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A Partial Adjustment Model of U.S. Electricity Demand by Region, Season, and Sector

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RESOURCES FOR THE FUTURE

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Abstract

Identifying the factors that influence electricity demand in the continental United States and mathematically characterizing them are important for developing electricity consumption projections. The price elasticity of demand is especially important, since the electricity price effects of policy implementation can be substantial and the demand response to policy-induced changes in prices can significantly affect the cost of policy compliance. This paper estimates electricity demand functions with particular attention paid to the demand stickiness that is imposed by the capital-intensive nature of electricity consumption and to regional, seasonal, and sectoral variation. The analysis uses a partial adjustment model of electricity demand that is estimated in a fixed-effects OLS framework. This model formulation allows for the price elasticity to be expressed in both its short-run and long-run forms. Price elasticities are found to be broadly consistent with the existing literature, but with important regional, seasonal, and sectoral differences.

Key Words: electricity, demand elasticities, energy demand, partial adjustment

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A Partial Adjustment Model of U.S. Electricity Demand by Region, Season, and Sector

Anthony Paul, Erica Myers, and Karen Palmer*

Introduction

The electricity sector in the United States is large and growing, accounting in 2007 for 2.6 percent of U.S. GDP and just over 40 percent of total U.S. energy consumption (U.S. EIA 2008b). Electricity consumption has nearly doubled in the past 30 years (U.S. EIA 2008b), and the Energy Information Administration (EIA) forecasts another 23 percent increase over the next two decades under business-as-usual conditions (U.S. EIA 2008a). Identifying the factors that influence electricity demand and mathematically characterizing them are important for developing such electricity consumption projections, and reliable projections are important for policymakers.

The institutions governing how electricity prices are set vary across the nation; nonetheless, changes in policy can affect prices under any regime, and the demand response to changing prices is important to both economic and environmental policy analysis. As an example, a federal climate change policy in the United States has the potential to substantially affect electricity prices. Ignoring the price responsiveness of consumers in projecting a climate policy outcome could lead to an overestimate of costs. Climate policy is only one of myriad federal-, regional-, and state-level policy proposals that could affect electricity prices. Electricity demand is responsive not only to own price but also to climatic conditions, population and economic growth, and prices of other fuels. To the extent that these drivers of electricity demand are predictable—significant uncertainty characterizes many of these variables, especially over

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the long term—an assessment of how they influence consumers' choices regarding electricity consumption facilitates informed policymaking.

Regional and seasonal differences in the mix of fuels and technologies used to produce electricity can drive regional and seasonal differences in the outcomes of any policy that affects electricity production. Demand behavior that varies regionally and seasonally could compound or mitigate such differences. Regional variation in demand behavior is to be expected, given regional differences in infrastructure,[1] the electricity-using capital stock, and consumer preferences that may be heterogeneous. In the nonresidential sectors, variations in the composition of local economic activity also suggest potential regional differences in demand behavior. Seasonal differences in electricity demand are driven by seasonal variation in the demand for energy services—heating, cooling, lighting, water heating, appliance use, and so forth. Since the types of energy services demanded vary seasonally and each energy service varies in electricity consumption intensity, so too will electricity demand show seasonal variation. These regional and seasonal differences may vary with the type of customers. The literature on electricity demand contains little simultaneous consideration of these geographical, temporal, and customer differences. This paper will address this issue by estimating separate, but identically formulated, demand functions for each of nine census divisions with seasonally differentiated coefficients. These demand functions are estimated separately for three customer classes—residential, commercial, and industrial—with identical functional forms but slight variation in the included independent variables.

We adopt a partial adjustment model structure that is an ad hoc formulation capturing the dynamics of the demand stickiness imposed by the capital-intensive nature of electricity consumption. The ideal model would be a structural model derived from a formulation that incorporates individuals and firms that maximize expected utility and profits, respectively, over electricity-using capital investments and electricity consumption to produce electricity services, along with all other goods, within a budget.[2] The data for this model would track purchases, utilization, prices, and characteristics of electricity-consuming equipment at the household and

1 These differences exist in the infrastructure for the delivery of energy to end users as well in the stock of buildings.

2 Dubin and McFadden (1984) use a random utility model to derive such a model, which can be used to jointly estimate energy-using equipment choice behavior and energy consumption. They then implement the model to look at space heating and water heating.

firm level over time. The description of characteristics would include the energy efficiency of the equipment as well as a description of other equipment features that map into the utility and profit functions of consumers and firms. However, these data do not exist, and there is ample evidence that the characterization of preferences necessary to construct a model that approximates the real-world behavior of consumers is unknown (see Train 1985 for the discount rates implied by consumers' energy-related decisions). The partial adjustment formulation is an alternative model of electricity demand that captures the dynamics of demand behavior, allowing for the elasticity of demand with respect to each of its determinants to be expressed in both its short-run and its long-run forms. We give special consideration in this paper to the price elasticities because of the aforementioned policy significance of the price variable.

The models are estimated using a fixed-effects OLS model specification. Because the partial adjustment model includes a lagged dependent variable, autocorrelation can asymptotically bias the coefficient estimates. This problem is addressed by reestimating the model in a two-stage least squares framework. The data are a state-level panel of monthly observations that span the period from 1990 to 2006 and include electricity consumption and prices along with a set of covariates that are assumed to drive consumption.

The paper is organized as follows. We begin with a review of the literature on electricity demand function estimation. Then we present the model that is estimated in this study and the results of the estimation. The conclusion includes some observations regarding the highlights and limitations of this analysis in addition to some suggestions for future research related to electricity demand.

Literature Review

In the absence of detailed household- and firm-level data on electricity consumption and electricity-consuming capital, researchers have turned to a variety of aggregated, ad hoc models of electricity demand.[3] We adopt the partial adjustment formulation that incorporates short-run responses to changes in contemporaneous variables, including price, and longer-run responses through a lagged consumption term. Houthakker and Taylor (1970) developed a dynamic model in which the current level of the state variable is determined by the cumulative effects of past

[3] See Bohi (1981), Bohi and Zimmerman (1984), and Taylor et al. (1984) for an overview of early demand estimation studies and alternative modeling methodologies, and see Dahl (1993) and Dahl and Roman (2004) for a review of energy demand elasticities estimation.

behavior, and the change in the level of the next period's state variable is partly determined by current decisions. Houthakker et al. (1974) and Houthakker (1980) used this approach to model residential electricity demand and estimate price elasticities at the national and regional levels. More recently, Bernstein and Griffin (2005) did a similar analysis estimating national and regional elasticities for the residential and commercial classes. A common finding among these studies is significant differences among the elasticity estimates across the regions. Hsing (1994) estimated elasticities using this approach for six southern states, correcting for cross-sectional heteroskedasticity and autocorrelation. He also finds that regional demand behavior deviates from national average behavior and that the empirical findings are sensitive to model specification. Beierlein et al. (1981) and Lin et al. (1987) used the partial adjustment model with error components and a seemingly unrelated regressions (EC-SUR) procedure to estimate demand equations for electricity and other energy use. Both of these studies simultaneously estimate equations for multiple customer classes and energy sources at a regional, annual level. They find that EC-SUR achieves more efficiency than the OLS and error components approaches.

One difficulty in estimating electricity demand is the potential simultaneity between price and quantity. Because of this problem, some researchers have promoted simultaneous equation approaches over partial adjustment models (Kamerschen and Porter 2004). Baltagi and Griffin (1997) and Baltagi et al. (2002) looked at the forecasting performance of several different estimation techniques with different levels of pooling for the gasoline market and the electricity and natural gas markets, respectively. For the electricity market, Baltagi et al. (2002) found that GLS ranks first among the models tested in predictive performance by having the lowest root mean squared errors (RSME) averaged over a five-year period. GLS was followed by within estimation (OLS with state fixed effects) and within two-stage least squares (2SLS), leading them to conclude that endogeneity problems did not seem to be severe. For the gasoline market, Baltagi and Griffin (1997) also found that standard estimation techniques outperformed simultaneous equation techniques and suggested that the relatively poor performance of the 2SLS estimators in capturing long-run dynamics might be due to the quality of the instruments.

Houthakker (1980), Bernstein and Griffin (2005), and Lin et al. (1987) found pronounced differences among U.S. census divisions in their regional model estimations. Many authors have argued for the importance of modeling at the regional level because unique regional impacts get lost in aggregate models (e.g., Houthakker and Taylor 1970; Houthakker 1980; Taylor et al. 1984). Maddala et al. (1997) explored the issue of pooling and found that heterogeneous time series estimates for each state yield inaccurate signs on the coefficients. They argued that panel data estimates are inaccurate as well because the hypothesis of homogeneity of the coefficients is rejected. They proposed estimating coefficients using shrinkage estimators as a preferred alternative. Baltagi and Griffin (1997) and Baltagi et al. (2002) found that homogeneous estimators were better at forecasting demand than their heterogeneous counterparts and that individual estimation offered the worst out of sample forecasts.

The Partial Adjustment Model

The derivation of the partial adjustment electricity demand model begins with a static representation of a long-run demand function in which $Q^*_{i,t}$ is the level of electricity consumption that would be achieved in U.S. state i at time t if the capital goods used in the consumption of electricity were perfectly mobile. In the parlance of Houthakker and Taylor (1970), $Q^*_{i,t}$ is the desired level of consumption. Assuming a Cobb Douglas relationship between desired demand and its drivers, Equation (1) defines the long-run demand curve as a function of electricity price, $P_{i,t}$, and a set of covariates, $X_{i,t}$. The long-run price elasticity of demand is denoted as ε_L, β is a vector of coefficients that describes the responsiveness of the long-run level of demand to the nonprice covariates, and α is a constant.

$$Q^*_{i,t} = f(P_{i,t}, X_{i,t}) = \alpha P_{i,t}^{\varepsilon_L} X_{i,t}^{\beta} \tag{1}$$

In reality, capital is not perfectly mobile, and there may exist a habitual component to electricity demand behavior. Thus, Equation (1) by itself is not a sufficient representation of the real-world behavior of electricity consumers. Following Houthakker et al. (1974), we introduce a function to capture the limited capability of consumers to adjust immediately to the long-run equilibrium level of consumption in response to a change in price, income, weather, or other factor. This limited capability is expressed in Equation (2) as parameters θ_1 and θ_{12}, the partial adjustment constraints. The parameter θ_1 captures both the strength of month-to-month behavioral inertia and the monthly rate of capital turnover for types of equipment that are operated in all months (e.g., refrigerators), and the parameter θ_{12} captures the strength of year-to-year behavioral inertia and the rate of capital turnover that has a seasonal usage pattern (e.g., air-conditioners). The parameters θ_1 and θ_{12} will take on values between zero and one, with zero corresponding to a scenario in which consumers are completely unable to adjust consumption toward the long-run equilibrium, and with one corresponding to a scenario in which the entire capital stock can turn over right away and no behavioral habit exists. Both of these scenarios are inconsistent with real-world behavior, and thus values between zero and one are anticipated.

(2) $$\left(\frac{Q_{i,t}{}^{2}}{Q_{i,t-1}Q_{i,t-12}}\right)=\left(\frac{Q^{*}_{i,t}}{Q_{i,t-1}}\right)^{\theta_1}\left(\frac{Q^{*}_{i,t}}{Q_{i,t-12}}\right)^{\theta_{12}}$$

Substituting Equation (1) into a log-log transformation of Equation (2) for $Q^{*}_{i,t}$ yields Equation (3), which can be econometrically estimated. This estimation, described in the following section, will yield the short-run price elasticity of electricity demand as the coefficient on the term $P_{i,t}$ and the long-run price elasticity will then be calculable as shown in Equation (4), using the values for θ_1 and θ_{12} that will also result from the econometric estimation.

(3) $$\ln Q_{i,t}=\frac{(1-\theta_1)}{2}\ln Q_{i,t-1}+\frac{(1-\theta_{12})}{2}\ln Q_{i,t-12}+\frac{(\theta_1+\theta_{12})}{2}\left(\varepsilon_L \ln P_{i,t}+\beta\ln X_{i,t}\right)$$

(4) $$\varepsilon_L=\frac{2\varepsilon_S}{(\theta_1+\theta_{12})}$$

Data and Estimation

In this paper we estimate Equation (3) separately for each of three customer classes and nine U.S. census divisions. The three customer classes are residential, commercial, and industrial. The data are a state-level panel of monthly observations spanning January 1990 through December 2006. To estimate seasonal variations, we interact many of the independent variables with indicators for each of three seasons: summer, winter, and spring-fall. The seasons correspond with the intra-annual pattern of electricity demand and the summertime ozone season. Summer covers the months from May through September, winter the months from December to February, and spring-fall includes all other months—March, April, October, and November. All monetary values are converted to 2004 dollars using the consumer price index for the residential and commercial classes and the producer price index for the industrial class.

Equation (5) is the general form of the model to be estimated for each region and customer class. The subscript *i* indexes each of the lower 48 states and the District of Columbia, *t* denotes time denominated in months, *c* is customer class, *S* is the set of three seasons, *m*(*t*) and *y*(*t*) are functions mapping time period *t* into the month and year in which *t* occurs, and *I*(•) is the indicator function. The contents of the *Q* and *inc* variables differ across customer classes. For the residential class, *Q* is electricity consumption per capita, for the commercial class it is consumption per customer, and for the industrial class it is total consumption. The *inc* variable is annual disposable income per capita for the residential class and is gross annual state product for the commercial and industrial classes.[4] *P* is the average retail electricity price; it varies by customer class. *HDD* and *CDD* stand for heating and cooling degree days, respectively. *DL* is the number of minutes of daylight in the capital of each state on the 15 day of each month, which varies across months but not across years. The *NGP* variable is the retail price for delivered natural gas and is included only for the residential class. *FE* are state-level fixed effects. The *HDD*, *CDD*, and *inc* variables are not interacted with seasonal dummy variables and therefore do not possess seasonally differentiated coefficients.

$$\ln\left(Q_{i,t}\right)=\sum_{s\in S}\left[\begin{array}{l}\beta_s^{Q1}I\left(m(t)\in s\right)\ln\left(Q_{i,t-1}\right)+\beta_s^{Q12}I\left(m(t)\in s\right)\ln\left(Q_{i,t-12}\right)+\\ \beta_s^{P}I\left(m(t)\in s\right)\ln\left(P_{i,t}\right)+\\ \beta_s^{NGP}I\left(m(t)\in s\right)\ln\left(NGP_{i,t-12}\right)+\beta_s^{DL}I\left(m(t)\in s\right)\ln\left(DL_i\right)\end{array}\right]+$$

$$\beta^{HDD}HDD_{i,t}+\beta^{CDD}CDD_{i,t}+\beta^{HDD12}HDD_{i,t-12}+\beta^{CDD12}CDD_{i,t-12}+ \tag{5}$$

$$\beta^{inc}\ln\left(inc_{i,y(t)}\right)+FE_i+\varepsilon_{i,t}$$

The electricity consumption and price data are from the EIA Database Monthly Electric Utility Sales and Revenue Data,[5] the natural gas price data are from the EIA Natural Gas Monthly and SEDS Consumption, Price, and Expenditure Estimates,[6] the heating and cooling degree day data are from the NOAA National Climatic Data Center, income and GSP data are from the Bureau of Economic Analysis, and the daylight data come from the Astronomical Applications Department of the U.S. Naval Observatory.

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4 The data for annual disposable income and gross annual state product have annual, not monthly, frequency.

5 The definition of the industrial and commercial sectors changed for Tennessee in 1997, as reflected in a large upward adjustment in commercial demand and a complementary downward adjustment in industrial demand between 1996 and 1997. We calculated the shares for both commercial and industrial demand for each month in 1997 as a proportion of total demand for the two sectors. We then treated these as fixed proportions and applied them to all previous years. There are similar discontinuities in the commercial and industrial electricity consumption data for Maryland in 1995 and then again in 2002. As with Tennessee, we applied the fixed proportions for industrial and commercial demand by month in 2002 to corresponding months in all previous years.

6 Annual data on natural gas price were available for all sectors for all years, but monthly price data were not available for the industrial sector prior to 2001. We calculated the share of annual demand in the industrial sector for each month in 2001. We then used these fixed proportions to estimate monthly-level demand for the previous years. Natural gas prices have clear patterns over the year, and it is more accurate to assume the same distribution of prices among months each year than to assume the same price for every month in a year.

As mentioned above, Q is expressed as electricity consumption per capita and per customer for the residential and commercial classes, but in aggregate for the industrial class. The industrial class is treated in this way for two reasons. First, electricity consumption per industrial customer varies widely because of heterogeneity in the production processes at industrial facilities. Second, industrial customers are, in the long-run, highly mobile compared with the other classes. Hence, the potential for entry and exit of industrial firms would confound the dependent variable, Q, if it were expressed on a per customer basis, since high prices would tend to drive down the numerator (aggregate consumption) while simultaneously driving down the denominator (number of customers).

Both the contemporaneous and the 12-month lags of the heating and cooling degree day variables are included in the model to explicitly capture the short-run utilization choices and the long-run capital choices made in response to temperature. This is necessary because we expect to derive coefficients with the same sign, positive, for both the contemporaneous temperature variables and the partial adjustment coefficients, θ_1 and θ_{12}. If these sign expectations are realized, and they will be, then the model would, in the absence of lagged temperature variables, be incapable of capturing any long-run capital response to temperature if they are negatively correlated. Including the lagged variables allows for short-run utilization choices to be manifest in the contemporaneous variables and long-run capital choices expressed in the lagged variables.

Two primary concerns with estimating Equation (5) are simultaneity between price and quantity and autocorrelation in the presence of lagged dependent variables, which can bias estimation. If electricity prices are determined partly as a function of quantity demanded, then coefficient estimates derived under OLS will be biased. The time period that we analyze, 1990–2006, was characterized by the transition from rate-of-return regulated electricity pricing to electricity market restructuring in many states and the continuation of rate-of-return regulation in others. For those states with ongoing rate-of-return regulation, the price of electricity is based on expectations of total costs and demand that are informed by data from past test years and is thus contemporaneously exogenous. Those states that made the transition to deregulated power markets simultaneously instituted exogenous rate caps. Therefore, electricity prices were largely determined by regulation in the time period we examine, which suggests that they were not a function of quantity demanded. In addition, regulated pricing and rate caps make the development of good instruments for price difficult. We therefore assume that prices are exogenous in this analysis.

As mentioned above, an autocorrelated error term in the presence of lagged dependent variables can lead to biased coefficient estimates. One way to deal with this problem is to use a

2SLS procedure to instrument for the lagged dependent variables by using estimated values, instead of observed values, for the lagged dependent variables. We explore the use of this procedure for estimating Equation (5) in the following section.

Results

The demand model that we estimate includes 27 equations, one for each of three customer classes and nine census divisions. As described in the prior section, because our estimated equations contain lagged dependent variables, we are concerned that autocorrelation may bias coefficient estimates obtained by OLS. We test for autocorrelation using the Ljung-Box test, which applies to each state within a region separately. Table 1 presents the percentage of states that fail to reject the null hypothesis of no autocorrelation in both the 12-month and the 1-month lag for each customer class. The results indicate that there is autocorrelation for a substantial fraction of the states within each region, particularly for the 12-period lag.

Table 1. Percentage of States Exhibiting Autocorrelation in OLS by Ljung-Box Test

	Residential		Commercial		Industrial	
	1 month	12 months	1 month	12 months	1 month	12 months
New England	33%	67%	83%	100%	67%	67%
Middle Atlantic	33%	33%	67%	100%	67%	100%
East North Central	40%	80%	60%	100%	80%	100%
West North Central	43%	71%	43%	86%	71%	100%
South Atlantic	33%	67%	56%	100%	56%	100%
East South Central	25%	75%	50%	100%	75%	100%
West South Central	25%	25%	50%	100%	50%	100%
Mountain	38%	100%	63%	100%	50%	100%
Pacific	67%	67%	33%	100%	67%	100%
National Average	37%	62%	55%	99%	65%	99%

To help remedy the problem of bias, we implement a 2SLS estimation approach in two ways. The first method is to instrument for the presence of the 1-month and 12-month lagged dependent variables using the exogenous variables and electricity prices lagged both 1 and 12 periods. The demand function coefficients resulting from this approach are generally unintuitive and questionable with many coefficients exhibiting theoretically implausible signs. The second method, appealing to the fact that 1 period lag autocorrelation tests show only moderate autocorrelation, instruments for only the 12-month lagged dependent variable using the exogenous variables, the dependant variable lagged 1 period, and electricity prices lagged 12 periods. The results of this 2SLS estimation are also questionable and yield many inappropriate signs. The poor performance of the 2SLS estimator may be explained by the quality of the instruments in the first stage (Baltagi and Griffin 1997). The predetermined lagged dependent variables, which have a lot of explanatory power in our OLS estimations, are left out of the first stage. Thus, the predicted values for lagged demand are a poor approximation of the true values, leading to unreliable second-stage estimation. Given that it is difficult to instrument well for lagged demand and that we have a relatively large sample size, we adopt OLS as a more accurate estimation procedure, and this section describes the results.

To make the discussion of the results more tractable, we aggregate the coefficients along two dimensions: region and time.[7] In Table 2 we present annual weighted average coefficients by region for each of the three customer classes, and in Tables 3a, 3b, and 3c, we present national weighted average coefficients by season. In each case the coefficient estimates are weighted by total demand for the relevant customer class, region, and time period, and implied aggregate standard errors are also presented.

Seasonal Regression Results

The results presented in Table 2 are generally in line with our expectations in terms of signs on the estimated coefficients. With respect to the partial adjustment parameters, the results show that demand for each customer class and in each season is positively related to 1-month lagged demand and to 12-month lagged demand. The coefficients on the contemporaneous price variable have the expected negative sign and are statistically significant.[8] Price effects are discussed in more detail in the section on elasticities, below.

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[7] The coefficient estimates for the 27 individual regressions are available from the authors upon request.

[8] In the underlying detailed regressions, there are a few exceptions to the expected sign result for the coefficient on the price variable, all in the Middle Atlantic region. The coefficient on electricity price is positive and insignificant in the spring-fall for residential customers and in both the summer and the winter for commercial customers.

For the residential and commercial customer classes, the coefficients on the contemporaneous weather variables, which are assumed not to vary by season, are typically highly significant and also have the expected positive signs. The residential and commercial regressions also include 12-month lagged terms on heating and cooling degree days. These lagged variables have the expected negative signs, consistent with a capital turnover story or with behavior to modify electricity demand, like installing more insulation.

Contemporaneous and 12-month lagged heating and cooling degree day variables are also included in the industrial equation. In the case of industrial customers, heating and cooling are less important components of electricity demand (although the extent to which this is true varies by industry) than they are for other types of customers. However, there may be other factors, such as monthly patterns of demand for final products or access to alternative fuels for particular processes, that might be correlated with temperature, and this effect could be picked up by the heating and cooling degree day variables. With the exception of contemporaneous cooling degree days, we find that these weather variables are insignificant on average for the industrial class.

In addition to heating and cooling, we also include a daylight variable in the demand equations. The amount of daylight alters demand for lighting and also heating and cooling because of solar heat gain effects in buildings. We find that when averaged across the entire nation, the minutes of daylight variable has a negative but insignificant effect on residential demand in all three seasons. These aggregate coefficients mask some significant and differentiated effects across regions that are explored below. If we break down the spring-fall results by region, we find that the effect of more minutes of daylight on residential electricity demand is mixed, with positive and significant effects in some of the southern regions, where heat gain is likely more of an issue, and negative effects in other regions, where reduced demand for lighting may trump other effects. In the commercial demand equation, the daylight variable has a positive and significant effect on electricity demand in the summer but is insignificant otherwise, as it is for the industrial sector in all seasons.

We also include 12-month lagged natural gas prices in all the demand equations to capture the potential effect of past increases in the price of a substitute fuel on electricity demand currently. The logic for using the prior year's price is to allow time for substitution away from natural gas–using equipment to electricity-using equipment or vice versa. Aggregating to the national level, we find that residential electricity demand responds positively to changes in lagged natural gas price in all seasons, but the positive response is not statistically significant.

For the commercial and industrial sectors, the coefficient on this price variable is negative in some seasons and positive in others, but also not statistically significant.

Table 2. National Weighted Average Coefficient Estimates by Customer Class and Season
(weighted standard errors in parentheses)

		Q_{t-1}	Q_{t-12}	P_t	$INC_t/GASP_t$	HDD_t	CDD_t	HDD_{t-12}	CDD_{t-12}	DL_t	NGP_{t-12}
Residential	Summer	0.22***	0.38***	-0.15***						-0.04	0.03
		(0.03)	(0.04)	(0.04)						(0.04)	(0.02)
	Winter	0.11***	0.59***	-0.11**						-0.03	0.01
		(0.03)	(0.04)	(0.04)						(0.04)	(0.02)
	Spring/Fall	0.20***	0.49***	-0.12***						-0.03	0.00
		(0.03)	(0.05)	(0.04)						(0.04)	(0.02)
	Annual Average	0.18***	0.47***	-0.13***	0.11***	4.0E-4***	1.2E-3***	-2.0E-4***	-3.6E-4***	-0.03	0.02
		(0.03)	(0.04)	(0.04)	(0.03)	(2.4E-5)	(4.8E-5)	(2.8E-5)	(7.2E-5)	(0.04)	(0.02)
Commercial	Summer	0.34***	0.37***	-0.12***						0.07*	0.00
		(0.04)	(0.05)	(0.03)						(0.04)	(0.01)
	Winter	0.23***	0.52***	-0.08**						0.04	-0.01
		(0.07)	(0.06)	(0.04)						(0.04)	(0.02)
	Spring/Fall	0.41***	0.34***	-0.10***						0.04	0.01
		(0.07)	(0.07)	(0.03)						(0.04)	(0.01)
	Annual Average	0.34***	0.40***	-0.11***	0.06**	1.2E-4***	5.3E-4***	-4.3E-5**	-2.1E-4***	0.05	0.00
		(0.06)	(0.06)	(0.03)	(0.03)	(2.0E-5)	(4.4E-5)	(2.0E-5)	(5.0E-5)	(0.04)	(0.01)
Industrial	Summer	0.50***	0.28***	-0.14***						0.04	0.00
		(0.06)	(0.06)	(0.03)						(0.04)	(0.01)
	Winter	0.47***	0.32***	-0.19***						0.04	-0.01
		(0.08)	(0.08)	(0.05)						(0.05)	(0.01)
	Spring/Fall	0.51***	0.28***	-0.15***						0.02	0.00
		(0.07)	(0.06)	(0.03)						(0.04)	(0.01)
	Annual Average	0.50***	0.29***	-0.16***	0.01	2.2E-5	1.5E-4***	1.1E-5	-3.5E-5	0.04	0.00
		(0.07)	(0.07)	(0.04)	(0.02)	(2.5E-5)	(5.2E-5)	(2.7E-5)	(4.9E-5)	(0.04)	(0.01)

Lastly, the demand regressions for all of the customer classes include a relevant income variable. For the residential equations, the income variable is per capita disposable income, and aggregating across regions, it has a positive coefficient.[9] The commercial regressions relate per customer electricity demand to gross state product. This relationship turns out to be positive and statistically significant. Gross state product is also used as the income variable in the industrial equations, where the national average result suggests much less significance but covers up important differences across regions, which are discussed below.

Regional Annual Results

The three panels of Table 3 illustrate how the results for each customer class vary across regions. For all three customer classes, the coefficients on the two lagged output variables are positive and highly significant in all cases. The coefficient on the electricity price variable also has the expected negative sign for all customer classes in all regions, although in the Middle Atlantic the price effect is not significantly different from zero for the residential and commercial classes.

At the regional level, the contemporaneous weather variables typically have a positive and significant effect on regional electricity demand for both the residential and the commercial customer classes. The 12-month lagged weather variables have the expected negative sign in all the residential regressions, although the sign on the lagged heating degree days variable deviates from expectations in the commercial regression for the Middle Atlantic. For the industrial sector, the contemporaneous cooling degree days variable has a positive and significant effect on electricity demand in almost all regions, while the coefficient on heating degree days is typically positive but insignificant. The coefficients on the lagged heating and cooling degree day variables are more mixed across the regions.

[9] In the Pacific region there is a statistically insignificant negative relationship between income and per capita residental electricity demand.

Table 3a. Regional Annual Weighted Average Coefficients for the Residential Customer Class
(weighted standard errors in parentheses)

Residential	Q_{t-1}	Q_{t-12}	P_t	$INC_t/GASP_t$	HDD_t	CDD_t	HDD_{t-12}	CDD_{t-12}	DL_t	NGP_{t-12}
New England	0.14***	0.52***	-0.17***	0.06**	2.6E-4***	1.1E-3***	-1.4E-4***	-4.3E-4***	-0.12***	0.02
	(0.04)	(0.05)	(0.03)	(0.02)	(1.6E-5)	(5.4E-5)	(1.8E-5)	(7.1E-5)	(0.04)	(0.02)
Middle Atlantic	0.21***	0.50***	-0.05	0.15***	2.9E-4***	1.3E-3***	-1.1E-4***	-3.8E-4***	-0.10***	0.02
	(0.03)	(0.05)	(0.05)	(0.04)	(1.9E-5)	(5.5E-5)	(2.3E-5)	(8.6E-5)	(0.03)	(0.02)
East North Central	0.12***	0.58***	-0.12***	0.10***	2.7E-4***	1.6E-3***	-1.7E-4***	-5.6E-4***	-0.07**	-0.01
	(0.03)	(0.05)	(0.03)	(0.03)	(1.5E-5)	(4.3E-5)	(2.4E-5)	(8.2E-5)	(0.03)	(0.02)
West North Central	0.12***	0.57***	-0.21***	0.03	2.6E-4***	1.5E-3***	-1.9E-4***	-6.1E-4***	-0.12***	0.00
	(0.02)	(0.03)	(0.04)	(0.03)	(1.2E-5)	(4.1E-5)	(1.3E-5)	(6.6E-5)	(0.02)	(0.01)
South Atlantic	0.17***	0.40***	-0.08**	0.21***	5.1E-4***	1.2E-3***	-2.8E-4***	-2.5E-4***	-0.08**	0.01
	(0.02)	(0.04)	(0.04)	(0.04)	(2.1E-5)	(3.8E-5)	(2.4E-5)	(6.4E-5)	(0.04)	(0.02)
East South Central	0.21***	0.34***	-0.32***	0.07	5.5E-4***	1.1E-3***	-1.6E-4***	-2.1E-4***	0.07	0.07**
	(0.03)	(0.05)	(0.06)	(0.05)	(3.5E-5)	(5.4E-5)	(4.1E-5)	(7.9E-5)	(0.06)	(0.03)
West South Central	0.25***	0.43***	-0.11***	0.13***	4.6E-4***	8.6E-4***	-2.5E-4***	-2.7E-4***	0.19***	0.01
	(0.03)	(0.04)	(0.04)	(0.03)	(3.4E-5)	(4.6E-5)	(3.5E-5)	(6.1E-5)	(0.06)	(0.03)
Mountain	0.10***	0.66***	-0.19***	0.02	2.7E-4***	9.1E-4***	-1.8E-4***	-4.8E-4***	-0.08***	0.03**
	(0.02)	(0.04)	(0.04)	(0.02)	(1.6E-5)	(4.7E-5)	(1.6E-5)	(5.4E-5)	(0.03)	(0.01)
Pacific	0.28***	0.43***	-0.13***	-0.02	4.6E-4***	1.2E-3***	-1.5E-4***	-2.8E-4***	-0.08***	0.02
	(0.04)	(0.05)	(0.04)	(0.02)	(3.1E-5)	(8.5E-5)	(3.2E-5)	(9.9E-5)	(0.03)	(0.02)
National Average	0.18***	0.47***	-0.13***	0.11***	4.0E-4***	1.2E-3***	-2.0E-4***	-3.6E-4***	-0.03	0.02
	(0.03)	(0.04)	(0.04)	(0.03)	(2.4E-5)	(4.8E-5)	(2.8E-5)	(7.2E-5)	(0.04)	(0.02)

Table 3b. Regional Annual Weighted Average Coefficients for the Commercial Customer Class
(weighted standard errors in parentheses)

Commercial	Q_{t-1}	Q_{t-12}	P_t	$INC_t/GASP_t$	HDD_t	CDD_t	HDD_{t-12}	CDD_{t-12}	DL_t	NGP_{t-12}
New England	0.46***	0.23***	-0.13***	0.08***	1.1E-4***	6.6E-4***	-2.6E-5	-9.6E-5	-0.07**	0.00
	(0.08)	(0.07)	(0.04)	(0.03)	(2.0E-5)	(5.4E-5)	(1.9E-5)	(7.3E-5)	(0.03)	(0.02)
Middle Atlantic	0.46***	0.24***	-0.01	0.19***	1.1E-4***	5.2E-4***	3.6E-5*	-7.8E-5	0.02	-0.01
	(0.05)	(0.06)	(0.03)	(0.05)	(1.8E-5)	(4.6E-5)	(1.8E-5)	(5.7E-5)	(0.03)	(0.01)
East North Central	0.22***	0.26***	-0.17***	0.16***	9.4E-5***	6.9E-4***	-5.8E-5***	-1.5E-4***	-0.03	-0.04**
	(0.08)	(0.08)	(0.05)	(0.05)	(1.8E-5)	(3.8E-5)	(2.0E-5)	(5.1E-5)	(0.04)	(0.02)
West North Central	0.44***	0.42***	-0.14***	0.03	1.0E-4***	6.7E-4***	-4.1E-5***	-3.5E-4***	0.01	-0.01
	(0.05)	(0.05)	(0.04)	(0.04)	(1.3E-5)	(4.4E-5)	(1.5E-5)	(5.6E-5)	(0.03)	(0.01)
South Atlantic	0.22***	0.61***	-0.04*	0.03**	1.7E-4***	5.0E-4***	-1.0E-4***	-3.9E-4***	0.11***	0.00
	(0.04)	(0.05)	(0.02)	(0.01)	(1.6E-5)	(2.5E-5)	(1.9E-5)	(3.0E-5)	(0.03)	(0.01)
East South Central	0.33***	0.48***	-0.22***	-0.05	1.5E-4***	4.5E-4***	-4.3E-5*	-3.2E-4***	0.19***	0.00
	(0.04)	(0.05)	(0.04)	(0.03)	(2.1E-5)	(3.6E-5)	(2.4E-5)	(4.0E-5)	(0.04)	(0.02)
West South Central	0.45***	0.31***	-0.08***	0.02	1.2E-4***	3.5E-4***	-2.1E-5	-1.4E-4***	0.17**	0.00
	(0.07)	(0.07)	(0.03)	(0.02)	(2.7E-5)	(3.6E-5)	(2.6E-5)	(3.8E-5)	(0.08)	(0.02)
Mountain	0.30***	0.51***	-0.14***	-0.02	8.8E-5***	4.4E-4***	-2.6E-5	-2.8E-4***	0.07**	0.02
	(0.05)	(0.05)	(0.04)	(0.02)	(1.7E-5)	(3.7E-5)	(1.7E-5)	(4.1E-5)	(0.03)	(0.01)
Pacific	0.36***	0.39***	-0.17***	0.03*	7.1E-5***	5.0E-4***	-4.0E-5	-4.9E-5	-0.03	0.03
	(0.05)	(0.06)	(0.04)	(0.02)	(2.7E-5)	(8.5E-5)	(2.5E-5)	(8.4E-5)	(0.02)	(0.02)
National Average	0.34***	0.40***	-0.11***	0.06**	1.2E-4***	5.3E-4***	-4.3E-5**	-2.1E-4***	0.05	0.00
	(0.06)	(0.06)	(0.03)	(0.03)	(2.0E-5)	(4.4E-5)	(2.0E-5)	(5.0E-5)	(0.04)	(0.01)

Table 3c. Regional Annual Weighted Average Coefficients for the Industrial Customer Class

(weighted standard errors in parentheses)

Industrial	Q_{t-1}	Q_{t-12}	P_t	$INC_t/GASP_t$	HDD_t	CDD_t	HDD_{t-12}	CDD_{t-12}	DL_t	NGP_{t-12}
New England	0.52***	0.27***	-0.08**	-0.06***	2.5E-5	2.5E-4***	-1.4E-5	-1.7E-4**	0.04	-0.01
	(0.06)	(0.06)	(0.03)	(0.02)	(2.1E-5)	(7.0E-5)	(2.0E-5)	(6.8E-5)	(0.03)	(0.01)
Middle Atlantic	0.51***	0.34***	-0.20***	-0.19***	4.5E-5**	2.9E-4***	9.9E-6	-1.4E-4**	0.07	0.01
	(0.08)	(0.08)	(0.04)	(0.03)	(2.1E-5)	(7.8E-5)	(2.2E-5)	(7.0E-5)	(0.05)	(0.01)
East North Central	0.55***	0.28***	-0.09***	0.01	2.5E-5	1.2E-4***	-9.3E-6	-8.8E-5**	0.10***	0.00
	(0.07)	(0.07)	(0.03)	(0.02)	(1.6E-5)	(4.3E-5)	(1.7E-5)	(4.1E-5)	(0.03)	(0.01)
West North Central	0.64***	0.27***	-0.11***	0.00	1.2E-5	1.8E-4***	2.5E-5*	-7.2E-5**	0.10***	0.00
	(0.05)	(0.05)	(0.04)	(0.02)	(1.3E-5)	(4.0E-5)	(1.3E-5)	(3.5E-5)	(0.02)	(0.01)
South Atlantic	0.32***	0.42***	-0.16***	0.02	2.3E-5	2.3E-4***	-2.9E-5	-1.1E-4**	-0.03	-0.01
	(0.07)	(0.08)	(0.04)	(0.02)	(3.0E-5)	(5.0E-5)	(3.5E-5)	(4.4E-5)	(0.05)	(0.01)
East South Central	0.43***	0.21***	-0.19***	0.03	1.4E-5	-2.0E-5	2.8E-5	5.9E-5	-0.06	0.02
	(0.07)	(0.07)	(0.05)	(0.04)	(2.3E-5)	(4.2E-5)	(2.4E-5)	(3.8E-5)	(0.04)	(0.01)
West South Central	0.43***	0.35***	-0.11***	0.08***	1.0E-6	6.1E-5*	-9.1E-6	-3.6E-5	0.01	0.00
	(0.06)	(0.05)	(0.03)	(0.02)	(2.8E-5)	(3.1E-5)	(3.2E-5)	(3.7E-5)	(0.05)	(0.01)
Mountain	0.59***	0.25***	-0.18***	0.04***	2.7E-5	1.7E-4***	1.6E-5	-5.5E-5	0.10**	0.01
	(0.06)	(0.05)	(0.05)	(0.01)	(2.4E-5)	(4.9E-5)	(2.6E-5)	(4.6E-5)	(0.05)	(0.01)
Pacific	0.67***	0.10**	-0.31***	0.02	4.0E-5	2.2E-4**	1.3E-4***	2.6E-4**	0.04	-0.02
	(0.05)	(0.05)	(0.04)	(0.02)	(4.2E-5)	(1.0E-4)	(4.1E-5)	(1.0E-4)	(0.04)	(0.02)
National Average	0.50***	0.29***	-0.16***	0.01	2.2E-5	1.5E-4***	1.1E-5	-3.5E-5	0.04	0.00
	(0.07)	(0.07)	(0.04)	(0.02)	(2.5E-5)	(5.2E-5)	(2.7E-5)	(4.9E-5)	(0.04)	(0.01)

When aggregated over the course of a year, the daylight variable has a negative effect on residential electricity demand for many regions. However, the effect of daylight is positive in the East South-Central and West South-Central regions, significantly so in the case of the latter. In these southern regions, the effect of increased demand for cooling is stronger than the effect of decreased demand for lighting as days get longer. In the other seven regions, the lower demand for lighting appears to be the stronger driver. For the commercial sector, the effect of daylight hours on regional demand is more mixed and typically not significant, although the annual numbers mask important seasonal effects within certain regions, some of which are negative and some of which are positive and thus are netted out in the annual aggregation. Daylight hours are also included in the industrial equations but are significant only where the annual average coefficient tends to be positive.

The findings regarding the effects of the relevant income variable vary significantly across the customer classes. For the residential class, income typically has a positive effect on annual demand, although it is insignificant in some regions. One exception is in the Pacific region, where increases in income have a negative but insignificant effect on demand. This result could be partially due to the fact that California, a high-income Pacific state, has strong energy efficiency programs and strict appliance and building standards that help temper growth in electricity demand. The coefficient values for gross state product, the measure of income used in the commercial sector regressions, is positive for five of the nine regions and not significantly different from zero in the others. For the income variable in the industrial demand equations, there is regional variability. In New England and the Middle Atlantic, the effect is significantly negative. In the rest of the country, the coefficient on gross state product is positive, significantly so in the West South-Central and Mountain regions.

Price Elasticities

The partial adjustment model that we use allows us to estimate both short-run and long-run price elasticities of demand for each customer class, region, and season. The short-run price elasticity is simply the coefficient on contemporaneous electricity price in the partial adjustment demand equation. The long-run elasticity is calculated using the short-run elasticity and the coefficients on the two lagged demand terms. Using Equation (4) combined with the notation of Equation (5), we define the short-run and long-run elasticities, respectively, for each customer class and census division, and for each season s, as follows:

(6) $$\varepsilon_s^{sr} = \beta_s^P$$

(7) $$\varepsilon_s^{lr} = \frac{\varepsilon_s^{sr}}{\left(1 - \beta_s^{Q1} - \beta_s^{Q12}\right)}$$

The 27 estimated demand equations yield 81 short- and long-run elasticity estimates. In Table 4, we present aggregate results in annual averages for each region and for the nation as a whole in the top panel, and in national averages for each season and for the year as a whole in the bottom panel. The results reported in the last row of Table 4 indicate that the national, annual average short-run price elasticities of demand are most elastic in the industrial class and least so in the commercial class. In the long run, the residential and industrial classes exhibit similar price responsiveness, with the commercial class being 25 percent less elastic. The aggregate short-run demand elasticity across all customer classes is –0.13, and the long-run elasticity is almost three times as great, at –0.36. In both the short and long run, demand for electricity is clearly price inelastic.

Table 4. Short-Run and Long-Run Price Elasticity of Electricity Demand

	Residential		Commercial		Industrial	
	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Annual Average						
New England	-0.17	-0.51	-0.13	-0.37	-0.08	-0.20
Middle Atlantic	-0.05	-0.14	-0.01	-0.02	-0.20	-0.48
East North Central	-0.12	-0.36	-0.17	-0.70	-0.09	-0.22
West North Central	-0.21	-0.61	-0.14	-0.34	-0.11	-0.25
South Atlantic	-0.08	-0.27	-0.04	-0.09	-0.16	-0.44
East South Central	-0.32	-1.16	-0.22	-0.54	-0.19	-0.61
West South Central	-0.11	-0.33	-0.08	-0.22	-0.11	-0.28
Mountain	-0.19	-0.49	-0.14	-0.34	-0.18	-0.42
Pacific	-0.13	-0.37	-0.17	-0.45	-0.31	-0.82
National Average	-0.13	-0.40	-0.11	-0.29	-0.16	-0.40
National Average						
Summer	-0.15	-0.52	-0.12	-0.34	-0.14	-0.36
Winter	-0.11	-0.32	-0.08	-0.22	-0.19	-0.48
Spring/Fall	-0.12	-0.35	-0.10	-0.27	-0.15	-0.39
Annual Average	-0.13	-0.40	-0.11	-0.29	-0.16	-0.40

Overall, the national average elasticity results reported in the last row of Table 4 appear to fall at the low end of or just outside the range of results reported in the literature. Table 5 shows results reported in several econometric studies that look at national electricity demand by customer class. Bohi and Zimmerman (1984) and Dahl and Roman (2004) are survey studies; the rest report original results. Our national average short- and long-run elasticity results for the residential class tend to be more inelastic than the finding in the literature, especially in the short run. For the commercial sector, our results are at the low end of the range, and our long-run elasticity for the industrial class is below the range of earlier studies. Our demand-weighted average elasticities across all customer classes, –0.13 in the short run and –0.36 in the long run, line up well with Dahl and Roman.

Table 5. National Electricty Own-Price Elasticity Estimates from the Literature

Customer Class	*Reference*	*Short-Run*	*Long-Run*
Residential	Bohi and Zimmerman (1984) (consensus)	–0.2	–0.7
	Dahl and Roman (2004)	–0.23	–0.43
	Supawat (2000)	–0.21	–0.98
	Espey and Espey (2004)	–0.35	–0.85
	Bernstein and Griffin (2005)	–0.24	–0.32
Commercial	Bohi and Zimmerman (1984)	0	–0.26
	Bernstein and Griffin (2005)	–0.21	–0.97
Industrial	Bohi and Zimmerman (1984) (dynamic)	–0.11	–3.26
	Dahl and Roman (2004)	–0.14	–0.56
	Taylor (1977)	–0.22	–1.63
All	Dahl and Roman (2004)	–0.14	–0.32

In addition to varying across customer class, elasticities also vary substantially across regions within a given customer class. Comparing the interquartile range with the median value suggests that the long-run and short-run commercial elasticities exhibit the most variation across regions. The bottom half of Table 4 displays the national average short- and long-run demand elasticities by customer class and season. This table shows that there tends to be some variability in price responsiveness across seasons, for all three customer classes. For the industrial class, both short- and long-run price responsiveness tends to be highest in the winter. However, for the other two customer classes, long-run price responsiveness tends to be highest in the summer and lowest in the winter. In the summer, cooling is one of the primary end-uses for electricity in the residential and commercial classes. Therefore, behavioral responses, such as adjustments in temperature settings, could have a significant effect on electricity bills. In the winter, electricity is not the primary energy source for heating, so there is less flexibility to modify behavior to reduce consumption.

Conclusion

The growing impetus for federal policies to restrict emissions of greenhouse gases in the United States and for complementary policies to reduce energy demand and encourage greater use of non-CO_2-emitting energy sources is leading to an explosion of policy proposals to accomplish these goals. Such policies will have implications for how electricity is produced and for the cost of electricity to consumers. To understand how these policies are likely to affect electricity demand and the electricity sector more generally, it's important to have a quantitative representation of electricity demand behavior. In this paper we use monthly data on electricity consumption and its covariates by customer class to estimate regional models of electricity demand with seasonally differentiated coefficients. We use a partial adjustment approach that provides a reduced-form representation of the effects of long-lived capital on electricity demand and allows us to estimate both the short- and the long-run price elasticities of demand. Within the context of an electricity market equilibrium model, these demand functions can be used to predict the effects on electricity demand of a range of policies that affect electricity prices.

We find that demand for electricity is highly price inelastic in the short run and less so in the long run and that price elasticities vary by customer class, region, and season. Consistent with earlier literature, we find a national, annual average short-run price elasticity across all customer classes of –0.13 and a long-run elasticity of –0.36. Industrial customers exhibit the greatest price responsiveness of demand in the short run, and residential and industrial customers have identical levels of price responsiveness in the long run. Commercial customers are the least price responsive of the three customer classes over both time frames. We also find important seasonal and regional differences in price responsiveness.

One important caveat to our findings is that recent changes in regulations and other factors will likely affect electricity demand in ways that are not captured in the model. These include more stringent energy efficiency standards for appliances and expanded efficiency programs managed by utilities and governments. A superior model of electricity demand would explicitly characterize the policies and programs that affect electricity consumption efficiency, but sufficient data are not currently available. Nonetheless, these effects are manifest in the consumption data that underpin the model and thus the application of these demand functions to forecasting analysis would implicitly assume that the energy efficiency programs of the past will be continued into the future at a constant level. Further research on the effects of energy efficiency programs on electricity demand at the state level will be required to untangle these effects.[10]

Ideally, electricity demand equations would be part of a structural model that includes information about capital stock and explicit decisions about capital turnover and utilization in response to changes in current and expected prices of electricity and other energy sources. Currently, the lack of data required to estimate such a model for the full range of end-uses of electricity means that any such model must necessarily focus on a subset of end-uses and therefore be of limited value for broad policy analysis. The model developed in this paper provides a useful reduced-form representation of electricity demand that can be incorporated into an equilibrium model of the electricity sector to provide important information about short-run and long-run responses to changes in electricity prices resulting from various policy initiatives.

[10] Loughran and Kulick (2004) look at the effects of energy efficiency spending on total electricity demand using utility-level data on energy efficiency expenditures. Horowitz (2004) uses information on reported electricity savings from energy efficiency programs by customer class to classify states as high or low performers with respect to energy efficiency programs and then uses a differences-in-differences analysis to explore the effects of demand side management performance on growth in electricity demand by customer class. One issue with this analysis is that the level of energy savings associated with efficiency programs is difficult to measure and thus potentially subject to substantial measurement error.

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