.44)
% in-door parking	-2.9e-2	-2.2e-2	-4.3e-2
	(-8.43)	(-4.10)	(-6.97)
% warehouse/vacant	-1.1e-2	-9.1e-3	-2.1e-3
	(-6.77)	(-3.67)	(-7.45)
% retail/service	6.4e-4	1.3e-3	-1.9e-2
	(0.42)	(0.60)	(-5.50)
% office space	-3.4e-3	-5.4e-3	-9.1e-3
	(-2.21)	(-2.32)	(-4.34)
log likelihood			*-4257*
% correctly predicted			*71*
Observations			*5605*

* (t-statistics in parentheses)

Commercial Sector Results

Table 3 presents the results of the multinomial logit fuel choice model for the commercial sector. Again, electricity alone is the base category. In this case the percent of correct predictions is 71%, slightly lower than the residential prediction. All explanatory variables are significant predictors of choice over at least one of the categories and sometimes all. Most of the climate variables are significant at the 1% level. January and July temperature and all fuel prices are statistically significant predictors of the fuel choice probabilities as are number of firm and building characteristics.

The corresponding marginal effects are more illustrative and are summarized in Table 4. The probability of choosing all fuel portfolios except electricity & natural gas declines as January temperature rises. An increase in July temperature positively influences the choice of electricity alone, and negatively influences all other choice probabilities. Since electricity is the primary cooling fuel it becomes more important as summer temperatures rise. Both January and July precipitation have a positive influence on the choice of electricity and a negative influence on the choice of electricity & natural gas. At least in the summer months this probably reflects the importance of cooling in places that are humid. The own price coefficients are all negative as expected.

Additional explanatory variables identify important influences on the choice probabilities. The year the building was built positively influences the probability of choosing electricity alone and negatively influences all other probabilities. This result is likely due to the heavy reliance on electricity in new commercial buildings. Metropolitan location has a positive influence on the choice of electricity & natural gas and a negative influence on electricity alone as well as electricity & fuel oil. The presence of multiple buildings in the commercial complex positively

TABLE 4. Marginal Effects for Commercial Fuel Choice Model

Variable	Electricity	Electricity & Natural Gas	Electricity & Fuel Oil	Electricity & District Heat
constant	-47.9550	37.7200	2.9586	7.2761
Jan. temp	-0.0012	0.0103	-0.0071	-0.0021
Jan. precip.	0.0112	-0.0131	0.0034	-0.0015
July temp.	0.0150	-0.0077	-0.0068	-0.0005
July precip.	0.0130	-0.0281	0.0147	0.0005
log elec. Price	-0.0899	0.0995	0.0142	-0.0238
log nat. gas price	0.5507	-0.7766	0.1724	0.0536
log fuel oil price	-0.2606	0.3152	-0.1501	0.0955
log dist. heat price	-0.1606	0.1389	0.0617	-0.0401
metropolitan	-0.1203	0.1130	-0.0117	0.0190
log sq ft	-0.0398	0.0309	0.0011	0.0078
log # floors	-0.0082	-0.0425	0.0246	0.0261
log year built	6.4308	-5.0384	-0.4187	-0.9738
multi-bldg facility	0.0842	-0.1263	-0.0208	0.0629
months open/year	-0.0217	0.0187	0.0041	-0.0012
# establishments	0.0017	-0.0006	-0.0010	-0.0001
% educational	-0.0006	0.0002	0.0005	-0.0001
% food service	-0.0017	0.0022	-0.0001	-0.0004
% assembly	-0.0001	0.0002	0.0001	-0.0002
% in-door parking	0.0055	-0.0049	0.0000	-0.0006
% warehouse/vacant	0.0021	-0.0016	0.0000	-0.0004
% retail/service	0.0000	0.0005	0.0001	-0.0006
% office space	0.0007	-0.0004	-0.0002	-0.0002

influences the choice of electricity alone and electricity & district heat. The former choice may be in order to reduce billing complexity. This explanation is also supported by the marginal effect on the number of establishments which is positive for electricity alone and negative for all other portfolios. In the latter case of district heat choice, the positive coefficient likely reflects the prevalence of district heat use in large multi-building facilities such as hospitals and universities.

Residential Sector Results

The results of the residential conditional expenditure analysis are presented in Tables 5. In the short run, building characteristics are held constant to reflect the constraints on building adjustments in the near term. In the long run, building characteristics are assumed to be endogenous, hence they are removed from the regressions to allow for adjustment.

Overall, the climate variables are better predictors of fuel choice than expenditures on the residential side. Yet, some interesting patterns appear in these results. An increase in January temperature at the mean causes expenditures to fall for all portfolios except electricity & LPG. The effect on electricity & fuel oil is not significant. Mirroring this phenomena, an increase in July temperature positively influences expenditures on all portfolios except electricity & LPG. These results illustrate the heating savings and cooling costs that accompany changes in climate. Increases in January precipitation positively influence expenditures on electricity alone and electricity & natural gas and negatively influence expenditures on alternative portfolios where significant. July precipitation has a significant and positive influence on electricity & natural gas as well as electricity & LPG at the mean.

The fuel prices have a significant influence on expenditures for all portfolios except electricity & kerosene. An increase in all prices except LPG leads to increased own-portfolio expenditures. Own-portfolio expenditures decline as the price of LPG rises illustrating a higher elasticity of demand for LPG since it is more easily substituted with alternative fuels. Expenditures on all fuel portfolios increase with the size of the home and family size. Expenditures decrease with the year built for electricity and electricity & natural gas, illustrating the beneficial effect of improved energy efficiency in new homes. Metropolitan location causes expenditures on electricity & natural gas to be higher. The insulatory value of a basement is identified by the negative influence it has on expenditures for all portfolios except electricity & kerosene where it is not a significant predictor. Appliances generally have a positive influence on expenditures over all portfolios. The selection term (lambda) is highly significant for electricity & natural gas only. Hence, it is important to incorporate this adjustment to prevent bias in the coefficient estimates.

TABLE 5. Residential Model - Conditional Expenditure Analysis

Variable	Electricity				Electricity & Natural Gas			
	Short Run		Long Run		Short Run		Long Run	
constant	54.443	(3.47)	44.077	(2.67)	28.842	(4.42)	15.831	(2.52)
lambda	-0.029	(-1.23)	-0.008	(-0.32)	-0.128	(-3.42)	-0.160	(-4.07)
Jan. temp	-0.008	(-1.67)	-0.010	(-1.97)	-0.007	(-3.81)	-0.007	(-3.95)
Jan. temp^2	-0.000	(-0.43)	0.000	(0.36)	-0.001	(-5.07)	-0.001	(-4.02)
Jan. precip	0.032	(2.91)	0.034	(2.91)	0.006	(1.25)	0.013	(2.44)
July temp	0.039	(4.42)	0.047	(5.41)	0.017	(4.94)	0.025	(7.43)
July temp^2	0.000	(0.23)	-0.001	(-0.55)	0.002	(3.99)	0.001	(2.14)
July precip	-0.003	(-0.35)	-0.004	(-0.41)	0.039	(8.02)	0.042	(8.38)
log elec. price	0.452	(4.90)	0.373	(6.27)	0.240	(8.79)	0.209	(7.44)
log nat. gas price								
log fuel oil price					0.300	(7.65)	0.323	(7.90)
log lpg price								
log kero. price								
metropolitan	0.009	(0.33)	0.022	(0.75)	0.028	(2.30)	0.025	(1.99)
log income	0.085	(4.90)	0.129	(7.28)	0.048	(5.88)	0.097	(11.88)
log home area	0.280	(8.23)	0.327	(12.38)	0.244	(16.17)	0.342	(29.41)
log # floors	-0.080	(-2.84)	-0.103	(-3.70)	-0.102	(-6.25)	-0.147	(-9.62)
log family size	0.245	(10.70)	0.249	(10.31)	0.209	(19.63)	0.218	(19.98)
log year built	-6.603	(-3.20)	-5.285	(-2.44)	-3.183	(-3.69)	-1.553	(-1.86)
log # doors/windows	0.097	(2.98)			0.122	(7.64)		
basement	-0.124	(-3.17)			-0.093	(-5.98)		
color TV/computer	0.079	(6.08)			0.050	(8.49)		
dish/cloth wash/dry	0.043	(1.14)			0.110	(6.45)		
central AC/AC units	0.211	(5.27)			0.094	(6.76)		
elec.wall un/rad.-heat	0.235	(7.38)			0.075	(3.39)		
cent. warm air- heat	0.106	(3.85)			0.095	(5.71)		
				Observations: .859				*Observations: 3073*

*(t-statistics in parentheses, blanks indicate that the variable was not included in the analysis)

TABLE 5. Residential Model - Conditional Expenditure Analysis (continued)

Variable	Electricity & Fuel Oil				Electricity & LPG			
	Short Run		**Long Run**		**Short Run**		**Long Run**	
constant	20.644	(1.49)	10.255	(0.67)	12.538	(0.60)	-3.715	(-0.19)
lambda	-0.028	(-1.08)	-0.061	(-2.10)	0.005	(0.12)	0.002	(0.04)
Jan. temp	-0.007	(-0.81)	-0.012	(-1.27)	0.010	(1.24)	0.018	(2.09)
Jan. temp^2	-0.002	(-3.26)	-0.001	(-2.14)	-0.001	(-1.53)	-0.001	(-2.28)
Jan. precip	-0.062	(-2.92)	-0.028	(-1.20)	-0.021	(-1.14)	-0.035	(-1.87)
July temp	0.032	(1.29)	0.056	(2.07)	-0.022	(-1.27)	-0.036	(-2.17)
July temp^2	0.010	(2.57)	0.008	(1.74)	0.001	(0.32)	0.002	(0.71)
July precip	-0.000	(-0.01)	-0.001	(-0.02)	0.021	(1.20)	0.036	(2.02)
log elec. price	0.183	(3.59)	0.184	(3.41)	0.193	(2.05)	0.128	(1.38)
log nat. gas price								
log fuel oil price	0.836	(7.91)	1.075	(9.39)				
log lpg price					-0.129	(-1.58)	-0.178	(-2.14)
log kero. price								
metropolitan	0.003	(0.11)	-0.019	(-0.54)	0.106	(1.12)	0.142	(1.46)
log income	0.027	(1.70)	0.070	(4.10)	0.047	(1.49)	0.090	(2.93)
log home area	0.180	(6.19)	0.289	(12.28)	0.181	(3.33)	0.246	(5.76)
log # floors	-0.037	(-1.26)	-0.043	(-1.37)	-0.912	(-2.15)	-0.722	(-1.78)
log family size	0.169	(7.43)	0.210	(8.52)	0.159	(3.65)	0.199	(4.57)
log year built	-2.056	(-1.12)	-0.737	(-0.37)	-0.999	(-0.37)	1.093	(0.42)
log # doors/windows	0.204	(6.02)			0.137	(2.01)		
basement	-0.095	(-3.33)			-0.123	(-1.77)		
color TV/computer	0.085	(7.31)			0.053	(2.23)		
dish/cloth wash/dry	0.091	(2.43)			0.213	(3.22)		
central AC/AC units	0.052	(1.38)			0.042	(0.80)		
elec.wall un/rad-heat	0.139	(3.00)			0.269	(2.39)		
cent. warm air-heat	0.052	(1.17)			0.097	(1.81)		
				Observations: 647				*Observations: 339*

*(t-statistics in parentheses, blanks indicate that the variable was not included in the analysis)

TABLE 5. Residential Model - Conditional Expenditure Analysis (continued)

Variable	Electricity & Kerosene			
	Short Run		**Long Run**	
constant	58.928	(1.77)	-14.358	(-0.48)
lambda	-0.123	(-1.58)	-0.135	(-1.68)
Jan. temp	-0.026	(-1.85)	-0.019	(-1.27)
Jan. temp^2	-0.002	(-1.40)	-0.002	(-1.55)
Jan. precip	-0.063	(-1.61)	-0.062	(-1.48)
July temp	0.133	(3.10)	0.110	(2.63)
July temp^2	0.020	(2.70)	0.023	(2.87)
July precip	-0.034	(-0.84)	-0.039	(-1.00)
log elec. price	-0.016	(-0.12)	-0.029	(-0.20)
log nat. gas price				
log fuel oil price				
log lpg price				
log kero. price	0.182	(0.80)	0.125	(0.52)
metropolitan	0.102	(1.30)	0.051	(0.61)
log income	0.096	(1.94)	0.110	(2.15)
log home area	0.129	(1.25)	0.202	(2.22)
log # floors	-0.433	(-2.23)	-0.287	(-1.50)
log family size	0.072	(1.20)	0.134	(2.14)
log year built	-7.085	(-1.61)	2.499	(0.63)
log # doors/windows	-0.117	(-1.21)		
basement	-0.009	(-0.08)		
color TV/computer	0.084	(2.40)		
dish/cloth wash/dry	0.345	(3.86)		
central AC/AC units	-0.150	(-1.97)		
elec.wall un/rad.-heat	0.139	(1.48)		
cent. warm air heat	0.211	(2.56)		
			Observations: 111	

*(t-statistics in parentheses, blanks indicate that the variable was not included in the analysis)

Commercial Sector Results

On the commercial side, Table 6 shows that January temperature exerts a statistically significant and negative influence on expenditures for electricity alone and electricity & fuel oil. July temperature has the strongest influence on electricity & natural gas and electricity & district heat where a negative relationship with expenditures is predicted. January precipitation has a strong positive influence on electricity & fuel oil expenditures and July precipitation negatively influences expenditures on this portfolio. In this case, it appears that a wetter winter induces higher heating costs and a wetter summer leads to savings for the particular fuels. July precipitation has a strong positive influence on electricity & district heat expenditures.

An increase in the price of electricity decreases expenditures on all fuel portfolios where significant. All other prices have a negative own-portfolio impact on expenditures except the price of district heat. District heat is characteristically used in large commercial facilities that have multiple buildings such as universities and hospitals. It is a difficult and costly task to transition from this fuel to an alternative, hence, the observed inelastic demand. The size of the building in square feet positively influences expenditures across the board as does the year built. New commercial buildings include many services such as central air, computer facilities and vending operations that appear to induce higher energy expenditures. Metropolitan location has a strong positive influence on expenditures for all fuel portfolios except electricity & district heat. This identifies the potential for a heat island effect in cities. The presence of an alternate fuel decreases expenditures on electricity alone and electricity & fuel oil. Additional explanatory variables illustrate that air conditioning, particularly in a computer room, and high energy consuming appliances have a strong and positive influence on electricity expenditures. Both the percentage of assembly activities and the percent of the building used as a warehouse or vacant have a strong

TABLE 6. Commercial Model - Conditional Expenditure Analysis

Variable	Electricity				Electricity & Natural Gas			
	Short Run		Long Run		Short Run		Long Run	
constant	-17.484	(-0.88)	-59.114	(-2.79)	-56.188	(-6.58)	-79.449	(-8.77)
lambda	-0.258	(-2.62)	-0.174	(-1.63)	0.126	(1.71)	0.106	(1.35)
Jan. temp	-0.041	(-3.49)	-0.042	(-3.26)	0.003	(0.59)	0.004	(0.67)
Jan. temp^2	0.001	(1.43)	0.002	(2.41)	0.000	(0.30)	0.000	(1.15)
Jan. precip	0.017	(0.51)	0.058	(1.65)	0.022	(1.49)	0.025	(1.61)
Jan. precip^2	-0.013	(-3.[illegible]1)	-0.018	(-3.81)	-0.014	(-6.25)	-0.017	(-6.96)
July temp	0.004	(0.20)	0.047	(2.03)	-0.054	(-5.99)	-0.044	(-4.54)
July temp^2	0.005	(1.75)	0.006	(1.66)	0.006	(3.64)	0.006	(3.27)
July precip	-0.023	(-0.98)	-0.035	(-1.38)	0.020	(1.62)	0.024	(1.74)
July precip^2	0.026	(3.28)	0.026	(3.03)	-0.007	(-1.40)	-0.008	(-1.57)
log elec. price	-0.614	(-9.47)	-0.824	(-11.85)	-0.429	(-10.21)	-0.555	(-12.42)
log nat. gas price					-0.249	(-2.98)	-0.235	(-2.65)
log fuel oil price								
log dist. heat price								
metropolitan	0.401	(5.39)	0.486	(6.61)	0.301	(9.14)	0.360	(10.15)
log sqft	0.458	(13.30)	0.617	(18.25)	0.519	(33.28)	0.687	(45.68)
log # floors	0.141	(1.55)	0.206	(2.23)	-0.094	(-2.58)	0.001	(0.03)
log year built	2.545	(0.97)	7.874	(2.82)	7.764	(6.85)	10.655	(8.87)
# establishments	-0.003	(-0.72)	-0.005	(-1.35)	0.021	(5.46)	0.019	(4.58)
alt. fuel used	-0.341	(-4.30)	-0.355	(-4.24)	-0.131	(-1.31)	-0.100	(-0.92)
% assembly	-0.003	(-2.44)	-0.004	(-2.92)	-0.007	(-11.97)	-0.007	(-11.58)
% educational	0.002	(0.90)	0.001	(0.40)	-0.004	(-6.13)	-0.004	(-6.12)
% food service	0.003	(1.58)	0.008	(3.30)	0.005	(7.83)	0.008	(10.28)
% warehouse/vacant.	-0.006	(-4.67)	-0.011	(-8.59)	-0.008	(-12.52)	-0.010	(-14.90)
% office space	-0.000	(-0.19)	0.003	(2.19)	-0.004	(-6.73)	-0.003	(-5.10)
% retail/service	0.000	(0.40)	0.000	(0.26)	-0.004	(-7.98)	-0.005	(-8.90)
% in-door parking	0.001	(0.49)	-0.006	(-1.97)	-0.004	(-1.83)	-0.007	(-2.98)
cools	0.579	(6.74)			0.080	(2.02)		
AC in computer rm	0.715	(4.84)			0.555	(9.43)		
elec. discount prog.	0.296	(5.33)			0.147	(5.72)		
refrig./ freezer	0.171	(2.51)			0.064	(1.86)		
ice/vend/wat mach	0.603	(9.02)			0.434	(13.54)		
roof : shingles	-0.114	(-1.58)			-0.077	(-2.44)		
roof: metal surface	-0.154	(-2.08)			-0.162	(-3.85)		
wall shingles/siding	-0.095	(-1.27)			-0.182	(-4.61)		
air duct - cool	-0.003	(-0.03)			0.091	(2.33)		
air duct - heat	0.116	(1.20)			0.063	(1.72)		
heat pump - cool	-0.416	(-2.77)			0.129	(1.47)		
heat pump - heat	0.376	(2.49)			0.078	(0.96)		
boilers	-0.053	(-0.34)			0.239	(6.17)		
tenant controls heat	-0.107	(-1.55)			-0.125	(-4.38)		
				Observations=1490				*Observations=3090*

TABLE 6. Commercial Model - Conditional Expenditure Analysis (continued)

Variable	Electricity & Fuel Oil				Electricity & District Heat			
	Short Run		Long Run		Short Run		Long Run	
constant	-49.949	(-2.39)	-32.516	(-1.43)	-126.720	(-5.16)	-126.670	(-5.19)
lambda	-0.053	(-0.58)	-0.134	(-1.33)	-0.257	(-2.21)	-0.305	(-2.55)
Jan. temp	-0.076	(-4.25)	-0.072	(-3.70)	0.011	(0.84)	0.010	(0.70)
Jan. temp^2	0.002	(1.73)	0.003	(1.84)	0.000	(0.17)	-0.000	(-0.06)
Jan. precip	0.151	(2.55)	0.182	(2.82)	-0.063	(-1.67)	0.003	(0.08)
Jan. precip^2	-0.017	(-1.94)	-0.023	(-2.36)	0.000	(0.01)	-0.005	(-1.29)
July temp	0.089	(1.75)	0.103	(1.85)	-0.071	(-2.73)	-0.032	(-1.26)
July temp^2	-0.012	(-1.29)	-0.014	(-1.43)	-0.003	(-0.67)	0.001	(0.25)
July precip	-0.142	(-2.78)	-0.162	(-2.86)	0.083	(2.36)	0.070	(2.14)
July precip^2	0.017	(0.84)	0.002	(0.08)	0.018	(1.48)	0.016	(1.27)
log elec. price	-0.247	(-2.62)	-0.468	(-4.68)	0.074	(0.72)	0.050	(0.47)
log nat. gas price								
log fuel oil price	-0.422	(-1.67)	-0.856	(-3.10)				
log dist. heat price					0.496	(4.53)	0.408	(3.67)
metropolitan	0.354	(5.04)	0.528	(7.14)	-0.150	(-1.28)	-0.280	(-2.38)
log sqft	0.541	(14.71)	0.655	(17.08)	0.853	(21.25)	0.876	(24.18)
log # floors	-0.025	(-0.29)	-0.038	(-0.42)	-0.214	(-2.73)	-0.136	(-1.65)
log year built	6.965	(2.51)	4.534	(1.51)	16.962	(5.20)	16.992	(5.23)
# establishments	0.020	(2.12)	0.019	(1.79)	-0.004	(-0.80)	-0.003	(-0.53)
alt. fuel used	-0.282	(-2.20)	-0.308	(-2.18)	0.004	(0.01)	0.054	(0.14)
% assembly	-0.005	(-4.08)	-0.008	(-6.00)	-0.005	(-4.40)	-0.005	(-3.84)
% educational	0.001	(0.53)	-0.001	(-0.52)	-0.004	(-3.97)	-0.005	(-4.39)
% food service	0.007	(3.91)	0.008	(3.85)	0.004	(2.04)	0.005	(2.24)
% warehouse/vacant.	-0.005	(-3.43)	-0.009	(-5.81)	-0.006	(-3.62)	-0.008	(-4.78)
% office space	-0.000	(-0.03)	0.000	(0.29)	0.002	(1.58)	0.003	(2.35)
% retail/service	-0.001	(-0.45)	-0.003	(-2.14)	0.000	(0.18)	-0.000	(-0.18)
% in-door parking	0.002	(0.68)	-0.001	(-0.31)	-0.004	(-0.26)	-0.004	(-0.22)
cools	0.197	(2.69)			0.203	(2.15)		
AC in computer rm	0.449	(3.43)			0.243	(2.74)		
elec. discount prog.	0.248	(4.24)			0.121	(2.76)		
refrig./ freezer	0.199	(2.62)			-0.071	(-0.75)		
ice/vend/wat mach	0.244	(3.53)			0.148	(1.16)		
roof : shingles	-0.322	(-4.30)			-0.013	(-0.12)		
roof: metal surface	-0.457	(-4.93)			0.138	(1.03)		
wall shingles/siding	-0.145	(-1.77)			0.288	(2.19)		
air duct - cool	0.214	(2.25)			0.121	(1.11)		
air duct - heat	-0.100	(-1.40)			-0.220	(-2.13)		
heat pump - cool	-0.002	(-0.01)			0.539	(2.39)		
heat pump - heat	0.079	(0.34)			-0.062	(-0.29)		
boilers	0.121	(1.53)			-0.655	(-6.04)		
tenant controls heat	-0.007	(-0.11)			0.073	(1.00)		
			Observations: 538				*Observations: 487*	

negative influence on expenditures across portfolios, probably due to lower space conditioning costs. The sample selection terms (lambda) is significant in two cases, highlighting the importance of using the selection correction method.

5. Climate Change Simulation

Climate Scenarios

A series of uniform climate change scenarios are simulated using the fuel choice-energy expenditure model. Combining the results yields an estimate of expected energy expenditures for the new climate regime which can be compared to expected expenditures in the baseline. Uniform climate scenarios assume that climate change is the same across different regions and climate zones in the US. The effect of a 1.5, 2.5 and 5° Celsius change in temperature on energy is tested. Current scientific evidence suggests that changes in climate are not likely to be uniform, and instead are expected to vary across regions, climate zones and countries. However, General Circulation Models (GCMs) which predict the climates from increased greenhouse gas concentrations, do not agree on regional seasonal variation. It appears that uniform scenarios are a reasonable approximation of the expected effect from existing models (Williams et al, 1997). This paper examines uniform scenarios leaving future research to consider the implications of individual GCM scenarios.

Economic Scenarios

Two economic simulations are presented. The first set measures the impact of climate change on the 1990 economy. Although not a realistic scenario given that climate change is expected to occur over the next century, this simulation provides comparability with previous estimates in the literature. The second simulation measures the impact of climate change on the 2060 energy sector since CO_2 levels are projected to be doubled at that time. A series of adjustments are made to predict expenditures in a 2060 economy in order to reflect population and economic growth as well as changes in fuel prices.

Population is projected to grow by approximately 19% over the period from 1990 to 2060 (IPCC 1990). In this chapter a uniform population increase across the country is assumed. GDP per capita is projected to grow by 223% over the same period (IPCC 1990). Energy expenditures are assumed to increase proportionately to the income elasticity of expenditures predicted in the residential model (0.10). This implies that energy expenditures will grow 22%. An additional adjustment is made to reflect the 2060 age of building stock. In 2060 the average building age is assumed to be 20 years. This change affects both the fuel choice and expenditure components.

In addition to accounting for major demand drivers such as GDP and population growth there is likely to be price-induced substitution away from particular types of energy over the next century as fossil fuel supplies begin to decline and prices rise. A Hotelling-type model is used to predict changes in fuel prices over the period. The Hotelling Rule states the net prices for depletable resources must rise at the rate of interest to compensate resource owners for holding onto stocks (Hotelling 1931):

$$(9) \qquad \frac{\dot{P}}{P} = r\left(1 - \frac{c}{P}\right)$$

where P is fuel price, c is extraction costs and r is the discount rate. For example, assuming that the discount rate is 4% and that extraction costs are approximately half of gross prices, according to the Hotelling Rule fuel prices would be expected to rise at an annual rate of about 2% on average. Researchers expect that electricity prices will increase at a slower rate than other fuel prices because of utilities' heavy reliance on more plentiful coal resources. Hence, electricity prices are assumed to increase at a rate of 1% annually while all other prices increase at an annual rate of 2%. These price changes affect both the fuel choice and expenditure components of the 2060 forecast. These scenarios are necessarily ad hoc due to uncertainty about future price paths, but should provide a sense of the range of impacts that alternatives paths will generate.

One additional constraint is placed on the commercial fuel choice model. District heat is a fuel choice that is expected to remain constrained over the long term. Buildings that consume district heat are generally large multi-complex facilities with a central physical plant such as universities and hospitals.[9] Hence, only multi-building facilities are allowed to "fuel switch" to district heat.

Simulation Results and Sensitivity Analysis

Tables 7 and 8 identify how the mean probability of choosing each fuel portfolio changes between 1990 and 2060, as well as across climate scenarios. The short run response to climate change is constrained. Households and firms are assumed to rely on baseline fuel portfolios in the short run, while in the long run they are able to engage in fuel switching.

Results for the residential sector are shown in Table 7. Although the probabilities vary between the 1990 and 2060 economies, the pattern of response to changes in climate is similar. With climate change the probability of choosing electricity alone increases due to the growing importance of cooling in household energy expenditures. Many households in warmer regions rely on electricity alone since, on the cooling side, it is virtually the only option. On the heating side, it has a high marginal cost but a low fixed cost, making it desirable to some households. The model results suggest that more households will prefer to move to this fuel as they begin to experience warmer temperatures. As this occurs, the probability of choosing electricity & natural gas remains relatively constant in the 1990 economy and falls in the 2060 economy. In addition, the probability of choosing the remaining fuels remains constant or declines in response to climate change. An interesting transition takes place between the 1990 and 2060 economies, largely due to increased prices and new construction. There is a large jump in the mean probability of choosing electricity alone and concomitant decrease in all other categories. On average, buildings that choose electricity alone are newer than buildings that choose alternative portfolios. In the 2060 scenario, homes are assumed to be built in 2040 on average. For this reason, the distribution of fuel choices follows that of newer 1990 homes, where electricity alone is a popular option. Also, the fact that electricity prices rise less rapidly than alternative fuel prices makes it an attractive option. The probability of choosing electricity & natural gas decreases due to movements into the electricity alone portfolio. Also, fuel oil, LPG and kerosene are being phased out in the 2060 economy. Some researchers believe fuel oil prices may increase more rapidly than natural gas prices due to increasing scarcity and environmental considerations. An alternative scenario that projects an increase of 3% per year in fuel oil prices leaving all other scenarios the same is tested. This drives the selection further out of fuel oil and into the electricity alone and electricity & natural gas alternatives.

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[9] 83% of commercial buildings that consume district heat are multi-complex facilities and 93% are in designated "urban" areas. In addition, the mean energy consumption in BTUs exceeds the mean of the sample by almost 3 times.

TABLE7. Mean Predicted Fuel Choice Probabilities

Residential Model - Baseline and Uniform Climate Change Scenarios

Year	p0 electricity	p1 electricity & nat. gas	p2 electricity & fuel oil	p3 electricity & LPG	p4 electricity & kerosene
1990					
BASELINE - Short Run	0.17	0.61	0.13	0.07	0.02
UNIFORM 1.5C-Long Run	0.19	0.61	0.12	0.06	0.02
UNIFORM 2.5C-Long Run	0.19	0.61	0.12	0.06	0.02
UNIFORM 5C-Long Run	0.22	0.60	0.10	0.06	0.02
2060					
BASELINE - Short Run	0.66	0.33	0.01	0.00	0.00
UNIFORM 1.5C-Long Run	0.68	0.31	0.01	0.00	0.00
UNIFORM 2.5C-Long Run	0.69	0.30	0.01	0.00	0.00
UNIFORM 5C-Long Run	0.72	0.27	0.01	0.00	0.00

A similar pattern of response to climate change occurs on the commercial side as illustrated in Table 8. In this case, as temperatures warm, the probability of choosing both electricity alone and electricity & natural gas increase while the other probabilities fall. Between 1990 and 2060 there is a shift to electricity alone. This not only reflects the newer age of buildings, but also the increased saturation of cooling, for which electricity is the primary fuel. In addition, the mean probability of choosing fuel oil rises and is likely due to cross-price induced effects. There is a corresponding movement away from electricity & natural gas and electricity & district heat. The latter is expected due to the specialized nature of district heat consumption. However, the extent to which commercial buildings shift into fuel oil and out of natural gas depends critically on the relative increase in the two fuel prices. In this scenario, the two prices are assumed to increase at the same rate, 2%. If, on the other hand, fuel oil prices increase more rapidly due to increased scarcity and environmental considerations, this effect will be more muted. An alternative scenario is tested assuming that fuel oil prices increase at 3% and natural gas prices continue to rise at 2%. In this case, the probability of choosing electricity & fuel oil is virtually the same as in the 1990 scenario. Also, while the mean probability of choosing electricity & natural gas still declines between 1990 and 2060, it does so much more moderately. Although a scenario like this alters the probabilities, it does not alter the magnitude or direction of the predicted climate change impacts.

TABLE 8. Mean Predicted Fuel Choice Probabilities
Commercial Model - Baseline and Uniform Climate Change Scenarios

Year	p0 electricity	p1 electricity & nat. gas	p2 electricity & fuel oil	p3 electricity & dist. heat/ other
1990				
BASELINE - Short Run	0.26	0.55	0.10	0.09
UNIFORM 1.5C-Long Run	0.29	0.55	0.08	0.08
UNIFORM 2.5C-Long Run	0.30	0.55	0.07	0.08
UNIFORM 5C-Long Run	0.33	0.56	0.04	0.07
2060				
BASELINE - Short Run	0.50	0.20	0.24	0.06
UNIFORM 1.5C-Long Run	0.55	0.20	0.20	0.05
UNIFORM 2.5C-Long Run	0.58	0.20	0.17	0.05
UNIFORM 5C-Long Run	0.64	0.20	0.11	0.05

Tables 9 and 10 identify the impact of climate change on the market for different fuels in 1990 and 2060. The pattern of change across climate scenarios is quite similar for the 1990 and 2060 economies. In the 2060 economy electricity expenditures expand more than five-fold while electricity & natural gas expand moderately. Expenditures on electricity & natural gas increase over this period even though the mean probability of choosing the fuel portfolio declines. This is due to expansion in population and incomes which drives an increase in demand. This effect is also illustrated in the growth of total expenditures between 1990 and 2060. Expenditures on electricity and fuel oil decline while electricity & LPG and electricity & kerosene drop out of the market in 2060. Moving from low to high degrees of climate change the adjustment in expenditures illustrates the changing nature of space conditioning demands. In the long run, where fuel choice is flexible, the electricity market expands more rapidly as climate change

TABLE 9. Residential Model - Expected Expenditures in Each Fuel Market

Baseline and Uniform Climate Change Scenarios (billion $)

Year	c0 electricity	c1 electricity & nat. gas	c2 electricity & fuel oil	c3 electricity & LPG	c4 electricity & kerosene	Total
1990						
BASELINE						
short run	19.8	63.2	16.3	8.2	2.8	110.3
long run	19.8	63.2	16.3	8.2	2.8	110.3
UNIFORM 1.5C						
short run	20.8	65.0	16.4	8.1	3.3	113.6
long run	22.9	65.2	16.3	7.4	3.3	115.1
UNIFORM 2.5C						
short run	21.5	65.8	17.0	7.9	3.9	116.1
long run	24.9	66.6	16.3	6.9	3.6	118.3
UNIFORM 5C						
short run	23.1	69.1	20.0	7.7	7.4	127.3
long run	30.4	70.3	17.2	5.9	5.2	129.0
2060						
BASELINE						
short run	108.9	88.3	15.9	0.0	0.0	213.1
long run	108.9	88.3	15.9	0.0	0.0	213.1
UNIFORM 1.5C						
short run	114.9	90.5	16.0	0.0	0.0	221.4
long run	120.3	85.8	14.5	0.0	0.0	220.6
UNIFORM 2.5C						
short run	118.4	91.7	16.6	0.0	0.0	226.7
long run	126.6	85.0	13.6	0.0	0.0	225.2
UNIFORM 5C						
short run	127.8	96.0	19.5	0.0	0.0	243.3
long run	143.0	83.1	12.3	0.0	0.0	238.4

worsens. For a change in climate on the order of 1.5° C in 2060 the market for electricity & natural gas expands, but for greater warming the market starts to contract as electricity alone picks up the slack. Across all climate scenarios the market for fuel oil declines. This is likely due to the fact that fuel oil is primarily a heating fuel.

On the commercial side, total expenditures increase between 1990 and 2060 as shown in Figure 10. However, this expansion is not nearly as great as in the residential case. The electricity market doubles in size between 1990 and 2060 while the markets for electricity & natural gas and electricity & fuel oil decline. Expenditures on electricity and district heat also increase due to the expense of using this fuel and relatively inelastic demand by existing users. Across climate scenarios, expenditures on electricity alone increase as a result of climate change. Expenditures on electricity & natural gas initially fall in the short run when fuel choice is constrained but rise in the long run as the market expands slightly and this portfolio becomes more desirable as climates change. Expenditures on electricity & fuel oil increase in the short run when fuel choice is constrained, but decrease in the long run as fuel choice becomes flexible and there is a movement out of this market. Expenditures on electricity & district heat exhibit a steady decline across increasing climate scenarios.

TABLE 10. Commercial Model - Expected Expenditures in Each Fuel Market

Baseline and Uniform Climate Change Scenarios (billion $)

Year	c0 electricity	c1 electricity & nat. gas	c2 electricity & fuel oil	c3 electricity & dist. heat/other	Total
1990					
BASELINE					
short run	12.2	40.0	6.2	13.6	72.0
long run	12.2	40.0	6.2	13.6	72.0
UNIFORM 1.5C					
short run	12.5	37.4	6.4	12.6	68.9
long run	14.8	38.1	5.4	12.4	70.7
UNIFORM 2.5C					
short run	12.7	36.4	6.4	11.8	67.3
long run	16.7	37.8	4.6	11.6	70.7
UNIFORM 5C					
short run	14.1	35.9	6.0	9.8	65.8
long run	23.8	38.7	2.8	9.8	75.1
2060					
BASELINE					
short run	26.0	17.2	6.4	45.8	95.4
long run	26.0	17.2	6.4	45.8	95.4
UNIFORM 1.5C					
short run	26.1	16.1	6.5	42.4	91.1
long run	30.9	16.4	5.6	44.2	97.1
UNIFORM 2.5C					
short run	26.4	15.6	6.5	39.6	88.1
long run	34.8	16.3	4.9	42.8	98.8
UNIFORM 5C					
short run	28.9	15.4	6.1	32.7	83.1
long run	48.8	16.7	3.1	39.6	108.2

The change in expected energy expenditures for each climate are presented in Table 11. These welfare estimates do not include building expenditures. The long run impacts are greater than the short run impacts in the 1990 economy as expected, but were relatively less in the 2060 economy. According to the theory presented in Section 2.4, this suggests that energy and capital are complementary in the 1990 economy and substitutes in the 2060 economy. Given our assumption that cooling will completely penetrate the market by 2060, it is possible that energy and capital will be complementary by then. In this case, the short run results may be more appropriate for 2060 and the long run results for 1990. The difference between the short run and long run estimates are small for the residential sector implying the bias from omitted building expenditures is negligible here. However, the difference is large for the commercial sector suggesting that future studies need to measure commercial building expenditure changes to capture the complete climate impact.

Focusing on the 2060 short run results, the simulations suggest that a mild warming of 1.5C would result in 2060 damages of $8.3 billion to the residential sector and 2060 benefits of $4.3 billion to the commercial energy sector. A warming of 2.5C, would increase residential damages to $13.6 billion and commercial benefits to $7.3 billion. Finally, a dramatic 5C warming would swell residential damages to $30 billion and commercial benefits to $12 billion. These results imply that mild warming will have harmful effects of about $4 billion on the United States energy sector but that these damages would increase sharply with large temperature changes.

TABLE 11. Total Welfare Impacts of Climate Change on Energy (billion $)

		UNIFORM 1.5	UNIFORM 2.5 C	UNIFORM 5 C
RESIDENTIAL				
1990				
	short run	-3.3	-5.8	-17.0
	long run	-4.8	-8.0	-18.7
2060				
	short run	-8.3	-13.6	-30.2
	long run	-7.5	-12.1	-25.3
COMMERCIAL				
1990				
	short run	3.1	4.7	6.2
	long run	1.3	1.3	-3.1
2060				
	short run	4.3	7.3	12.3
	long run	-1.7	-3.4	-12.8

8. CONCLUSIONS

This discrete-continuous model of the impact of climate change on fuel choice and energy expenditures provides valuable insights regarding the nature of climate change adjustment in the US energy sector. This is the first study to explicitly consider the nature of climate change impacts on fuel choice and specific energy markets. The model results indicate that the fuel choice component is an important aspect of the climate adjustment. In fact, in some cases fuel choice is more sensitive to climate variables than expenditures. Hence, building adjustments and particularly space conditioning equipment adjustments are important. The ability to alter fuel choice in the long run substantially impacts the results. The fuel choice model highlights the fact that unless alternative mechanisms for cooling are developed, electricity is likely to dominate the energy market in 2060 on both the residential and commercial side. This is a result of both climate and economic factors.

The model projects that climate change will increase energy costs in the residential sector by $7.5 billion to $30 billion in damages (2060). The total welfare measure including building costs is expected to lie between these two measures since energy and capital exhibit a substitute relationship in this case. This represents a 0.03 to 0.15% loss in 2060 GNP. On the commercial side, impacts range from $12 billion in benefits to $13 billion in damages (2060). This implies that costs and benefits in this sector could range between ± 0.06 % of 2060 GNP. A substitute relationship between energy and capital dominates these results as well. In this case, the total welfare impact, including building costs, is expected to be even greater than the short run benefits. These estimated impacts also lie within the range predicted by previous studies. Based on expert opinion, Nordhaus (1991a) and Cline (1992) predict electricity damages ranging from $2.4 billion to $11.2 billion and non-electric benefits ranging from $1.7 billion to $1.2 billion, respectively. Using an engineering methodology, Rosenthal et al (1995) predict net benefits on the order of $5 billion. Chapter 1 considered the responsiveness of aggregate energy expenditures to climate change. The range of welfare impacts suggested by the aggregate expenditure model is on the same order as this study. One interesting difference between the models is the relationship between short and long run impacts The potential for long run damages is more pronounced in the current fuel-choice/conditional expenditure model. These damages are primarily due to the significant switch in fuel choice to electricity, additions of cooling capacity and expenditures on cooling. This provides further evidence that building adjustments may be even more important than indicated in the aggregate expenditure approach. Hence, the inclusion of a fuel choice component allows new and interesting insights into the climate adjustment. In addition, the fact that the two studies predict impacts on the same order of magnitude provides useful policy evidence.

There is further work to pursue in this area. Since climate change is a global phenomena, impact estimates are needed around the world. Both the pattern and type of energy use can vary significantly between developed and developing countries. An important next step is to study the nature of impacts in developing countries in order to develop an aggregate estimate of world energy impacts. In addition, these results should be combined with other impact and cost studies in order to develop an integrated assessment of the costs of controlling climate change and the corresponding benefits.

APPENDIX: Data Definitions

Definitions of Independent Variables: Residential Regression Models

Variable	Definition
basement	1 if home has basement, 0 otherwise
burn wood	1 if wood is burned as alternative heat source, 0 otherwise
color TV/computer	1 if household has computer or color TV, 0 otherwise
cent. warm air-heat	1 if household uses central warm air for heat, 0 otherwise
central AC/AC units	1 if household has central air conditioning or wall units, 0 otherwise
dish/cloth wash/dry	1 if household has dishwasher, clothes washer, clothes dryer, 0 otherwise
elec. wall un/rad.-heat	1 if household uses electric wall units or radiators to heat, 0 otherwise
Jan. temp	average January temperature(demeaned) - degrees C
Jan. temp^2	average January temperature(demeaned) squared
Jan. precip	average January precipitation(demeaned) - inches
July temp	average July temperature(demeaned) - degrees C
July temp^2	average July temperature(demeaned) squared
July precip	average July precipitation(demeaned) - inches
lambda	sample selection variable
log age of head	head householder age
log # doors/windows	number of doors and windows in home
log elec. price	average electricity price
log fuel oil price	average fuel oil price
log kero. price	average kerosene price
log income	average household income for relevant income range
log lpg price	average liquid petroleum gas price
log nat. gas price	average natural gas price
log # floors	number of floors in home
log family size	number of household members
log home area	size of home in square feet
log year built	year home constructed
mobile home	1 if home is mobile type, 0 otherwise
more than 1 unit	1 if more than 1 unit, 0 otherwise
nat. gas available	1 if natural gas is available, 0 otherwise

Definitions of Independent Variables: Commercial Regression Models

Variable	Definition
AC in comp. room	1 if there is air conditioning in comp. room, 0 otherwise
air ducts - cool	1 if air ducts used for cooling, 0 otherwise
air ducts - heat	1 if air ducts used for heating, 0 otherwise
alt. fuel used	1 if alternate fuel is used, 0 otherwise
boilers	1 if boiler used, 0 otherwise
com. ref/freezer	1 if commercial freezer or refrigerator used, 0 otherwise
cools	1 if use air conditioning, 0 otherwise
elec. discount pgm.	1 if participate in electricity discount program, 0 otherwise
heat pump - cool	1 if heat pumps used for cooling, 0 otherwise
heat pump - heat	1 if heat pumps used for heating, 0 otherwise
ice/vend/wat mach	1 if ice, vending or water machines used, 0 otherwise
Jan. temp	average January temperature(demeaned) - degrees C
Jan. temp^2	average January temperature(demeaned) squared
Jan. precip	average January precipitation(demeaned) - inches
Jan. precip^2	average January precipitation (demeaned) squared
July temp	average July temperature(demeaned) - degrees C
July temp^2	average July temperature(demeaned) squared
July. precip	average July precipitation(demeaned) - inches
July precip^2	average July precipitation(demeaned) squared
lambda	sample selection variable
log dist. heat price	average district heat price
log elec. price	average electric price
log fuel oil price	average fuel oil price
log nat. gas price	average natural gas price
log # floors	number of floors
log square feet	building size - square feet
log year built	year construction completed
months open/year	number of months open
multi-bldg facility	1 if facility has multiple buildings, 0 otherwise
# establishments	number of establishments in building
% assembly	percent assembly operations
% educational activities	percent non-refrigerated warehouse and vacant
% food service activities	percent food service
% in-door parking	percent in-door parking garage
% office space	percent office
% retail/service	percent retail/services
% warehouse/vacant	percent warehouse/vacant
refrig./ freezer	1 if have refrigerator/freezer, 0 otherwise
roof : shingles	1 if roof material is shingles, 0 otherwise
roof: metal surface	1 if roof material is metal surface, 0 otherwise
tenant controls heat	1 if tenant controls heat, 0 otherwise
wall shingles/siding	1 if wall material is siding/shingles, 0 otherwise

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