DISCUSSION PAPER

October 2010 ■ RFF DP 10-57

A New Look at Residential Electricity Demand Using Household Expenditure Data

Harrison Fell, Shanjun Li, and Anthony Paul

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES
FOR THE FUTURE

A New Look at Residential Electricity Demand Using Household Expenditure Data

Harrison Fell, Shanjun Li, and Anthony Paul

Abstract

We estimate residential electricity demand for different regions of the country, assuming that consumers respond to average electricity prices. We circumvent the need for individual billing information by developing a novel generalized method of moments approach that allows us to estimate demand based on household electricity expenditure data from the Consumer Expenditure Survey, which does not have quantity and price information. We find that price elasticity estimates vary across the four census regions—the South at –1.02 is the most price-elastic region and the Northeast at –0.82 is the least—and are essentially equivalent across income quartiles. In general, these price elasticity estimates are considerably larger in magnitude than those found in other studies using household-level data that assume that consumers respond to marginal prices. We also apply our elasticity estimates in a U.S. climate policy simulation to determine how these elasticity estimates alter consumption and price outcomes compared to the more conservative elasticity estimates commonly used in policy analysis.

Key Words: residential electricity demand, consumer expenditure survey, generalized method of moments

JEL Classification Numbers: C5, D12, Q4

Contents

A New Look at Residential Electricity Demand Using Household Expenditure Data

Harrison Fell, Shanjun Li, and Anthony Paul*

I. Introduction

The recent focus of the U.S. Congress on federal energy policy, which could substantially alter electricity prices, has elevated the importance of characterizing electricity demand behavior. This is particularly true for the burgeoning literature on the incidence of such policies (e.g., Burtraw et al. 2009; Hassett et al. 2009; and Shammin and Bullard 2009). A key parameter in incidence analysis is the household-level price elasticity of demand for electricity. Studies on residential electricity demand have been conducted for many decades, but few of them are based on household data, are national in scope, and allow for regional price elasticity heterogeneity.[1] This paper offers a new technique to estimate residential electricity demand for different regions in the U.S. using household expenditure data, under the assumption that consumers respond to average prices.

Many of the residential electricity demand estimations that use nationwide data are based on panel data, aggregated at the state level (e.g., Houthakker 1980; Maddala et al. 1997; and Bernstein and Griffin 2005). These studies have the advantage of being able to provide regional elasticities, both long-run and short-run, across the nation. However, one should use caution when applying elasticity estimates from these aggregate studies to policy analysis at the household level, as is often done in incidence analyses of climate policy. As Dubin and McFadden (1984) point out, demand estimations using aggregate data may be subject to misspecification bias due to aggregation over electricity usage and price. For example, if the underlying electricity demand at the household level takes nonlinear form (e.g., log–log), demand elasticities estimated using aggregate data (e.g., at the state level) will not represent household-level demand behavior.

* Fell and Li are fellows, and Paul is the Center for Climate and Electricity Policy fellow, at Resources for the Future, Washington, DC. The authors thank Dallas Burtraw for comments and discussions about this work and Josh Blonz for his excellent research assistance. This work was partially funded by a grant from the Center for International Climate and Environmental Research – Norway.

[1] See Taylor (1975) and Bohi (1981) for surveys of early electricity demand studies and Espey and Espey (2004) for a more recent collection of residential electricity demand elasticity estimates.

Several studies employ household-level data (e.g., Barnes et al. 1981; Dubin and McFadden 1984; Herriges and King 1994; and Reiss and White 2005), but these studies are constrained to geographically narrow regions because there is no national data set of electricity rate structures or of household-specific billing information. Given regional household heterogeneity, it may be inappropriate to apply estimates from these area-specific studies to all areas of the country. On a more practical note, getting geographically specific rate structure data for the entire nation and appropriately matching it up to individual households or obtaining household billing information for large geographic areas of the country is quite difficult because of the diversity of rate structures across the country and the proprietary nature of individual billing information.[2]

More importantly, all of the aforementioned studies using household-level data are based on the assumption that households know their marginal rate schedules and optimize accordingly. Although assuming that households respond to marginal prices is theoretically consistent in a utility-maximizing framework, it may not be a realistic representation of consumer behavior in electricity markets. The first reason for this is that many electric utilities, like some other public utilities, offer multitariff pricing where the marginal price for a household depends on the household's consumption. Deciphering an electricity bill to determine the rate structure is often not straightforward, and usually the bill arrives after the period of consumption has concluded. Thus, in many instances consumers may not be aware of their actual rate structure or their marginal price. Second, it may be unrealistic to assume that consumers can monitor and control their consumption at any given point in time during a billing period. If this is the case, then even if consumers know the rate structure, it is difficult for them to optimize consumption based on the marginal price.

Given these attributes of residential electricity consumption, the assumption that consumers respond to marginal price would be unlikely to hold for the average consumer. Indeed, this has been supported by increasing empirical evidence. Using data from seven Ohio utilities with decreasing-block rate schedules, Shin (1985) finds evidence that consumers respond to average prices from the utility bill rather than marginal prices. Based on residential billing data from Southern California Edison, which implements increasing-block pricing, Borenstein

[2] For example, in Reiss and White (2005), a study using rate structure data from Southern California, electricity rates had to be matched up indirectly with individual household data. Applying such techniques nationwide would quickly become intractable.

(2009) finds no evidence of bunching around the points where the marginal price increases, contrary to what a model of perfectly informed and optimizing consumers would imply.[3] In addition, he shows that the average price is a better indicator of consumer demand response than the marginal price. A recent paper by Ito (2010) using household billing data from two utilities in Southern California obtains the same finding that consumers are more likely to respond to average prices than to marginal prices.

Our study contributes to the literature by addressing the need for nationwide elasticity estimates using household-level data, under the assumption that consumers respond to average prices. Because gathering detailed rate structure data at the national level is impractical, we develop an empirical strategy based on the generalized method of moments (GMM) that allows demand estimation based on publicly available data sets. The main source of data is the Bureau of Labor Statistics' Consumer Expenditure Survey (CEX), which are supplemented with state-level data from the Electric Power Monthly reports produced by the Energy Information Administration (EIA). Though the CEX provides only expenditure data, our empirical approach permits estimations of household-level demand functions without observing household electricity usage or price schedules.

Our results show considerable differences in price elasticities across census regions, with elasticities ranging from –0.82 to –1.02 in the baseline model. These estimates are noticeably larger than other residential demand estimates using household-level data. However, as we demonstrate below, this difference is most likely attributable to the assumption that households respond to average electricity prices as opposed to marginal prices. This result suggests that further research is warranted to understand the prices to which consumers really respond in electricity demand. In addition to price elasticity, we also find small income elasticities, as is common in the electricity demand literature.

The remainder of the paper is organized as follows. In section 2, we present our data. This is followed with a discussion of our empirical method and a Monte Carlo analysis to gauge the effectiveness of the empirical method in section 3. In section 4, we use a simple graphic example to illustrate potential differences that can emerge in demand estimations based on average- or marginal-price responsiveness. Section 5 presents the results of the demand

[3] If consumers were responding to marginal prices, then in a multipart tariff rate structure one would expect to see a concentration of households at consumption levels just below the cut-off points for the rate change. Instead, Borenstein (2009) finds a much smoother distribution of consumption.

estimation, and section 6 illustrates the significance of demand elasticity assumptions in a policy analysis context. In the final section we give concluding remarks.

II. Data

Two data sets on household-level electricity usage are national in scope and publicly available: CEX and EIA's Residential Energy Consumption Survey (RECS). The CEX collects data through quarterly interviews of about 7,500 households.[4] The survey asks respondents to provide detailed expenditure information, including monthly electricity expenditures, but does not address quantity or price information for electricity use. The RECS collects information on residential energy use from fewer than 5,000 households and is conducted about every five years. It provides both electricity consumption (quantity) and expenditure data. Both surveys collect data on housing characteristics, appliances holdings, and household demographics.

We use the CEX data for our analysis for the following reasons. First, the CEX data have a much larger sample, with approximately 90,000 observations (7,500 households for 12 months) each year compared to fewer than 5,000 annual observations from RECS. Second, as mentioned above, the expenditure data from the CEX are available at the month level, the decision period we use in the demand analysis, whereas the data from RECS are at the annual level.[5] Finally, the state information for households is available only for the four most populous states in RECS for the purpose of confidentiality. On the other hand, the CEX data provide location information at the state level for all households. Because they lack state location, use of the RECS data would prevent us from using state-level cost shifters as the instruments for electricity price in the demand analysis and would restrict our ability to get regional price elasticities.

Our empirical analysis is conducted using the CEX data from 2004 to 2006. To reduce sampling errors and avoid instances of no observations in some months, we keep only the states that have at least 2,500 total observations in the survey over the period 2004–2006. This elimination process gives us a final sample of observations spanning 22 different states. The average number of observations in a month for each state ranges from 38 to 537 with a mean of 140. As will be shown in the next section, some of the moment conditions used for estimation

[4] The survey program also conducts a diary survey, in which respondents record all expenditures. However, we only use data from the program's quarterly interview survey. For more information on how the survey is conducted and the data available through the survey see http://www.bls.gov/cex/.

[5] Though the interviews are conducted quarterly, they ask questions about month-specific expenditures.

match average monthly household electricity usage predicted by the model to observed data for each state. Table 1 lists the states used in our analysis and the total number of observations by census region.

Table 2 provides summary statistics for monthly household electricity expenditure, average electricity price, imputed average household usage, and other variables that are treated as demand covariates. Average monthly household electricity expenditure, derived from the CEX, is highest in the South region at an average of $143, whereas it is lowest in the Midwest region at an average of $96. The average electricity price is based on state-level EIA data from Electric Power Monthly (based on EIA Form 826), where it is computed as the total revenue of electricity suppliers divided by the total electricity supplied. The state average price is highest in the Northeast region and lowest in the Midwest region. Based on the EIA average prices and the CEX expenditure data, we impute the naïve electricity usage for each household, shown as the "Quantity" row in the table.[6] The households in the South region use the most, whereas those in the Northeast region use the least.

The other explanatory variables in the demand analysis include house demographics, housing characteristics, and electric appliance holdings from the CEX data. We also obtain monthly heating degree days (HDD) and cooling degree days (CDD) for each state from the National Oceanic and Atmospheric Administration. These two temperature variables are interacted with appliances in the demand equation.

Our empirical method shown below necessitates instrument variables for electricity price. These variables should shift price schedules but do not affect consumption directly. Although local distribution companies, the entities that typically sell electricity to households, have largely regulated price schedules, these schedules often allow for built-in adjustments based on fluctuations in electricity generation costs, especially fuel costs. In addition, utilities often obtain power supply through procurements in advance to meet a larger share of their service obligations. We therefore use, as cost shifters, lagged prices of natural gas and coal (quarterly and yearly moving averages), as well as states' electricity generation profiles and the interaction between generation profiles and generation fuel prices. Coal and natural gas prices come from

[6] We consider this a "naïve" electricity usage measure because dividing household-level expenditures by a state average price neglects the reality that average prices at the household level will depend on a household's usage. Thus, basing a demand estimation on these naïve usage and state average price measures will pose not only standard simultaneity issues, but also measurement error issues. These points are discussed in more detail below.

EIA. Because these price data are often missing at the state level, we use national-level prices. The electricity generation profile data, which give the percentage breakdown of total generation by fuel type in each state, are also available through EIA.[7] We use the lagged values of these variables because electric utilities often procure a large of portion of power to be distributed ahead of schedule. In addition, lagged cost shifters are more likely to be exogenous to current demand shocks.

Figure 1 plots monthly national prices for residential electricity, coal, and natural gas from 2003 to 2006. All three series are trending up, with natural gas prices the most volatile and coal prices the least. Table 3 provides summary statistics of generation fuel profile variables. Across the four census regions, natural gas accounts for the largest share of generation in the West region (36 percent) whereas coal is used most extensively in the Midwest (70 percent). Nuclear and hydropower have the largest share in the West (40 percent) and Northeast regions (39 percent).

III. Empirical Strategy

Utilities frequently use nonlinear price schedules in selling electricity. The nonlinearity could be due to an up-front fixed charge, such as a transmission charge, and/or block pricing. The assumption maintained in most of the literature on electricity demand since Taylor's (1975) survey is that consumers are perfectly informed about the price schedule and are able to perfectly optimize on the margin at every moment: consuming the amount where the marginal value of electricity is equal to the marginal price. Although this assumption is theoretically appealing, it is unlikely to hold in reality. First, it is costly for consumers to obtain their price schedules because they are often not explicitly shown on electricity bills and because electricity bills arrive after consumption choices are made. In addition, price schedules are subject to month-to-month changes. Second, as electricity is billed from month-to-month, the above assumptions require consumers to make perfect predictions about their demand shocks, like a heat wave that raises the value of air-conditioning, for the whole month at the beginning of each month.

---

[7] Data for coal prices were downloaded from http://www.eia.doe.gov/cneaf/electricity/page/ferc423.html, and natural gas prices were downloaded from http://tonto.eia.doe.gov/dnav/ng/ng_sum_lsum_a_epg0_peu_dmcf_m.htm. State-specific electricity generation mix data were downloaded from http://www.eia.doe.gov/cneaf/electricity/epa/epa_sprdshts.html.

In light of increasing empirical evidence that consumers are more likely to respond to average prices rather than marginal prices (e.g., Shin 1985; Borenstein 2009; and Ito 2010), the goal of this paper is to obtain demand estimates under the assumption that consumers respond to average prices. This is a departure from, and in our view an improvement upon, the conventional assumption that consumers respond to marginal prices. At the very least, it offers an alternative demand estimation to the marginal price-response literature.

Method

Our empirical framework is set up based on the CEX data. As discussed above, although CEX provides a national representative sample, it does not have information on electricity price and quantity. Rather, it reports monthly household expenditure on electricity. Some previous studies using CEX data, such as Branch (1993), have used monthly state average prices from EIA as the price variable and constructed the quantity variable by dividing expenditure by the state average price, as we did above for our naïve usage variable. Although this method appears to be straightforward, the estimates could be biased due to at least two sources: measurement error and simultaneity. Measurement error arises because the average price faced by a given household will depend on its quantity consumed and, thus, will not typically be the same as the state average price given by EIA.

To illustrate the simultaneity problem, one can assume that the underlying demand function takes a double-log form commonly used in the literature on electricity demand

$$\ln q_{ist} = \beta \ln p_{ist} + x_{ist}\gamma + e_{ist}, \tag{1}$$

where t is the month index, s the state index, and i the household index. q_{ist} is the quantity of electricity used by household i in state s and month t, and p_{ist} is the average price for that household in month t. Under nonlinear price schedules, the average price depends on the quantity—in other words, p_{ist} is a function of q_{ist}. The simultaneous determination of household electricity usage and the price for that level of usage underlies the traditional simultaneity problem. The vector x_{ist} contains other variables that affect electricity demand, such as household demographics, appliance holdings, and weather conditions. The final variable, e_{ist}, is the demand shock and is assumed to be normally distributed with mean zero and $\text{var}(e_{ist}) = \sigma_e^2$.

Without observing both p_{ist} and q_{ist}, one could apply the naïve method that uses state average price $\overline{p}_{st}$ and imputed quantity $\overline{q}_{ist} = \frac{c_{ist}}{\overline{p}_{st}}$, where c_{ist} is monthly household expenditure, in equation (1), and it would become

$$\begin{aligned}\ln \overline{q}_{ist} &= \beta \ln \overline{p}_{st} + x_{ist}\gamma + (\ln \overline{q}_{ist} - \ln q_{ist}) + \beta(\ln p_{ist} - \ln \overline{p}_{st}) + e_{ist} \\ &= \beta \ln \overline{p}_{st} + x_{ist}\gamma + [\ln(\frac{c_{ist}}{\overline{p}_{st}}) - \ln(\frac{c_{ist}}{p_{ist}})] + \beta(\ln p_{ist} - \ln \overline{p}_{st}) + e_{ist} \\ &= \beta \ln \overline{p}_{st} + x_{ist}\gamma + (1+\beta)(\ln p_{ist} - \ln \overline{p}_{st}) + e_{ist} \\ &= \beta \ln \overline{p}_{st} + x_{ist}\gamma + v_{ist},\end{aligned} \tag{2}$$

where v_{ist} is the composite error term. If one were to estimate (2) taking v_{ist} as the error term, the estimates of both β and γ would be biased for two reasons, as long as β is not equal to –1. First, because the error term v_{ist} includes the state average price variable $\overline{p}_{st}$, $\ln \overline{p}_{st}$ is endogenous. Second, because demand factors x_{ist} affect electricity usage q_{ist}, which in turn would determine the average price paid by the household p_{ist}, x_{ist} is also endogenous as a result of the inclusion of p_{ist} in the error term. Because of the large number of endogenous variables in the equation, it would be impractical to use instrumental variable methods. In addition, the *a priori* direction of bias from the ordinary least squares (OLS) estimate is unknown: both $\overline{p}_{st}$ and x_{ist} are correlated with the error term, and it is unclear what direction the partial correlation between $(\ln p_{ist} - \ln \overline{p}_{st})$ and the explanatory variable takes.

We develop a new empirical strategy using GMM to estimate the demand function with the expenditure data from CEX and some auxiliary data that do not rely on the naïve quantity variable imputed from state average prices. Because we do not observe q_{ist} and p_{ist}, we cannot take equation (1) directly to the data. Instead, we further specify the average-price schedule faced by the household as the following

$$\ln p_{ist} = \alpha_s \ln q_{ist} + z_{ist}\delta + \varepsilon_{ist} \tag{3}$$

where α_s is the state-specific slope for the price schedule, and z_{ist} is a vector of observed variables that shift the price schedule, such as cost shifters, month dummies, and state dummies. This specification allows both the intercept and the slope of the average-price schedule to vary across states. ε_{ist} is the approximation error and is assumed to be normally distributed with mean zero and variance $\mathrm{var}(\varepsilon_{ist}) = \sigma_{\varepsilon}^2$.

Household electricity usage and average price are determined by the demand equation and the price schedule. Solving for q_{ist} and p_{ist} from (1) and (3), we get

$$\ln q_{ist} = x_{ist}\gamma / (1-\beta\alpha_s) + z_{ist}\delta\beta / (1-\beta\alpha_s) + (e_{ist} + \beta\varepsilon_{ist}) / (1-\beta\alpha_s) \tag{4}$$

$$\ln p_{ist} = x_{ist}\gamma\alpha_s / (1-\beta\alpha_s) + z_{ist}\delta / (1-\beta\alpha_s) + (\alpha_s e_{ist} + \varepsilon_{ist}) / (1-\beta\alpha_s) \tag{5}$$

Given that the total expenditure $c_{ist} = q_{ist} \times q_{ist}$, $\ln c_{ist} = \ln q_{ist} + \ln p_{ist}$. With this, equations (4) and (5) allow us to express the total expenditure in logarithm as the following

$$\begin{aligned} \ln c_{ist} &= x_{ist}\gamma(1+\alpha_s)/(1-\beta\alpha_s) + z_{ist}\delta(1+\beta)/(1-\beta\alpha_s) \\ &+ [(1+a_s)e_{ist} + (1+\beta)\varepsilon_{ist}]/(1-\beta\alpha_s) \end{aligned} \tag{6}$$

Because we have data on electricity expenditure, equation (6) provides us with the basis for the first set of moment conditions. We define the predicted value of the log expenditure as

$$\ln \hat{c}_{ist} = x_{ist}\gamma(1+\alpha_s)/(1-\beta\alpha_s) + z_{ist}\delta(1+\beta)/(1-\beta\alpha_s) \tag{7}$$

And the first set of moment conditions is given by

$$E_{i,s,t}([x_{ist} \quad z_{ist}]'(\ln c_{ist} - \ln \hat{c}_{ist})) = 0 \tag{8}$$

Recognizing that some variables, such as month dummies and state dummies, are common in both x_{ist} and z_{ist}, we write the moment conditions this way to save notation. In essence, these moment conditions match the predicted expenditures (in log) with the observed ones. The first set of moment conditions alone does not provide enough restrictions to identify the model parameters. This is intuitive: one cannot separately identify the demand and price functions with only data on expenditure.

Taking advantage of state average prices available from EIA, we construct the second set of moment conditions.[8] Based on the state-level average price, we compute the state-level average quantity of household electricity usage, denoted by $\bar{q}_{st}$. The second set of moment conditions match the average quantity $\bar{q}_{st}$ with the predictions from our model. From equation (4), the expected value of electricity usage for a household, $\hat{q}_{ist}$, is given by

$$\hat{q}_{ist} = E(q_{ist}) = \exp(x_{ist}\gamma/(1-\beta\alpha_s) + z_{ist}\delta\beta/(1-\beta\alpha_s) + 0.5(\sigma_e^2 + \beta^2\sigma_\varepsilon^2)/(1-\beta\alpha_s)^2) \tag{9}$$

where the last term in the parenthesis is half of the variance of the composite error term in equation (4).[9] We define $\hat{\bar{q}}_{st}$ as the average of $\hat{q}_{ist}$ for all households in state s and month t (i.e.,

---

[8] EIA's Electric Power Monthly report, available for download at http://www.eia.doe.gov/fuelelectric.html, gives monthly average electricity prices by state.

[9] Given that e_{ist} and ε_{ist} are independent normally distributed random variables, $\ln q_{ist}$ is normally distributed. This implies that q_{ist} is log-normally distributed. Equation (9) is thus the expected value of a log-normally distributed variable.

$\hat{\bar{q}}_{st} = \frac{1}{I}\sum_{i=1}^{I} E(q_{ist})$). Based on $E[q_{ist} - \hat{q}_{ist} \mid x_{ist}, z_{ist}] = 0$, the second set of moment conditions can be constructed as

$$E_{ist}([x_{ist} \quad z_{ist}]'(\bar{q}_{st} - \hat{\bar{q}}_{st})) = 0 \tag{10}$$

Although the number of moment conditions constructed so far is larger than the number of model parameters, the standard errors of the two errors terms, σ_e and σ_ε, cannot be separately identified, given that they both enter moment conditions only through the last term in equation (9). We add another set of moment conditions based on the variance of errors in predicting log expenditure. Following equation (6), we get

$$E_{ist}(\ln c_{ist} - \ln \hat{c}_{ist})^2 - [(1+a_s)^2\sigma_e^2 + (1+\beta)^2\sigma_\varepsilon^2]/(1-\beta\alpha_s)^2 = 0 \tag{11}$$

We stack the three sets of moment conditions and use an iterative GMM procedure to estimate all the model parameters. In obtaining the starting values for the GMM procedure, we first estimate equations (1) and (3) using two-stage least squares, where we take the state-level average prices as the price variable for all households in the corresponding state. We use the identity matrix as the initial weighting matrix and construct the efficient weighting matrix based on parameter estimates from the first iteration.

The underlying model of our analysis assumes that consumers respond to average price in their electricity usage decisions. The interaction between the household demand function and the average-price schedule determines monthly electricity usage and average price at the household level. In addition to the challenge of not observing either household quantity or price data directly, we also face the common simultaneity identification challenge in the empirical demand and supply analysis: quantity and price are determined simultaneously. To deal with the simultaneity problem, our procedure, cast in a system of two equations (i.e., equations (1) and (3)), essentially uses demand-side variables, such as household demographics and appliance holding, to serve as instruments for the quantity variable in the price equation (3), and uses cost shifters, such as shares of fuel types in electricity generation and their interactions with fuel cost, to serve as instruments for the price variable in the demand equation (1).

Notably, although the nature of the CEX gives us some longitudinal information, the relatively short time span analyzed and the lack of detailed product information does not give us sufficient information to estimate the relationship between electricity prices and appliance replacement. We therefore consider our estimates short-run demand estimates.

Monte Carlo Analysis

The empirical strategy outlined above aims to estimate the demand function for residential electricity at the household level for different regions of the country in the absence of household-level price and quantity data. It uses the expenditure data from CEX together with state average electricity prices in a GMM framework. Before showing the estimation results, we present a Monte Carlo analysis to illustrate the effectiveness of the empirical strategy.

The Monte Carlo analysis is based on four states, each of which has more than 2,500 households in the CEX in the Northeast Region (Massachusetts, New Jersey, New York, and Pennsylvania). We first generate price and quantity data for each household, using the demand and price equations (4) and (5) and based on a vector of household characteristics from CEX, cost shifters, and a given set of parameters. The household characteristics, a subset of those listed in Table 2, include household income, number of rooms in the house, and household size. The cost shifters, a subset of those listed in Table 3, include the share of electricity generated using natural gas during the past three months, the share of electricity from coal, and that from nuclear and hydropower. Based on these variables and parameters, we generate monthly expenditure data at the household level and monthly state average electricity price and quantity. We then use both OLS and the GMM approach discussed above to recover the parameters used to generate the data. The OLS approach uses equation (2), where state average electricity prices are used in place of household average prices and quantities are imputed using monthly expenditure divided by state average prices.

Table 4 compares the values of the parameters used to generate the data (the true parameters) to their estimates from OLS and GMM for the different average-price schedules. In all three cases, the GMM method is able to recover the true parameters in the demand equation, whereas the OLS method gives the biased estimates, especially for *log*(*price*), the key variable of interest. To save space, we do not report the results for the 17 dummy variables (4 state dummies, 2 year dummies, and 11 month dummies).

The first panel presents the results for the demand equation where the average-price schedules in all four states are assumed to be upward sloping, with slopes of 0.4, 0.3, 0.2, and 0.1, respectively. The true parameter for *log*(*price*) in the demand equation is –0.8. Whereas the OLS provides an estimate of –0.512 with a standard error of 0.096, the estimate from the GMM approach is –0.837 with a standard error of 0.088. In addition, the OLS estimate on *log*(*household size*) is also statistically different from its true value of 0.4, whereas the GMM estimate is not at any conventional significance level.

The second case is based on simulations where the average-price schedules in all four states are downward sloping, with slopes of –0.4, –0.3, –0.2, and –0.1, respectively. All other parameters are kept the same as in the first panel. The parameter estimates from OLS for the four demand variables shown in the table are all statistically different from their true values, whereas none of the GMM estimates are. The most striking bias from OLS is still in the parameter estimate for *log*(*price*). The estimate from OLS is –1.117 with a standard error of 0.059, compared with the true value of 0.8.

The third panel provides results for simulations that assume positive slopes for the average-price schedule in the first two states but negative slopes in the other two states. In this case, the OLS results are closer to the true values than in the previous cases. Nevertheless, the coefficient estimate on *log*(*price*) is still statistically different from the true parameter at the 10 percent significance level.

The key finding of the simulations is that the GMM approach is effectively able to recover the true parameters, whereas the OLS estimates could result in substantial bias. Although the bias for the coefficient estimate on *log*(*price*) has the same direction as the slopes of the average-price schedules in the first two cases, this finding may not be robust to the addition of more demand-side variables in the regression. As discussed above from equation (2), the direction of bias depends on the *partial* correlation between a particular variable (e.g., *log*(*price*)) and the error term.

IV. Price Elasticities: Average-Price vs. Marginal-Price Response

Assuming that consumers are marginal-price responders in empirical studies if they actually respond to average price could have important implications for price elasticity estimates. In the case of block pricing, a change in average price would imply a larger change in marginal price. Therefore, one would expect demand curves estimated based on average-price responsiveness to be more price elastic than those based on marginal-price responsiveness.

To illustrate the potential for differences in price elasticity estimates based on the two different assumptions, consider the following simple example presented graphically in Figure 2. To understand how the price elasticity is identified, assume that the market consists of three households, A, B, and C, where A and B are on the lower tier of the price schedule and C is on the higher tier. Assume that the quantity demanded, Q_i, is linear and fully determined by income, X_i, and price, P_i, such that $Q_i = \alpha X_i - \beta P_i$, i = (A, B, C). P_i is the price that consumers respond to and it could either be the marginal price or the average price. For concreteness, suppose we observe that ($Q_A = 3$, $X_A = 15$), ($Q_B = 4$, $X_B = 20$), ($Q_C = 6$, $X_C = 40$). We assume that there is no fixed cost, and because A and B pay the same marginal price, they also pay an identical average price, say $P_1 = 0.10$. Household C pays a marginal price on the higher portion of the two-part marginal pricing schedule, and it is assumed to be $P_2 = 0.15$.

We now show how to identify demand parameters under the assumption that consumers respond to marginal prices in their electricity usage decisions. Given that households A and B face the same price, the parameter α can be identified by dividing the difference in quantity consumed between households A and B by the difference in X. In this example, that leads to an estimate of $\alpha = (4 - 3)/(20 - 15) = 0.2$. The effect of a change in marginal price on demand can be determined by adjusting C's income level to that of B's. Given $\alpha = 0.2$, if B and C paid the same price for electricity, then C would consume four more units than B. Thus, if a hypothetical household, B', had the same income level as B but faced the same marginal price as C ($P_2 = 0.15$), it would consume four fewer units than C, resulting in two units of electricity. Connecting points X, corresponding to $P_2 = 0.15$ and $Q'_B = 2$, and Z, corresponding to $P_1 = 0.10$ and $Q_B = 4$, where both have the same income but different marginal prices, we obtain the demand curve for the case where consumers respond to marginal prices. The slope of the demand curve, D^{MP}, is $\beta = (4 - 2)/(0.1 - 0.15) = -40$. This implies a price elasticity, evaluated at Q_B, for the marginal-price demand curve of $\varepsilon^m = \beta/Q_B \times P_1 = -1$. This way of identifying the price elasticity underlies the identification strategy used by Reiss and White (2005), where consumers are assumed to respond to marginal prices.

To identify the demand curve for the case where consumers respond to average prices, note that if the cut-off quantity $Q^* = 4.5$, average prices paid by the three households are $\overline{P}_A = \overline{P}_B = 0.10$ and $\overline{P}_C = 0.1125$. Using the same identification strategy as described above, α would again be 0.2. Again, a hypothetical household, B', with the same income level as B but facing the same average price of 0.1125 as C, would therefore consume two units of electricity (four units less than C). Connecting points Y, corresponding to $P_2 = 0.1125$ and $Q'_B = 2$, and Z, where both have the same income but different *average* prices, we obtain the demand curve under the assumption of average-price response, D^{AP}. This results in a much flatter demand slope of $\beta = -160$ and price elasticity at Q_B of $\varepsilon^a = -4$.

This simple illustration shows that, for the same observations, estimating the demand function under the assumption of average-price responsiveness will result in much more elastic demand than that estimated under the assumption of marginal-price responsiveness.[10] The degree to which the price elasticities will differ is, of course, a function of the data used. Because we do not have individual rate structures for all individuals in our sample, we are not able to estimate the corresponding demand curves under the assumption of marginal-price responsiveness. However, using rate structure data for households served by Southern California Edison, Borenstein (2009) is able to estimate elasticities with respect to both marginal prices and average prices. He finds that the demand function specified over average prices results in an elasticity estimate at least double (in magnitude) that from the demand function specified over marginal prices.

V. Estimation Results

In this section, we first present estimation results for the baseline model, in which price elasticities are assumed to be invariant to income levels. We then present results for models relaxing this assumption. Note that the term *baseline* refers not the method of estimation, but to the set of variables and observations included in the model. The baseline and alternative models are estimated by the GMM procedure described above and by OLS.

Baseline Model

We estimate the empirical model outlined in the sections above separately for each of the four census regions—Midwest, Northeast, South, and West. We do this for two reasons. First, as a result of differences in weather conditions and appliance holdings, for example, demand parameters (e.g., on electricity price and month dummies) differ across regions. Estimation by region allows for region-specific demand parameters. Ideally, we would like to have even more regionally specific demand parameters by estimating the model state by state. However, state-level estimations are infeasible because there is not enough variation in instrumental variables for electricity prices (i.e., cost shifters) to identify the model. Second, the empirical method is data-intensive and computationally intensive because of the larger number of moment conditions and parameters. Estimating the model by region made the problem computationally tractable.

In the baseline model, we drop observations in the upper and lower 2.5 percentiles of electricity expenditure from each region to avoid the effects of outliers (e.g., college

---

[10] Note also that a similar example using a decreasing-block price schedule would yield the same result with respect to price elasticities as the increasing-block price schedule example described above.

dormitories), possible data entry errors, and households generating a large proportion of electricity by themselves (e.g., through solar panels). For example, the maximum monthly electricity expenditure is $2,946 by a household with an annual income of $157,720. Assuming constant monthly income implies the highly unlikely possibility that more than 22 percent of monthly income was spent on electricity. At the other extreme, we have 31 observations with a monthly expenditure of $10. Among these observations, the household income ranges from $4,071 to $440,910 with a mean of $61,229. We suspect that, if this is not due to data entry error, then some of the observations may come from households that have used self-generated electricity or subsidized electricity through a low-income assistance program. In addition, the use of a linear function to approximate a nonlinear average-price function may not work well at low or high values of consumption in the case of tiered pricing. As mentioned above, we also drop states with fewer than 2,500 observations from the sample to ensure a reasonably large number of observations in each state for each month, which is particularly important for the consistency of the second set of moment conditions. We perform robustness checks with respect to data censoring, and the results are provided below.

Table 5 presents parameter estimates for the baseline model by census region from OLS. The electricity demand also includes state dummies, year dummies, and month dummies, but the parameters associated with these variables were omitted for brevity. Due to the log–log specification used, the parameter on *log*(*price*) in the first row provides price elasticity estimates. The differences in price elasticities across the four regions are substantial and are challenging to explain. According to the OLS results, the West region is the most price elastic with an elasticity of –1.02, whereas the Northeast region is the least price elastic with an elasticity of –0.385. Income elasticities, on the other hand, are very similar across the regions, ranging from 0.061 in the Midwest to 0.072 in the West. Other demand parameters generally have intuitive signs. The appliances in the table, especially electric space heating, increase electricity demand significantly. In the Northeast region, having electric heating increases electricity demand by almost 31 percent at the mean level of HDD (4.55). As discussed above, the OLS estimates could suffer bias as a result of both simultaneity and measurement error issues, and the direction of bias is unknown *a priori*.

Table 6 presents estimation results from GMM. The first row presents price elasticity estimates and their standard errors. Comparing this with the OLS results, two differences are obvious. First, the estimates of price elasticities from GMM in all four regions are noticeably different from their OLS counterparts. The GMM estimates in the first three regions are at least double the OLS results, whereas the elasticity estimate for the West region changes less substantially from –1.02 to –0.88. Second, although significant differences in elasticities remain across regions in the GMM results, the differences are much smaller than those observed from OLS.

Based on the GMM results, the Northeast region is the least price elastic with an elasticity of –0.82, whereas the South region is the most price elastic with an elasticity of –1.02. This result is as expected. Electricity usage is a result of the flow of services from a household's electricity-using appliances. Therefore, a household's ability to respond to a change in electricity price will depend largely on the type and number of appliances for which usage can easily be adjusted. For example, using an end-use demand specification, Reiss and White (2005) show that electricity price changes have the largest demand effects among households with electric space heating and air conditioning, two appliances that often account for a large portion of total household consumption and have easy-to-vary usage. The South region has the highest share of electric space heating at 54 percent compared to only 10 percent in the Northeast. In addition, air conditioning ownership (both central and window air conditioning) is 99 percent in the South compared to only 80 percent in the Northeast region, as shown in Table 2. Altering the use of these appliances is a significant end-use margin on which households can adjust electricity usage. Thus, households with electric space heating and air conditioning are likely to have more price-elastic demands. In the Northeast and Midwest regions, home heating often plays a relatively more significant role than home cooling, but because many homes have natural gas heating, there is not as obvious an end use on which to alter electricity consumption.

The other noticeable feature of our price elasticity estimates is that we find demand to be roughly twice to three times more price elastic than do several other studies using household-level data (e.g., Barnes et al. 1981; Dubin and McFadden 1984; Herriges and King 1994; Reiss and White 2005). All of these studies are based on household-level data matched with actual rate schedules faced by households in specific geographic areas. As pointed out by Dubin and McFadden (1984), household-level data are preferred over aggregate data (e.g., aggregated at the state level) because it could avoid misspecification bias due to date aggregation over electricity usage and price. Using household data in 23 large U.S. metropolitan areas from 1972 to 1973 in the CEX, Barnes et al. (1981) obtain a price elasticity estimate of –0.55. Dubin and McFadden (1984) use a 1975 household survey and estimate a price elasticity of –0.26. Based on data from a controlled experiment in Wisconsin from 1984 to 1985, in which participants were subject to five different rate schedules, Herriges and King (1994) obtain a price elasticity of –0.02 for the summer season and –0.04 for the winter. Reiss and White (2005) use the California subsample of the 1993 and 1997 survey waves of RECS and obtain a price elasticity of –0.39.

The first difference between our study and those four studies is that we are using representative national-level data rather than data from a particular region. More importantly, those studies assume that households respond to marginal prices, whereas we assume that households respond to average prices. As illustrated in the previous section, this difference can lead to drastically different estimated price elasticities. The question of which price consumers respond to in electricity demand is beyond the scope of this study but, as previously mentioned, mounting evidence suggests that consumers respond to average prices, and that result stands to reason. Nevertheless, the importance of this question is underscored by the significant difference between our results and those from studies assuming marginal-price responsiveness.

The second row of Table 6 shows estimates of income elasticities across four regions from the GMM procedure. Differences also exist between these estimates and those from OLS, although the differences are not as large as those in the price elasticity estimates. For example, the largest disparity in estimates comes from the income elasticity estimate for the Midwest region, which is 0.061 from OLS and 0.109 from GMM. The South region has the smallest income elasticity of 0.051 based on GMM results. Unlike the price elasticity estimates, these small income elasticity estimates are within the range found in previous studies. Barnes et al. (1981) obtain an income elasticity estimate of 0.20, whereas Dubin and McFadden (1984) get an estimate of 0.02. Herriges and King (1994) provide an estimate of 0.45, whereas Reiss and White (2005) find no statistically significant income effect.

The remaining parameter estimates in Table 6 correspond to housing characteristics, demographic information, and appliance holding variables. The characteristics of the housing unit we control for include a variable for house size (# of rooms), variables on housing unit age, a dummy if the housing unit is owned (Owned House), and a dummy if the unit is a single-family dwelling (Single House). As expected, we find that electricity consumption increases with increasing house size in all regions. Interpretation of the remaining housing characteristics is not as straightforward.

With respect to the house age characteristics, we control for the age of the house (House Age), a dummy equaling one if the house was built before 1970 (D_{70}), and the interaction between these variables (D_{70}*House Age).[11] The positive parameter estimates on House Age in all regions except the Midwest imply that electricity usage increases with house age for those built after 1970. The interaction between D_{70} and House Age allows the age effect on electricity usage to be different for houses built before 1970 from those built after. Except for the Midwest region, the parameter estimates on the interaction term are all negative, suggesting that the age effect in these regions is smaller for pre-1970 houses than for post-1970 houses. This result could be because much older houses have been renovated and, consequently, have been made more energy efficient.

For the house ownership dummy variable, we find a positive and statistically significant effect of homeownership on electricity consumption. This may seem surprising at first glance. One would expect that homeowners would be more likely to purchase an energy-efficient capital stock because they will accrue the benefits from such stock over a longer period, leading to conditionally lower electricity consumption than renters. Indeed, in a recent study using RECS data, Davis (2010) finds that renters are more likely to have fewer Energy Star appliances than homeowners. However, the ownership of energy-efficient appliances may be counteracted by more time spent in the housing unit and/or a greater frequency of appliance usage. Though we have no specific data on these issues, some evidence from our data appears to be consistent with the notion that homeowners are at home more often and/or use appliances more frequently. For example, if more senior individuals are more likely to spend time in the home than younger individuals, given our positive homeownership effect, we would expect that seniors would occupy a greater percentage of owned homes than rented homes. Indeed, our data show that 40 percent of homeowners, but only 18 percent of renters, are over the age of 64. Similarly, one might also expect that having more children may lead to more hours spent in the home and greater use of energy-intensive appliances such as washers and dryers. Again, our data show that the average number of children under the age of 18 in owned homes for individuals under the age of 64 is 0.9, compared to 0.8 for renters under the age of 64.

With respect to appliance holdings, we find that most of the parameter estimates for appliance holding have statistically significant values and intuitive signs. For instance, our

[11] We use 1970 as a somewhat arbitrary cut-off point between “older” construction and “newer” construction. We have also tried cut-off years above and below 1970 and these do not substantially change our results. Additionally, if this was a totally arbitrary and meaningless cut-off, we would expect to find a statistically insignificant parameter estimate on D_{70}.

demand estimation shows that electricity demand increases when households have electric space heating, air conditioners (window units or central air conditioning), a swimming pool, or an electric cooking appliance. Except for the interaction term between CDD and Swimming Pool in the South region, all of the interaction terms between appliance and weather variables (CDD and HDD) have positive signs, as intuition would suggest.

Although our paper is focused on electricity demand, the identification relies on using cost shifters as instruments, a common strategy in demand estimation. The baseline model uses 10 instruments: quarterly and yearly moving average lagged share of electricity generation from coal, the share from natural gas, that from hydro and nuclear, the interaction between the share from coal with lagged coal price, and the interaction between the share from natural gas with lagged natural gas price. The estimation results show that most of the cost shifters are statistically significant. The yearly moving average variables generally have a larger effect than do the quarterly variables, indicating that electricity prices are often affected by supply conditions even one year prior to production. We conduct a robustness check on the use of instruments in the next section, together with other sensitivity analyses.

Additional Specifications

In considering the distributional impacts of policies that affect electricity prices, like federal energy or climate policy, policymakers are concerned not only with geographical distributions of cost, but also with distributional effects across income groups. That is, households with different income levels may be affected differently by policies that affect electricity price. Our first alternative specification is therefore to examine if there is heterogeneity in price sensitivity across income groups. To that end, we interact *log*(*price*) with income interval dummies that capture four levels of household income: below $25,000, between $25,000 and $45,000, between $45,000 and $80,000, and above 80,000.

Table 7 shows parameter estimates for the four interaction terms between price and income dummies. Parameter estimates for the other variables are very close to those reported in the previous two tables and are omitted from this table. Panel 1 of Table 7 shows the OLS results, and Panel 2 shows the GMM results. Both panels show no economically significant differences in price elasticities across income categories. There could be multiple reasons why we fail to detect significant differences in price elasticities across income groups. First, although lower income groups respond to higher prices by using electricity-consuming products less, higher income groups may respond to higher prices by buying more energy-efficient products but maintaining product use levels. Second, lower-income households may cut back their usage of many commonly found electricity-intensive appliances (e.g., air conditioning) more than higher-income households, but high-income households may also have more nonessential electricity-consuming products (not controlled in the estimation) that can easily be used less when electricity prices are high. If this is the case, elasticity estimates should be relatively constant across income classes.

As stated above, the data exclusion made on the presented results was to remove households with the top and bottom 2.5 percent of electricity expenditure and individuals from states with fewer than 2,500 observations. Additional estimations were conducted in which we also dropped all individuals with household incomes below $10,000, in an attempt to exclude those with potentially subsidized electricity prices (e.g., in subsidized housing) or nondeclared income sources. The results of this estimation, by GMM, are presented in Table 8. The price elasticity estimates are nearly identical to those in Table 6, where there was no censoring based on income. The changes in income elasticities are more noticeable. For example, it increases from 0.071 to 0.102 for the Northeast region. This suggests that households with incomes below $10,000 have smaller income elasticities.

The purpose of dropping observations in the top and bottom 2.5 percent of electricity expenditure is to remove outliers and to obtain a better approximation of the average-price schedule using a linear function. The next specification, in which we drop observations in the top and bottom 1 percent of electricity expenditure, examines the sensitivity of the results with respect to this censoring. The results, presented in Table 9, are close to the results from the baseline model in Table 6. The biggest change in price elasticity estimates is for the West region, where it changes from 0.878 to 0.915.

All previous specifications use 10 cost shifters as instruments for electricity price to form moment conditions. The last alternative specification uses 5 of the 10 lagged cost shifters employed in the baseline model: the average share of electricity generated by coal during the past 12 months, that by natural gas, that by nuclear and hydropower, the interaction between the average coal price during the past 12 months and the coal share of generation, and the interaction between natural gas price and the natural gas share of generation. The other five variables not used in this specification are those measured based on quarterly averages. Table 10 shows the parameter estimates for the demand equations for the four regions. Most of the estimates are very similar to those from the baseline model in Table 6. The noticeable differences are in price elasticity estimates for the Northeast and Midwest regions: they are 0.74 and 1.02 in this specification compared to 0.82 and 0.96 in the baseline model. Nevertheless, demand is still more price elastic in the South and Midwest regions than in the other two regions.

VI. Policy Analysis Simulations

As discussed above, our price elasticity estimates are considerably larger than those based on the assumption of marginal-price responsiveness. The question, however, remains as to how these different estimates will alter analyses of federal policies that affect electricity prices. To examine this issue, we use simulations to study a federal carbon dioxide (CO_2) emissions regulation similar to that proposed in H.R. 2454 (U.S. House of Representatives 2009), the Waxman–Markey climate bill.

The simulations are conducted using Resource for the Future's Haiku electricity market model,[12] a deterministic and highly parameterized simulation model of the electricity sector in the 48 contiguous U.S. states. It calculates information similar to that of the Electricity Market Module of the National Energy Modeling System that is maintained and used by EIA. This analysis hinges on the demand side of the Haiku model, which employs a partial adjustment specification of electricity demand.

We conduct the simulations under three different residential price elasticity of demand parameterizations. In the first parameterization, we use the rather low short-run price elasticity estimates generated by Paul et al. (2009b) that vary by region and season. We denote this the ε_L case to signify the low elasticity estimates.[13] The Paul et al. (2009b) model was based on state-aggregated data and includes both short-run and long-run elasticity estimates. In the second parameterization, we replace the short-run price elasticities of Paul et al. (2009b) with a more moderate estimate of –0.4, the ε_M case. This value is in line with the price elasticity estimated in Reiss and White (2005) which, as stated above, is based on marginal-price responsiveness from household-level data in California.[14] This elasticity is applied to all regions covered under the simulation. In our final parameterization, we use the region-specific price elasticities estimated above as the short-run elasticity in the policy simulation. We denote this the ε_H case to signify our higher elasticity estimates. All other features of the model, such as long-run price elasticities, other residential demand covariates, and all of the coefficients for the industrial and commercial sector demand functions, are those estimated in Paul et al. (2009b).

[12] Complete model documentation is available in Paul et al. (2009a).

[13] The regionally specific residential short-run elasticity estimates in Paul et al. (2009b) range from –0.01 to –0.32, with a national average of –0.13.

[14] Note that Reiss and White (2005) estimate end use-specific elasticities. The value –0.4 is in line with their average elasticity estimate across these end uses and across households in their sample.

The simulation outputs give us, among many other variables, average residential electricity prices and total consumption at the region level and national CO_2 emissions allowance prices. The model is run over the 2010 to 2035 horizon, with the CO_2 emissions control policy beginning in 2012 and holding cumulative economywide CO_2 emissions constant across scenarios.[15] We show the policy simulation results for four years (2012, 2016, 2025, and 2035) for each of the parameterization cases. We also show percentage changes relative to the *Annual Energy Outlook 2010* reference case (U.S. EIA 2010). National results are given in Table 11, and regional results are in Table 12.

The national-level results show that the policy tends to increase electricity prices relative to the reference case and that the price impact tends to grow over time. The details of why this pattern emerges are not important for this analysis, but it hinges on a leftward shift of the electricity supply curves, and we are interested in how the assumption about short-run price elasticities impacts consumption, electricity prices, and allowance prices under this supply-side shift. The simulations show that, especially in the long run, federal climate policy will engender a significantly greater reduction in electricity consumption if consumers are more price elastic. This may have important negative welfare consequences for households, though it will be partly offset by a corresponding reduction in allowance prices. By 2035, the allowance price under the ε_H scenario is 4 percent lower than under the ε_L scenario. This would have a positive welfare impact on households because, under an economywide emissions cap, all goods and services that have any carbon intensity of production will become more expansive as allowance prices rise.

Another factor that mitigates the household welfare impacts of consumption reductions is the electricity price. Table 11 shows an approximate $3/MWh difference in electricity prices from the ε_L case to the ε_H that holds fairly constant throughout the time span examined. The price difference may seem surprisingly low given the rather large differences in electricity consumption from ε_L to ε_H, however the demand parameters of the other customer classes (commercial and industrial) are held constant across these scenarios, and these residential consumption reductions represent only a part of total electricity demand. Furthermore, the electricity price reductions that emerge under the higher elasticity scenarios result in an increase in consumption by the other customer classes. These factors, along with the observation that the

[15] Haiku includes a marginal abatement cost curve that allows for allowance price-responsive rest-of-economy emissions. It also includes supply curves for domestic and international carbon offsets that are constrained according to the offsets specification of H.R. 2454.

long-run supply curves for electricity production in Haiku are relatively elastic, yield relatively small changes in electricity price.

The region-specific price and consumption patterns largely follow the national patterns, but there are some differences. For instance, in the West region, we find very little difference in electricity prices across elasticity parameterizations, whereas in the Midwest, the price differences from ε_L to ε_H are much more pronounced. This is largely due to the differences between these regions in production technologies. The West region has significant hydroelectric generation and resources for nonemitting renewable electricity production. Thus, the region will incur a relatively small shift in electricity production costs as a result of this cap-and-trade system, and therefore small price increases. Conversely, electricity generation in the Midwest region is predominantly from coal, which will incur the largest shift in production costs with the introduction of an emissions price. The larger shift in the supply curve will, of course, lead to larger price differentials across the elasticity parameterizations. We also find that, unlike the price pattern observed at the national level, electricity prices in the Northeast and Midwest regions are not strictly increasing over time. This is due to the timing of investment in nuclear capacity and the retirement of existing capacity in these regions.

We generally find decreasing regional consumption as we go from the ε_L to ε_H parameterizations, as in the national results. An exception to this is the consumption pattern in the South region in 2012. For that year, we see that consumption under the ε_H setting is actually greater than that under the ε_L parameterization. How can this be? The answer is, in part, due to the complex dynamic investment decisions faced by generation capacity owners. In this particular case, the inclusion of an allowance price leads to greater generation revenues for marginal natural gas electricity generators, particularly in later years of the policy as allowance and electricity prices increase. Electricity prices also include the cost generators incur to have excess reserve capacity that is needed only in the highest demand periods, which we call the reserve cost. Because generators earn larger generation revenues in later periods under a cap-and-trade policy, the equilibrium reserve costs are lower in the near term compared to a case with no emissions control policy. Depending on the price elasticity assumptions, which affect both the emissions allowance price in general and the electricity price, the long-run investment choices may be such that increasing allowance prices lead to a decrease in reserve costs that more than offset the increase in generation costs due to an emissions price. The elasticities under the ε_H setting, combined with the generation technologies of the South region, lead to just such an outcome.

In general, this simulation example yields mostly predictable results, particularly when viewed in aggregate at the national level. However, the results do show some regional differences that highlight how changes in the elasticity assumptions can lead to some particularly interesting and nonintuitive regional pricing and consumption patterns under an electricity price-raising cap-and-trade policy.

VII. Conclusion

Given the recent push to craft a federal energy policy in the U.S., —in which alterations to the portfolio of electricity generators, and therefore to electricity prices and consumption, are likely to be central components—there is a pressing need to obtain accurate electricity demand estimates for all parts of the country. Undertaking such a task poses several challenges, most notably that electricity rate structure data for all parts of the U.S. are not easily obtainable. Hence, most electricity demand models that use household-level data are conducted for very specific regions for which the researchers were able to obtain specific rate structure data.

To avoid the need for specific rate structure data, we develop a novel GMM approach that allows us to recover residential electricity demand parameters and average-price schedule parameters based on electricity expenditure data (along with demand covariates and some other easily obtainable aggregate price and quantity information). We then apply this technique to detailed household-level data in the CEX, which includes monthly household electricity expenditures, but not electricity prices or quantities, over the period 2004–2006. We estimate demand and average-price schedule equations for four census regions separately.

We find that price elasticities vary across the four census regions, with the South region having the most price-elastic demand with an elasticity of –1.02 and the Northeast region having the least price-elastic demand at –0.82. In general, these price elasticity estimates are considerably larger in magnitude than those of other studies of residential electricity demand using household-level data. As we show through a simple example, it is not unreasonable for our estimates to be larger than those derived in studies that assume that households respond to marginal electricity prices because we explicitly assume that households respond to average electricity prices. As noted above, several studies present some empirical evidence, albeit confined to specific geographic regions, to support the notion that average-price responsiveness is a more appropriate assumption than marginal-price responsiveness.

To put these elasticity estimates into a policy-relevant perspective, we conducted a policy study, using a model parameterization based on the estimates derived here, to simulate the recently proposed U.S. climate policy legislation, H.R. 2454 (Waxman–Markey). The outcomes from this policy study, in terms of regional and national electricity prices, consumption, and emissions allowance prices, were then compared to outcomes using more conservative price elasticity parameterizations, typical of marginal price-responsive demand estimation studies. Not surprisingly, we find that, on a national level, simulations using the elasticity estimates derived here compared to more conservative elasticity estimates leads to a greater reduction in electricity consumption as a result of the implementation of the policy and lower emissions allowance prices. From a regional perspective, we find that the decreases in consumption brought about by the policy are not uniform and have considerable heterogeneity depending on the elasticity used. In fact, we find that in the South region, using our larger price elasticities leads to a near-term increase in electricity consumption under the policy relative to the no-policy baseline and relative to the more conservative elasticity parameterizations. This result is due to the complex interaction of dynamic capital investment decisions and price elasticities embedded in our analysis framework. Furthermore, this regional result highlights the important role elasticity assumptions can play in expected policy outcomes.

Though we believe this study provides a novel approach to estimating electricity demand without specific rate structure data and provides valuable regional elasticity estimates, it leaves several issues unexplored. First, because we do not have specific bill information, we cannot validate our average price-responsiveness assumption. This is clearly an important consideration that goes far beyond the current study. In addition, because of the short time frame examined, we do not account for capital adjustment by households. Estimating capital adjustment price responses, and how these responses vary across income groups, would be very valuable in determining the expected outcomes of national energy policies aimed at improving energy efficiency. However, such estimates would require more detailed data than what is available in the CEX.

References

Barnes, R., R. Gillingham, and R. Hagemann. 1981. The Short-Run Residential Demand for Electricity. *Review of Economics and Statistics* 63: 541–551.

Bernstein, M.A., and J. Griffin. 2005. *Regional Differences in Price-Elasticity of Demand for Energy*. The Rand Corporation Technical Report. Santa Monica, CA: The Rand Corporation.

Bohi, D.R. 1981. *Analyzing Demand Behavior: A Study of Energy Elasticities.* Baltimore, MD: Johns Hopkins University Press and Resources for the Future.

Borenstein, S. 2009. To What Electricity Price Do Consumers Respond? Residential Demand Elasticity under Increasing-Block Pricing. Working paper. Berkeley, CA: University of California Berkeley.

Branch, Raphael. 1993. Short Run Income Elasticity of Demand for Residential Electricity Using Consumer Expenditure Survey Data. *Energy Journal* 14(4): 111–121.

Burtraw, D., R. Sweeney, and M. Walls. 2009. The Incidence of U.S. Climate Policy: Alternative Uses of Revenues from a Cap-and-Trade Auction. *National Tax Journal* 62: 497–518.

Davis, L.W. 2010. Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances? NBER working paper no. 16114. Cambridge, MA: National Bureau of Economic Research.

Dubin, J.A., and D.L. McFadden. 1984. An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica* 52: 345–362.

EIA (Energy Information Administration). 2010. *Annual Energy Outlook 2010*. DOE/EIA-0383(2010). Washington, DC: EIA.

Espey, J.A., and M. Espey. 2004. Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities. *Journal of Agricultural and Applied Economics* 36: 65–81.

Hassett, K., A. Marthur, and G.E. Metcalf. 2009. The Incidence of a U.S. Carbon Tax: A Lifetime and Regional Analysis. *Energy Journal* 30: 155–178.

Herriges, J.A., and K.K. King. 1994. Residential Demand for Electricity under Inverted Block Rates: Evidence from a Controlled Experiment. *Journal of Business and Economic Statistics* 12: 419–430.

Houthakker, H.S. 1980. Residential Electricity Revisited. *Energy Journal* 1: 29–41.

Ito, Koichiro. 2010. How Do Consumers Respond to Nonlinear Pricing? Evidence from Household Electricity Demand. Working paper. Berkeley, CA: University of California Berkeley.

Maddala, G.S., R.P. Trost, H. Li, and F. Joutz. 1997. Estimation of Short-Run and Long-Run Elasticities of Energy Demand from Panel Data Using Shrinkage Estimators. *Journal of Business and Economic Statistics* 15: 90–100.

Paul, A., D. Burtraw, and K. Palmer. 2009a. *Haiku Documentation: RFF's Electricity Market Model Version 2.0*. Washington, DC: Resources for the Future.

Paul, A., K. Palmer, and E. Myers. 2009b. A Partial Adjustment Model of U.S. Electricity Demand by Region, Season, and Sector. Discussion paper 08-50. Washington, DC: Resources for the Future.

Reiss, P.C., and M.W. White. 2005. Household Electricity Demand, Revisited. *The Review of Economic Studies* 72: 853–883.

Shammin, M.R., and C.W. Bullard. 2009. Impacts of Cap-and-Trade Policies for Reducing Greenhouse Gas Emissions on U.S. Households. *Ecological Economics* 68: 2432–2438.

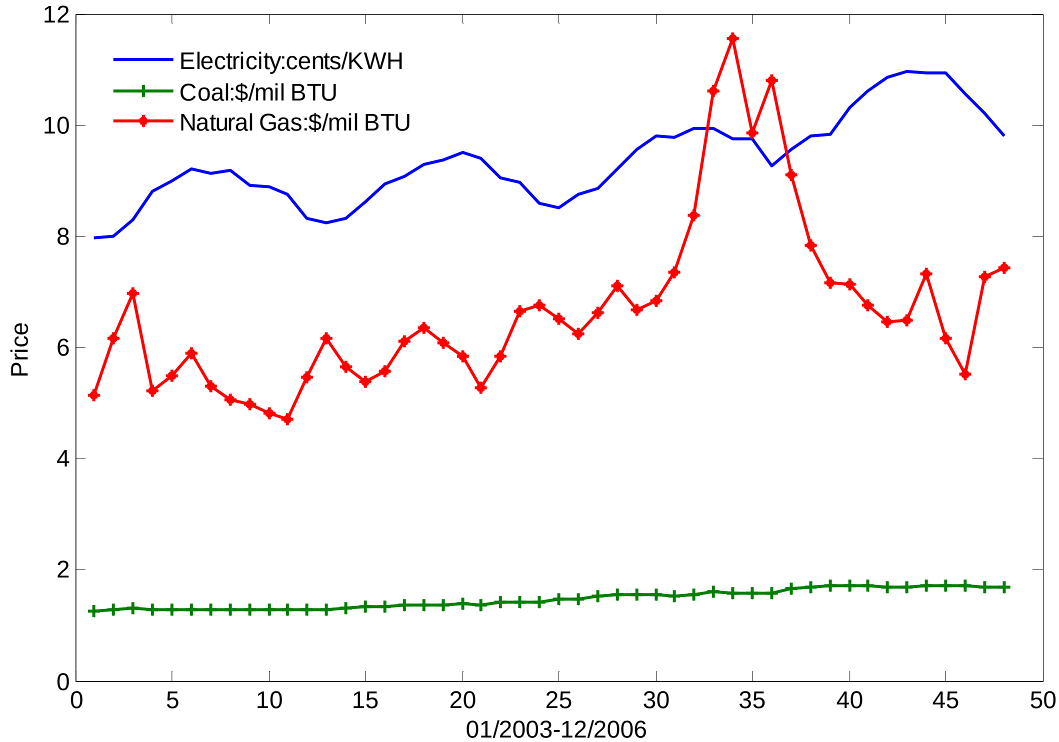
Shin, J. 1985. Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand. *Review of Economics and Statistics* 67: 591–598.

Taylor, L.D. 1975. The Demand for Electricity: A Survey. *Bell Journal of Economics* 6: 74–110.

U.S. House of Representatives. 2009. American Clean Energy and Security Act of 2009, H.R. 2454, 111th Congress.

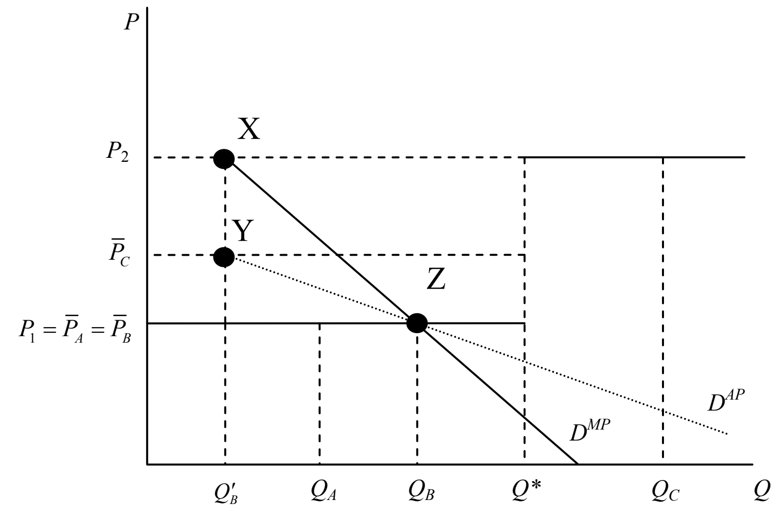
Figures

Figure 1. Monthly Prices of Electricity, Coal, and Natural Gas 2003–2006



Notes: Btu, British thermal unit; kWh, kilowatt-hour.

Figure 2. Marginal-Price versus Average-Price Demand Curves



Notes: D^{AP} denotes the implied demand curve when consumers respond to average price, whereas D^{MP} is the demand curve when consumers respond to marginal price.

Tables

Table 1. States in Analysis by U.S. Census Region

ID	Northeast	South	Midwest	West
1	Massachusetts	Florida	Illinois	Arizona
2	New Jersey	Georgia	Indiana	California
3	New York	Maryland	Michigan	Colorado
4	Pennsylvania	South Carolina	Minnesota	Oregon
5		Texas	Missouri	Washington
6		Virginia	Ohio	
7			Wisconsin	
Obs.	21,862	33,876	28,206	27,234

Notes: Twenty-two states are used for the analysis, each with at least 2,500 (household-month) observations in the CEX data from 2004 to 2006.

Table 2. Summary Statistics of Demand-Side Variables by Census Region

		Northeast		South		Midwest		West	
Variables	**Description**	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Expenditure	Monthly expenditure in $	112.7	68.8	142.8	73.8	95.8	52.2	98.0	63.6
State Price	Average price in ¢/kWh	12.87	2.65	9.87	1.46	8.81	0.96	11.07	2.78
Quantity	Imputed quantity in 100 kWh	8.90	5.24	14.54	7.29	10.97	6.05	9.46	6.62
Income	Income in $	7.34	6.01	6.83	5.61	7.07	5.47	7.29	5.73
# of Rooms	Number of rooms in housing unit	6.51	2.12	6.41	1.97	6.65	2.02	6.09	1.89
Household Size	Number living in housing unit	2.60	1.40	2.65	1.40	2.61	1.39	2.81	1.61
House Age	Age of housing unit	5.40	3.77	2.92	2.28	4.18	3.01	3.36	2.30
D_{70}	D_{70} = 1 if unit built before 1970, 0 otherwise	0.68	0.47	0.34	0.47	0.54	0.50	0.42	0.49
Respondent Age	Survey respondent age	52.85	16.03	51.12	15.94	51.88	15.69	50.24	16.17
Electric Heat	Equal to1 if unit has electric heat, 0 otherwise	0.10	0.30	0.54	0.50	0.09	0.28	0.24	0.43
Central AC	Equal to1 if unit has central AC, 0 otherwise	0.43	0.49	0.87	0.34	0.75	0.43	0.50	0.50
Window AC	Equal to1 if unit has window AC, 0 otherwise	0.37	0.48	0.12	0.32	0.17	0.37	0.09	0.29
Swim Pool	Equal to1 if unit has swimming pool, 0 otherwise	0.12	0.33	0.14	0.35	0.09	0.29	0.17	0.37
Electric Cooking	Equal to1 if unit has electric stove, 0 otherwise	0.45	0.50	0.72	0.45	0.53	0.50	0.51	0.50
CDD	65 – pop. weighted mean temp; (°F), if temp < 65	0.67	1.03	1.96	1.93	0.68	1.02	0.90	1.48
HDD	Pop. weighted mean temp; (°F) – 65, if temp > 65	4.55	4.09	1.93	2.50	5.06	4.54	2.78	2.64
Owned House	Equal to 1 if housing unit is owned	0.83	0.37	0.86	0.35	0.89	0.31	0.79	0.41
Single House	Equal to 1 if housing unit is an unattached unit	0.68	0.47	0.75	0.43	0.81	0.39	0.74	0.44

Notes: AC is air conditioning.

Table 3. Summary Statistics of Cost Shifters by Census Region

Variables	Description	Northeast Mean	Northeast S.D.	South Mean	South S.D.	Midwest Mean	Midwest S.D.	West Mean	West S.D.
% Nat. Gas_1	% of generation from natural gas, last 3 months	0.20	0.15	0.25	0.20	0.04	0.04	0.36	0.15
% $Coal_1$	% of generation from coal, last 3 months	0.33	0.18	0.44	0.13	0.70	0.16	0.15	0.23
P_1^{NG}	Average natural gas price, last 3 months	1.36	1.04	1.75	1.42	0.31	0.28	2.51	1.20
P_1^{C}	Average coal price, last 3 months	0.50	0.29	0.66	0.20	1.05	0.25	0.22	0.34
% $(Nuke+Hydro)_1$	% of generation from nuclear+hydro, last 3 months	0.39	0.12	0.24	0.14	0.23	0.15	0.40	0.20
% Nat. Gas_2	% of generation from natural gas, last 12 months	0.19	0.14	0.25	0.19	0.04	0.03	0.36	0.15
% $Coal_2$	% of generation from coal, last 12 months	0.33	0.18	0.44	0.12	0.71	0.16	0.15	0.23
P_2^{NG}	Average natural gas price, last 12 months	1.29	0.97	1.68	1.39	0.29	0.25	2.43	1.08
P_2^{C}	Average coal price, last 12 months	0.48	0.27	0.64	0.19	1.02	0.24	0.22	0.33
% $(Nuke+Hydro)_2$	% of generation from nuclear+hydro, last 12 months	0.39	0.12	0.24	0.14	0.23	0.15	0.40	0.20

Notes: Prices are in \$/million Btu for coal and \$/thousand $feet^3$ for natural gas.

Table 4. Monte Carlo Results for the Demand Equation

Demand equation		OLS results		GMM results	
Dependent variable: Log(quantity)	**True**	**Estimates**	**S.E.**	**Estimates**	**S.E.**
Panel 1: Upward sloping price schedule (slopes: 0.4, 0.3, 0.2, 0.1)					
Log(price)	–0.8	–0.512	0.096	–0.837	0.088
Log(income)	0.2	0.199	0.005	0.195	0.006
Log(room number)	0.3	0.306	0.011	0.301	0.012
Log(household size)	0.4	0.420	0.007	0.412	0.011
σ_e^2	0.2			0.211	0.093
Panel 2: Downward sloping price schedule (slopes: –0.4, –0.3, –0.2, –0.1)					
Log(price)	–0.8	–1.117	0.059	–0.860	0.069
Log(income)	0.2	0.182	0.004	0.188	0.009
Log(room number)	0.3	0.280	0.01	0.290	0.016
Log(household size)	0.4	0.384	0.006	0.397	0.018
σ_e^2	0.2			0.188	0.052
Panel 3: Mixed sloping across state (slopes: 0.4, 0.3, –0.2, –0.1)					
Log(price)	–0.8	–0.716	0.051	–0.820	0.045
Log(income)	0.2	0.191	0.004	0.196	0.006
Log(room number)	0.3	0.292	0.010	0.302	0.012
Log(household size)	0.4	0.406	0.006	0.414	0.01
σ_e^2	0.2			0.213	0.058

Notes: Monte Carlo simulations are based on observations from the four states in the Northeast region, each with at least 2,500 observations in the CEX data from 2004 to 2006. Total number of observations: 21,862. Parameters are estimated using both OLS and GMM. Equations include four state dummies, two year dummies, and 11 month dummies.

Table 5. Demand Equation Estimates from OLS: Baseline Model

	Northeast		South		Midwest		West	
	Para.	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
Log(price)	**–0.385**	**0.064**	**–0.423**	**0.049**	**–0.472**	**0.068**	**–1.020**	**0.075**
Log(Income)	0.067	0.005	0.066	0.004	0.061	0.005	0.072	0.005
Log(#of rooms)	0.279	0.013	0.310	0.010	0.299	0.012	0.339	0.013
Log(household size)	0.265	0.007	0.212	0.005	0.247	0.006	0.211	0.007
Log(house age)	0.038	0.008	0.043	0.004	0.001	0.006	0.039	0.006
D_{70}*Log(house age)	–0.051	0.013	–0.035	0.015	0.054	0.013	–0.032	0.019
D_{70}	0.010	0.021	0.003	0.024	–0.080	0.020	0.024	0.030
Log(respondent age)	–0.007	0.012	0.031	0.009	0.105	0.010	0.128	0.011
Electric Heat	0.181	0.017	0.167	0.008	0.166	0.015	0.104	0.012
Central AC	0.081	0.011	0.009	0.015	0.023	0.012	0.098	0.009
Window AC	0.023	0.010	0.046	0.016	0.008	0.013	0.042	0.014
Swim Pool	0.089	0.012	0.146	0.011	0.031	0.012	0.150	0.011
Electric Cooking	0.076	0.007	0.030	0.006	0.076	0.006	0.057	0.008
CDD	0.029	0.014	0.037	0.008	0.005	0.012	0.032	0.008
HDD	–0.010	0.004	0.019	0.003	–0.003	0.003	0.010	0.004
CDD*(Central AC)	0.047	0.009	0.023	0.006	0.045	0.010	0.061	0.006
CDD*(Window AC)	0.020	0.009	0.005	0.006	0.005	0.011	0.025	0.009
HDD*(Electric Heat)	0.028	0.003	0.021	0.002	0.017	0.002	0.040	0.003
CDD*(Swim Pool)	0.003	0.010	–0.011	0.004	0.045	0.010	0.001	0.005
Owned House	0.176	0.011	0.077	0.008	0.058	0.011	0.039	0.010
Single House	0.022	0.009	0.045	0.007	0.134	0.010	0.191	0.010
No. of observations	21,862		33,876		28,206		27,234	

Notes: The price variable using OLS is the monthly state average from EIA. The quantity is imputed using the household expenditure divided by this price variable. The demand equations also include state dummies, year dummies, and month dummies.

Table 6. Demand Equation Estimates from GMM: Baseline Model

	Northeast		South		Midwest		West	
	Para.	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
Log(price)	**–0.824**	**0.039**	**–1.021**	**0.006**	**–0.964**	**0.006**	**–0.879**	**0.008**
Log(Income)	0.071	0.005	0.051	0.003	0.109	0.005	0.089	0.005
Log(#of rooms)	0.267	0.013	0.249	0.010	0.268	0.013	0.377	0.014
Log(household size)	0.249	0.008	0.202	0.006	0.276	0.009	0.205	0.007
Log(house age)	0.033	0.007	0.052	0.003	0.023	0.005	0.043	0.006
D_{70}*Log(house age)	–0.051	0.012	–0.014	0.014	0.033	0.013	–0.044	0.020
D_{70}	0.016	0.019	–0.031	0.022	–0.033	0.022	0.033	0.032
Log(respondent age)	–0.006	0.011	0.012	0.007	0.126	0.011	0.179	0.012
Electric Heat	0.190	0.014	0.241	0.008	0.313	0.013	0.073	0.012
Central AC	0.051	0.010	0.000	0.009	0.064	0.012	0.083	0.009
Window AC	0.010	0.010	0.069	0.008	0.017	0.014	0.050	0.014
Swim Pool	0.093	0.011	0.090	0.008	0.128	0.010	0.142	0.011
Electric Cooking	0.082	0.007	0.018	0.005	0.094	0.006	0.065	0.008
CDD	0.024	0.008	–0.025	0.003	0.049	0.009	–0.032	0.003
HDD	–0.012	0.001	0.010	0.000	–0.003	0.000	–0.015	0.001
CDD*(Central AC)	0.065	0.006	0.039	0.003	–0.031	0.008	0.074	0.004
CDD*(Window AC)	0.030	0.008	–0.022	0.003	–0.054	0.011	0.019	0.009
HDD*(Electric Heat)	0.020	0.002	–0.014	0.001	0.006	0.000	0.073	0.003
CDD*(Swim Pool)	–0.003	0.008	0.004	0.002	–0.095	0.007	–0.003	0.005
Owned House	0.165	0.011	0.083	0.008	0.068	0.013	0.014	0.011
Single House	0.011	0.009	0.056	0.006	0.125	0.011	0.227	0.011
σ_e^2	0.188	0.051	0.150	0.022	0.245	0.036	0.264	0.032
No. of observations	21,862		33,876		28,206		27,234	

Notes: The equations also include state dummies, year dummies, and month dummies.

Table 7. Income-Specific Price Elasticities by Census Region

	Northeast		South		Midwest		West	
	Para.	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
Panel 1: OLS Results								
Log(price)*1(Income<25k)	–0.377	0.064	–0.416	0.050	–0.455	0.069	–1.008	0.075
Log(price)*1(25k≤Income<45k)	–0.397	0.064	–0.426	0.049	–0.473	0.068	–1.037	0.075
Log(price)*1(45k≤Income<80k)	–0.397	0.064	–0.432	0.049	–0.465	0.068	–1.047	0.075
Log(price)*1(Income≥80k)	–0.384	0.064	–0.407	0.049	–0.475	0.068	–1.026	0.075
Panel 2: GMM Results								
Log(price)*1(Income<25k)	–0.816	0.039	–1.023	0.006	–0.962	0.007	–0.876	0.010
Log(price)*1(25k≤Income<45k)	–0.841	0.039	–1.024	0.006	–0.969	0.006	–0.882	0.011
Log(price)*1(45k≤Income<80k)	–0.834	0.039	–1.024	0.007	–0.965	0.007	–0.880	0.011
Log(price)*1(Income≥80k)	–0.824	0.039	–1.006	0.008	–0.968	0.007	–0.866	0.011

Notes: The equations include all of the other explanatory variables as shown in Tables 5 and 6. The coefficient estimates on those variables are omitted here.

Table 8. Demand Equation Estimates from GMM (Household Income ≥ $10,000)

	Northeast		South		Midwest		West	
	Para.	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
Log(price)	**–0.834**	**0.039**	**–1.022**	**0.006**	**–0.971**	**0.005**	**–0.881**	**0.008**
Log(Income)	0.102	0.006	0.067	0.004	0.125	0.006	0.113	0.006
Log(#of rooms)	0.244	0.014	0.237	0.011	0.252	0.013	0.369	0.015
Log(household size)	0.246	0.009	0.202	0.007	0.265	0.008	0.202	0.007
Log(house age)	0.035	0.007	0.055	0.004	0.023	0.005	0.043	0.006
D_{70}*Log(house age)	–0.044	0.013	0.000	0.014	0.019	0.013	–0.038	0.020
D_{70}	0.006	0.020	–0.052	0.022	–0.009	0.022	0.025	0.032
Log(respondent age)	0.012	0.011	0.017	0.008	0.138	0.011	0.187	0.013
Electric Heat	0.197	0.014	0.237	0.009	0.310	0.012	0.075	0.012
Central AC	0.042	0.010	–0.006	0.010	0.060	0.012	0.082	0.009
Window AC	0.004	0.010	0.063	0.008	0.018	0.014	0.046	0.015
Swim Pool	0.097	0.011	0.086	0.008	0.127	0.010	0.146	0.011
Electric Cooking	0.082	0.007	0.016	0.006	0.006	0.015	0.066	0.009
CDD	0.018	0.009	–0.032	0.003	0.050	0.008	–0.033	0.003
HDD	–0.014	0.001	0.001	0.093	–0.003	0.000	–0.017	0.001
CDD*(Central AC)	0.070	0.006	0.046	0.003	–0.035	0.008	0.078	0.004
CDD*(Window AC)	0.031	0.008	–0.018	0.003	–0.051	0.011	0.015	0.010
HDD*(Electric Heat)	0.022	0.002	–0.014	0.001	0.005	0.000	0.074	0.003
CDD*(Swim Pool)	0.008	0.009	0.006	0.002	–0.085	0.007	–0.004	0.005
Owned House	0.169	0.011	0.084	0.008	0.081	0.013	0.003	0.011
Single House	0.003	0.009	0.058	0.006	0.123	0.011	0.226	0.011
σ_e^2	0.184	0.051	0.148	0.022	0.234	0.034	0.263	0.032
No. of observations	21,197		32,752		27,497		26,475	

Notes: Observations with income less than $10,000 are dropped. The equations also include state dummies, year dummies, and month dummies.

Table 9. Demand Equation Estimates from GMM (without Lower and Upper 1 Percent of Households)

	Northeast		South		Midwest		West	
	Para.	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
Log(price)	**–0.824**	**0.042**	**–1.046**	**0.010**	**–0.975**	**0.005**	**–0.915**	**0.008**
Log(Income)	0.076	0.005	0.055	0.004	0.107	0.005	0.096	0.005
Log(#of rooms)	0.296	0.015	0.257	0.012	0.304	0.013	0.440	0.015
Log(household size)	0.260	0.009	0.215	0.008	0.288	0.008	0.241	0.008
Log(house age)	0.033	0.008	0.047	0.004	0.013	0.005	0.036	0.006
D_{70}*Log(house age)	–0.055	0.013	0.188	0.011	0.035	0.013	–0.070	0.021
D_{70}	0.026	0.020	–0.337	0.019	–0.023	0.022	0.093	0.033
Log(respondent age)	–0.013	0.011	0.026	0.007	0.134	0.011	0.180	0.013
Electric Heat	0.157	0.015	0.187	0.008	0.340	0.011	0.084	0.012
Central AC	0.057	0.010	0.016	0.011	0.061	0.012	0.098	0.009
Window AC	0.000	0.010	0.073	0.011	–0.016	0.014	0.044	0.015
Swim Pool	0.085	0.011	0.119	0.008	0.140	0.010	0.185	0.012
Electric Cooking	0.087	0.007	0.041	0.006	0.085	0.007	0.079	0.009
CDD	0.045	0.011	–0.033	0.004	0.015	0.010	–0.019	0.004
HDD	–0.014	0.001	0.005	0.000	–0.004	0.000	–0.012	0.001
CDD*(Central AC)	0.066	0.006	0.043	0.004	0.004	0.009	0.074	0.005
CDD*(Window AC)	0.032	0.008	0.002	0.003	0.012	0.011	0.001	0.010
HDD*(Electric Heat)	0.032	0.002	–0.002	0.001	0.008	0.000	0.071	0.003
CDD*(Swim Pool)	0.007	0.008	0.013	0.002	–0.090	0.006	–0.012	0.005
Owned House	0.159	0.012	0.088	0.008	0.069	0.013	0.022	0.011
Single House	0.016	0.009	0.042	0.006	0.146	0.011	0.243	0.011
σ_e^2	0.203	0.059	0.149	0.026	0.245	0.032	0.296	0.034
No. of observations	22,532		34,929		29,086		28,112	

Notes: Observations below 1 percentile or above 1 percentile of the monthly expenditure distribution are dropped. The equations also include state dummies, year dummies and month dummies.

Table 10. Demand Equation Estimates from GMM (Five Cost Shifters)

	Northeast		South		Midwest		West	
	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
Log(price)	**–0.742**	**0.044**	**–1.031**	**0.008**	**–1.015**	**0.003**	**–0.868**	**0.009**
Log(Income)	0.065	0.005	0.049	0.003	0.080	0.005	0.074	0.005
Log(#of rooms)	0.245	0.014	0.244	0.011	0.280	0.011	0.342	0.013
Log(household size)	0.229	0.009	0.195	0.007	0.220	0.006	0.188	0.007
Log(house age)	0.029	0.007	0.050	0.004	0.011	0.005	0.041	0.005
D_{70}*Log(house age)	–0.045	0.012	–0.023	0.013	0.024	0.011	–0.032	0.018
D_{70}	0.013	0.018	–0.016	0.021	–0.027	0.018	0.020	0.029
Log(respondent age)	–0.006	0.010	0.011	0.007	0.116	0.009	0.135	0.011
Electric Heat	0.147	0.014	0.240	0.009	0.149	0.011	0.092	0.011
Central AC	0.043	0.009	–0.032	0.010	0.000	0.011	0.024	0.008
Window AC	0.008	0.009	0.059	0.010	–0.034	0.012	0.042	0.013
Swim Pool	0.085	0.010	0.093	0.008	0.164	0.007	0.115	0.010
Electric Cooking	0.076	0.006	0.010	0.005	0.073	0.006	0.059	0.008
CDD	0.039	0.009	–0.043	0.004	–0.019	0.009	–0.078	0.005
HDD	–0.011	0.001	0.010	0.001	–0.004	0.000	–0.007	0.001
CDD*(Central AC)	0.068	0.006	0.055	0.004	0.037	0.009	0.131	0.005
CDD*(Window AC)	0.028	0.008	–0.003	0.003	0.019	0.010	0.013	0.010
HDD*(Electric Heat)	0.025	0.002	–0.014	0.001	0.016	0.001	0.052	0.002
CDD*(Swim Pool)	–0.003	0.008	0.010	0.002	–0.094	0.005	0.011	0.005
Owned House	0.155	0.011	0.088	0.008	0.051	0.011	0.038	0.010
Single House	0.008	0.008	0.055	0.006	0.111	0.009	0.188	0.010
σ_e^2	0.164	0.051	0.145	0.023	0.159	0.020	0.223	0.030
No. of observations	21,862		33,876		28,206		27,234	

Notes: The five instruments for electricity price used here are the five cost shifters measured during the past 12 months. The equations also include state dummies, year dummies, and month dummies.

Table 11. National Policy Simulation Results

ε	2012 P^E	2012 Q	2012 P^A	2016 P^E	2016 Q	2016 P^A	2025 P^E	2025 Q	2025 P^A	2035 P^E	2035 Q	2035 P^A
ε_L	114.2	1,377	11.4	118.8	1,350	15.6	121.6	1,467	31.1	139.5	1,577	67.0
	7.5%	–2.4%		9.9%	–3.9%		10.2%	–4.9%		17.6%	–7.0%	
ε_M	112.8	1,343	11.1	117.4	1,276	15.1	120.3	1,393	30.1	138.3	1,430	65.4
	6.2%	–4.8%		8.6%	–9.2%		9.0%	–9.8%		16.6%	–15.7%	
ε_H	111.4	1,294	10.9	116.7	1,163	14.9	118.7	1,281	29.7	136.7	1,222	64.5
	4.8%	–8.3%		7.9%	–17.3%		7.5%	–17.0%		15.3%	–28.0%	

Notes: P^E and Q are the national average residential electricity price ($/MWh) and national residential quantity consumed (TWh), respectively, for the year given. P^A is the allowance price ($/ton CO_2) in the cap-and-trade system for the given year.

Table 12. Regional Policy Simulation Results

Northeast

	2012		2016		2025		2035	
ε	P^E	Q	P^E	Q	P^E	Q	P^E	Q
ε_L	153.1	182.1	153.9	177.9	149.0	197.5	173.5	212.4
	8.6%	–2.3%	7.0%	–2.9%	0.4%	–1.1%	8.4%	–2.8%
ε_M	152.3	174.8	152.7	169.1	147.0	201.1	171.8	204.5
	8.0%	–6.2%	6.2%	–7.7%	–1.0%	0.7%	7.3%	–6.4%
ε_H	151.5	166.3	152.0	160.8	144.9	204.8	169.6	196.4
	7.5%	–10.8%	5.8%	–12.2%	–2.4%	2.5%	5.9%	–10.0%

South

	2012		2016		2025		2035	
ε	P^E	Q	P^E	Q	P^E	Q	P^E	Q
ε_L	105.1	674.9	113.8	664.8	122.0	715.3	138.2	774.7
	4.4%	–1.0%	11.0%	–2.9%	16.4%	–5.2%	21.6%	–6.5%
ε_M	103.4	674.0	112.0	636.4	120.2	662.4	136.5	690.4
	2.6%	–1.2%	9.3%	–7.1%	14.6%	–12.2%	20.1%	–16.7%
ε_H	102.2	675.9	111.2	585.7	118.6	572.4	134.7	559.8
	1.5%	–0.9%	8.5%	–14.5%	13.2%	–24.1%	18.5%	–32.5%

Midwest

	2012		2016		2025		2035	
ε	P^E	Q	P^E	Q	P^E	Q	P^E	Q
ε_L	111.1	281.9	113.6	272.3	103.6	302.5	124.6	317.1
	17.5%	–5.0%	16.9%	–7.3%	4.7%	–5.2%	21.1%	–9.3%
ε_M	109.7	261.3	112.3	242.1	102.2	293.1	122.4	289.5
	16.1%	–12.0%	15.5%	–17.6%	3.3%	–8.1%	19.0%	–17.2%
ε_H	108.0	224.7	110.7	194.1	99.3	287.7	118.7	256.5
	14.3%	–24.3%	13.8%	–33.9%	0.4%	–9.8%	15.3%	–26.7%

West

	2012		2016		2025		2035	
ε	P^E	Q	P^E	Q	P^E	Q	P^E	Q
ε_L	114.0	237.6	112.5	235.0	120.8	252.1	134.1	273.2
	3.9%	–3.0%	2.2%	–3.5%	8.7%	–6.8%	11.4%	–8.9%
ε_M	114.2	232.4	111.8	228.7	120.5	236.1	134.1	245.3
	4.0%	–5.2%	1.6%	–6.1%	8.5%	–12.7%	11.4%	–18.2%
ε_H	113.0	227.0	110.7	222.0	119.6	216.4	133.6	209.4
	2.9%	–7.4%	0.6%	–8.9%	7.6%	–20.0%	11.0%	–30.2%

Notes: P^E and Q are the average residential electricity price ($/MWh) and total residential quantity consumed (TWh), respectively, for the year and region given.