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A New Look at Residential Electricity Demand Using Household Expenditure Data*

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**ABSTRACT**
The recent push for a federal energy policy that could substantially change electricity prices in the U.S. highlights the need to obtain accurate residential electricity demand estimates. Many electricity demand estimates have been obtained based on the assumption that consumers optimize with respect to known marginal prices, but increasing empirical evidence suggests that consumers are more likely to respond to average prices. Under this assumption, this paper develops a new strategy based on GMM to estimate household electricity demand. Our approach allows a national-level demand estimation from publicly available expenditure data and utility-level consumption data, complementing studies that use individual billing data which are richer yet often proprietary. We estimate the price elasticity near -1, which is at the upper end (in magnitude) among the estimates from previous studies. We 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.
**Keywords:** Electricity Demand, CEX, GMM, Cap-and-trade.
**JEL Classification:** C5, D12, Q4.

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# 1 Introduction

The recent focus of the U.S. Congress on federal energy policies such as a carbon cap-and-trade program or a carbon tax, which could substantially alter the electricity market, has elevated the importance of characterizing electricity demand behavior. A growing body of literature on the incidence of such policies has emerged (e.g., Burtraw et al. 2009; Hassett et al. 2009; Shammin and Bullard 2009) and one of the key parameters in these incidence analyses is the price elasticity of residential demand for electricity.

Studies on residential electricity demand have been conducted for many decades. These studies differ significantly in data and methods used and provide a wide range of estimates for the price elasticity of demand, from zero to less than -1.[1] Most of the studies can broadly be classified into one of three groups – those based on nationwide data aggregated to the state or region level, those using household level data with imputed price and quantity data, and those using detailed and often proprietary household level data. This paper develops a new empirical strategy based on the Generalized Methods of Moments (GMM) to estimate residential electricity demand using publicly available household level data under the assumption that consumers respond to average prices. We believe that this proposed method offers several desirable features not found in the three common types of studies on electricity demand.

The first set of studies uses nationwide panel data, often aggregated at the state level, and have the advantage of being able to provide regional elasticities, both long-run and short-run, across the nation (e.g., Houthakker 1980; Maddala et al. 1997; Bernstein and Graffin 2005). 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 energy and 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.

The second set of studies employs household-level data that are also public and na-

[1] Espey and Espey (2004) provide a meta analysis on over 100 studies and Alberini et al. (2011) contains a good comparison of 17 more recent studies.

tional in scope but some important information such as household level prices are often missing. Branch (1993) uses Consumer Expenditure Survey (CEX) from the Bureau of Labor Statistics and a recent study by Alberini et al. (2011) is based on the American Housing Survey. Both national surveys contain household electricity expenditure but not price and quantity information. In Branch (1993), the state-level average electricity price is used as the household-level price while Alberini et al. (2011) uses average prices of a given utility. Both of these studies then impute the quantity consumed based on expenditure and the employed average price. As we discuss below in more detail, because of the nonlinear structure of price schedules commonly used in retail electricity, the estimates based on imputed data could suffer bias from both measurement error and simultaneity.

The third set of studies also employs household-level data but different from the second set, they often involve some piece of private electricity billing or rate structure information (e.g., Barnes et al. 1981; Dubin and McFadden 1984; Herriges and King 1994; Reiss and White 2005; Borenstein 2009; Ito 2011). These studies are typically constrained to geographically narrow regions because there is no national data set of electricity rate structures or of household-specific billing information.[2] Given regional household heterogeneity, one has to be cautious in applying estimates from these area-specific studies to all areas of the country. On a more practical note, getting geographically specific rate structure data appropriately matched to individual households for multiple areas or obtaining household billing information is often infeasible because of the diversity of rate structures across the country and the proprietary nature of individual billing data.[3]

More importantly, the first four of the six aforementioned studies using rich 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

[2]An exception to this is Barnes et al. 1981. This study uses data from 26 major metropolitan areas and matches that data to rate structure information obtained for each city individually. Nevertheless, it assumes that consumers respond to marginal prices.

[3]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 to multiple geographic regions would quickly become intractable.

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 multi-part tariff 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.[4]

Given these attributes of residential electricity consumption, the assumption that consumers respond to marginal prices is likely to be violated 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 (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.[5] 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 (2011) 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.

[4]Without any knowledge of the rate structure or an ability to control usage, consumers could not accurately respond to average prices either. However, given information provided in electricity bills, we believe it may be more plausible that consumers are acting "as if" they were responding to average, rather than marginal, price.

[5]If consumers were responding to marginal prices, then in a multi-part 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.

Our study contributes to the literature by developing an empirical strategy using GMM that allows demand estimation to be based on publicly available data sets at the state or national level. The estimation in the paper is based on Consumer Expenditure Survey (CEX) supplemented with state- and utility-level data from 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. However, unlike existing studies using household-level data, our estimation strategy neither necessitate individual billing data nor require imputation of price and quantity data.

We find a near unitary price elasticity of demand and a rather inelastic income elasticity of demand (0.11) in our baseline model. These estimates are robust to changes in specifications and data alterations. Our price elasticity estimates are consistent with the notion that consumers are targeting particular total bill values, an idea that is perhaps not all to unrealistic given consumers limited ability to precisely control usage and to fully understand rate structures. In addition, our estimate of price elasticity is at the upper end (in magnitude) among a large set of price elasticity estimates using household-level data. Our price elasticity estimates are not, however, unprecedented. Using Residential Electricity Consumption Survey (RECS), Metcalf and Hassett (1999) obtain estimates from -0.73 to -1.13 for households with electric heat and almost zero for those who heat with natural gas.[6] Similarly, based on data in 50 largest MSAs, Alberini et al. (2011) provide a price elasticity estimate of -0.74 in the short-run from a partial adjustment model.

Our estimates are significantly larger than studies that use household-level data and are based on the assumption of marginal price response (e.g., Barnes et al. 1981; Dubin and McFadden 1984; Herriges and King 1994; Reiss and White 2005). The estimates range from -0.02 to -0.55 in these four studies. As we demonstrate below, the assumption of

[6]RECS, conducted by the Energy Information Administration (EIA), contains both expenditure and consumption data from billing records for a small number of households. So the average price during a billing cycle can be calculated at the household level. In addition to the smaller sample size compared to CEX, the location information is only available for the four most populous states in RECS.

marginal price response could lead to smaller elasticity estimates (in magnitude) than the assumption of average price response.

With a focus on testing what price consumers response to, the novel studies of Borenstein (2009) and Ito (2011) provide elasticity estimates under both assumptions. Their elasticity estimates with respect to the average price, -0.10 to -0.20 are generally smaller in magnitude than ours. The estimates from Borenstein (2009) vary noticeably across adjacent time periods from 2000 to 2006 with the largest estimate in magnitude being -0.96. In Section 5.3, we provide a lengthy discussion on why our estimate may differ from these two studies, despite sharing the assumption of average price responsiveness.

The remainder of the paper is organized as follows. In section 2, we present our empirical method and in section 3, we discuss the data used. Section 4 presents a Monte Carlo analysis to examine our empirical method. The results of the estimations and comparisons to previous studies are discussed in section 5. Section 6 conducts policy analysis simulations. In the final section we give concluding remarks.

# 2 Empirical Strategy

Our empirical framework is set up based on the CEX data. 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. As noted above, some previous studies using CEX data, such as Branch (1993) and Metcalf and Hassett (1999), have used monthly state average prices from the EIA as the price variable and constructed the quantity variable by dividing expenditure by the state average price, as we will do for one version of our model. Although this method is 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 state-average price given by the EIA, while the simultaneity issue comes from the fact that household electricity usage and the price for that level of usage are determined at the same time.

To illustrate these challenges, assume that the underlying demand function takes the commonly used double-log form in the literature on electricity demand:

$$lnq_{ist} = \beta lnp_{ist} + x_{ist}\gamma + e_{ist}, \tag{1}$$

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 $t$ while $p_{ist}$ is the average price for that household in month $t$. Under non-linear price schedules, the average price depends on the quantity, i.e., $p_{ist}$ is a function of $q_{ist}$. The vector $x_{its}$ 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 var($e_{ist}$)=$\sigma_e^2$.

Without observing both $p_{ist}$ and $q_{ist}$, one could apply the naive method, taken before in the literature, that uses state-average price $\bar{p}_{st}$ and imputed quantity $\bar{q}_{ist} = c_{ist}/\bar{p}_{st}$, where $c_{ist}$ is monthly household expenditure, to replace quantity and price variables in equation (1). The equation would become

$$\begin{aligned} ln\bar{q}_{ist} &= \beta ln\bar{p}_{st} + x_{ist}\gamma + (ln\bar{q}_{ist} - lnq_{ist}) + \beta(lnp_{ist} - ln\bar{p}_{st}) + e_{ist} \\ &= \beta ln\bar{p}_{st} + x_{ist}\gamma + [ln(c_{ist}/\bar{p}_{st}) - ln(c_{ist}/p_{ist})] + \beta(lnp_{ist} - ln\bar{p}_{st}) + e_{ist} \\ &= \beta ln\bar{p}_{st} + x_{ist}\gamma + (1+\beta)(lnp_{ist} - ln\bar{p}_{st}) + e_{ist} \\ &= \beta ln\bar{p}_{st} + x_{ist}\gamma + \nu_{ist}, \end{aligned} \tag{2}$$

where $\bar{q}_{ist}$ again is the imputed individual quantity base on state-average price. $v_{ist}$ is the composite error term. If one were to estimate (2) taking $v_{ist}$ as the error term, the estimates on both $\beta$ and $\gamma$ could be biased for two reasons. First, since the error term $v_{ist}$ includes state average price variable $\bar{p}_{st}$, $ln\bar{p}_{st}$ 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 due to 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 OLS estimation is unknown: both $\bar{p}_{st}$ and $x_{ist}$ are correlated with the error term and it is unclear what direction the partial correlation between $(lnp_{ist} - ln\bar{p}_{st})$ and the explanatory variables take.

We develop a new empirical strategy based on the generalized methods of moments (GMM) to estimate the demand function with the expenditure data from CEX. Our strategy also necessitates data on average household electricity consumption at the utility level, which are publicly available from EIA. Rather than using all households from CEX, Our main analysis is conducted on households for which we can identify the utility company that serves the household. This is because our method requires the specification of the average price schedule, which could vary by utility company.

We use $u$ to denote a utility company in the following discussion. Recall that since we do not observe either price or quantity at the household level, we cannot take equation (1) directly to the data. Instead we further specify the average price schedule faced by the household served by utility $u$ as the following:

$$lnp_{iut} = \alpha_u lnq_{iut} + z_{iut}\delta + \epsilon_{iut}, \tag{3}$$

where $\alpha_u$ is the utility specific slope for the price schedule and $z_{iut}$ is a vector of observed variables that shift the price schedule, such as cost shifters, month dummies and utility dummies. This specification allows both the intercept and the slope of the average price schedule to vary across utilities. $\epsilon_{iut}$ is the approximation error and is assumed to be normally distributed with mean zero and variance var($\epsilon_{iut}$)=$\sigma_\epsilon^2$.

The household electricity usage and average price are determined by the demand equation and the price schedule. Solving for $q_{iut}$ and $p_{iut}$ from equations (1) and (3), we get:

$$lnq_{iut} = x_{iut}\gamma/(1-\beta\alpha_u) + z_{iut}\delta\beta/(1-\beta\alpha_u) + (e_{iut} + \beta\epsilon_{iut})/(1-\beta\alpha_u). \tag{4}$$

$$lnp_{iut} = x_{iut}\gamma\alpha_u/(1-\beta\alpha_u) + z_{iut}\delta/(1-\beta\alpha_u) + (\alpha_u e_{iut} + \epsilon_{iut})/(1-\beta\alpha_u). \tag{5}$$

Given that the total expenditure $c_{iut} = q_{iut}p_{iut}$, the above two equations allow us to express the total expenditure in logarithm as the following:

$$\begin{aligned} lnc_{iut} = \quad & x_{iut}\gamma(1+\alpha_u)/(1-\beta\alpha_u) + z_{iut}\delta(1+\beta)/(1-\beta\alpha_u) \\ & +[(1+\alpha_u)e_{iut} + (1+\beta)\epsilon_{iut}]/(1-\beta\alpha_u). \end{aligned} \tag{6}$$

Since we have data on electricity expenditure, the equation above provides us with the basis for the first set of moment conditions. Define the predicted value of the log expenditure as:

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

The first set of moment conditions is given by:

$$E_{i,u,t}\Big([x_{iut} \quad z_{iut}]'(lnc_{iut} - ln\hat{c}_{iut})\Big) = 0. \tag{8}$$

Recognizing that some variables, such as month dummies and state dummies, are common in both $x_{iut}$ and $z_{iut}$, 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. Intuitively, one cannot separately identify the demand and price functions with only data on expenditures.

Taking advantage of average household electricity quantity at the utility level, available from EIA and denoted by $\bar{q}_{ut}$, we construct the second set of moment conditions, which match the average quantity with the predictions from our model. From equation (4), the expected value of electricity usage for a household, $\hat{q}_{iut}$, is given by:

$$\hat{q}_{iut} = E(q_{iut}) = exp\Big(x_{iut}\gamma/(1-\beta\alpha_u) + z_{iut}\delta\beta/(1-\beta\alpha_u) + 0.5(\sigma_e^2 + \beta^2\sigma_\epsilon^2)/(1-\beta\alpha_u)^2\Big), \tag{9}$$

where the last term in the parenthesis is half of the variance of the composite error term in equation (4).[7] Define $\hat{\bar{q}}_{ut}$ as the average of for all households in utility $u$ and month $t$ (i.e., $\hat{\bar{q}}_{ut} = \sum_i^I E(q_{iut})/I$). Based on $E[q_{iut} - \hat{q}_{iut}|x_{iut}, z_{iut}] = 0$, the second set of moment conditions can be constructed as:

$$E_{i,u,t}\Big([x_{iut} \quad z_{iut}]'(\bar{q}_{iut} - \hat{\bar{q}}_{iut})\Big) = 0. \tag{10}$$

Although the number of moment conditions constructed so far is larger than the number of model parameters, the standard deviations of the two errors terms, $\sigma_e^2$ and $\sigma_\epsilon^2$, cannot be

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

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

$$E_{i,u,t}(lnc_{iut} - ln\hat{c}_{iut})^2 - [(1+\alpha_u)^2\sigma_e^2 + (1+\beta)^2\sigma_\epsilon^2]/(1-\beta\alpha_u)^2 = 0. \tag{11}$$

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 2SLS where we take the utility-level average prices as the price variable for all the households in the utility and then use this price variable and household expenditure to impute household quantity. 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 prices 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 directly, we also face the common identification challenge of simultaneity 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).

It is worth pointing out that while 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.

# 3 Data

As discussed above, the primary source of data for our demand estimation comes from the consumer expenditure survey (CEX), monthly over the period 2006 - 2008. The CEX collects data through quarterly interviews on a random sample of about 7,500 households.[8] Importantly, the survey asks respondents to provide detailed expenditure information, including monthly electricity expenditures, though does not address quantity or price information for electricity use. An important caveat of the CEX data is that it contains missing values for a large number of observations and imputed values are often provided for these observations. We exclude these observations in our analysis since the imputation would not be consistent with our estimation approach.

The CEX survey also collects information on household demographics, housing type, appliance holdings, and income. We use this data, combined with relevant cooling degree days (CDD) and heating degree days (HDD) as demand shifters ($x_{iut}$).[9] A list of the variables we use as demand shifters, along with summary statistics, is provided in Table 1.

In order to improve the accuracy of estimates derived from our empirical methodology, we take several steps to refine the examined sample. These refinements are primarily made to increase the validity of second set of moment conditions. Recall that the second set of moment conditions are based on setting population-average electricity consumption equal to the derived sample-average consumption. The EIA provides average household electricity consumption at the utility level.[10] Ideally, one would like to form the second

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[8]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/.

[9]CDDs and HDDs are defined as max(Average Temperature in Fahrenheit - 65, 0) and max(65 - Average Temperature in Fahrenheit, 0), respectively. Average temperature data are city-specific temperatures provided by the University of Dayton website. The specific cities used are those matching the PSU-state combination described below.

[10]EIA form 861 provides annual residential electricity consumption and the total number of residential customers served for each utility. EIA form 826 provides monthly residential electricity consumption for each utility. Together, they imply monthly average household consumption at the utility level.

set of moment conditions by matching the derived sample-average consumption from CEX respondents living in a given utility service territory to the average consumption of that utility as computed from the EIA data. Unfortunately, the CEX does not give sufficiently detailed geographic identifiers to perform such a direct matching process.

The most geographically detailed information provided in the CEX data is the state the respondent resides in and, if the respondent comes from a primary sampling unit (PSU), the PSU they live in. A PSU is a group of counties, similar to metropolitan statistical areas, and constitutes the sampling frame from which housing units are chosen.[11]. The CEX public data only identifies 21 large PSUs (population over 4 million), some of which cross state boundaries. They are plotted in Figure 1. Given information about utility service territories, we can then refine our sample by considering only those respondents who reside in PSU-state combinations that are mostly serviced by a single utility. To do this we first overlay utility service areas on the PSU map to determine which utilities are operating in each of the PSUs as the geographic unions of PSUs and utility service territories. To make sure that the majority of observed households in a given PSU-state region are covered by a single utility, our baseline scenario considers only PSU-states that have 90 percent of its customers serviced by a single utility.

To mitigate concerns that utility-level average quantity measures are being driven by areas outside the PSU-state that are still covered by the utility in question, we further refine our baseline scenario to consider only PSU-states whose primary electricity service provider has at least 50 percent of its customers inside the PSU-state.[12] The list of PSU-states combinations that meet this requirement is given in Table 2 and a plot of the utility-level average prices and average quantities associated with those PSU-states is given in Figure 2.[13] From Figure 2, we see that for each PSU-state there is observable variation across time

[11]For more detailed information on how the data is collected, see Johnson-Herring et al. (2002)

[12]The percent of customers serviced by the utility in question that live in the specific PSU-state is proxied by population data. More specifically, based on census track data, we calculate the total population living in the utilitys service territory and then calculate what percent of that population is in the geographic union of the utility service territory and PSU-state.

[13]It should also be noted that we applied many different screening criterion to form our data set, some of

in average prices and quantities and also considerable price and quantity variation across the PSU-states used in our baseline estimation.

To estimate the average price equation, our empirical method necessitates instrumental variables for electricity price. These variables should shift price schedules, but 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 fuel prices.

Coal price data comes from two different sources, both generated by the EIA. For PSU-state combinations associated with states where electricity is generated and distributed by regulated utilities (i.e., cost-of-service regions), coal prices are monthly quantity-weighted average prices derived from EIA forms 423 and 923.[14] Since these forms generally exclude data from independent power producers, we use national average monthly coal prices from EIA's Electric Power Monthly reports, for observations in regions with competitive wholesale electricity pricing. Natural gas prices were derived from the monthly state average residential natural gas prices given in EIA's Natural Gas Monthly reports.[15] Monthly electricity generation shares by fuel type for each state associated with PSU-state combinations we use in the study are derived from the EIA's Electric Power Monthly reports. A summary

which are included in our robustness checks, and our estimation results appeared robust to these variations.

[14]The EIA 423 form was merged into schedule 2 of the EIA 923 in 2008, so we use both forms. These forms give fuel costs at the generation-plant level from which a quantity-weighted \$/MBtu coal price can be derived.

[15]The EIAs Natural Gas Monthly reports also give monthly state average natural gas prices for gas delivered to electric generators. However, due to confidentiality restrictions, the prices for some states withheld. Since the natural gas prices of residential consumers and electric generators are highly correlated and no prices are withheld in the monthly state average natural gas prices for residential consumers, we use the residential gas price series.

of the cost shifters is given in Table 3 and plots of selected variables are given in Figure 3. From the plots we see that over the time span analyzed there is considerable variation in lagged natural gas and coal prices. We also observe an increase in generation shares of natural gas. The increase is primarily attributed to the large increase in natural gas generation in PSU-states A424-CA (San Diego, CA region) and A109-NY (New York, NY region).

# 4 Monte Carlo Analysis

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 the six PSU-state combinations that clear the screening criteria described above: San Francisco, CA; San Diego, CA; Baltimore, MD; New York, NY; Chicago, IL; Philadelphia, PA. We first generate price and quantity data for each household using the demand and price equations (4) and (5). The input for data generation includes a vector of household characteristics from CEX, cost shifters, and a given set of parameters for the two equations. The household characteristics, a subset of those listed in Table 2, include household income, number of rooms in the house, household size, HDD interacted with an electric heat dummy, and CDD interacted with an air conditioning dummy. The cost shifters, a subset of those listed in Table 3, include the shares of electricity generated during the past three months using natural gas, coal, and nuclear plus hydro.

Based on these variables and parameters, we generate monthly expenditure data at the household level and monthly state average electricity prices and quantities. 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 (3), 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 reports the values of the parameters used to generate the data (the true parameters) and their estimates from OLS and GMM for six different cases. The parameter estimates are based on 100 runs in each case. We conduct analysis for demand with different elasticities: -0.3 reported in the first three panels and -1.2 in the last three panels. Three scenarios of price schedules are considered: upward sloping in all PSU-state combinations, downward sloping, and mixed slope across PSU-state combinations. In all six cases, the GMM method is able to recover the true parameters precisely in the demand equation while the OLS method gives biased estimates, especially for log(price), the key variable of interest. The bias is especially large for the demand specification with the price elasticity of -0.3 in panels 1-3. We do not report the results for the dummies variables (six state dummies, two year dummies, and 11 month dummies) in the demand equation or the parameters in the price equation to save space. But all of them are recovered quite precisely from GMM as well.

# 5 Estimation Results

In this section, we first present results from the baseline estimation. We then present results for robustness checks. The term baseline refers not to the method of estimation, but to the set of variables and observations included in the model. The baseline and alternative estimations are carried out using the GMM procedure described above and by OLS.

## 5.1 Baseline Estimation

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. Thus, in the baseline estimation, we drop observations in the upper and lower 2.5 percentile of electricity expenditure to avoid the effects of outliers (e.g., college dorms, those with subsidized electricity), possible data entry errors, as well as households with a large proportion of electricity being generated by themselves (e.g., through solar panels). For example, the maximum monthly electricity expenditure in the data is $2,946 from a household with an annual income is $157,720. Assuming constant monthly income implies the highly unlikely possibility that over 22 percent of monthly income was spent on electricity. In the other extreme, there are 31 observations with 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 if not data entry error, some of the observations may come from households that have used self-generated electricity or subsidized electricity through some low income assistance program.

We also drop PSU-states with fewer than 1,000 observations from the sample to ensure a reasonably large number of observations in each state in each month, which is particularly important for the consistency of the second set of moment conditions. Finally, we drop households with incomes less than $10,000 to further avoid possibilities of low-income utility assistance. We perform robustness checks with respect to data censoring and the results are provided below.

Table 5 presents parameter estimates from OLS and GMM. Both estimations include PSU-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. There exists a substantial difference in price elasticity estimates from the two methods: -0.101 from OLS and -0.982 from GMM. As discussed above, the OLS estimates could suffer bias due to both simultaneity and measurement error issues and the direction of bias is unknown *a priori*. In addition, the coefficient estimates on most of the other variables also exhibit large differences from OLS and GMM. This highlights that the bias in the naive OLS approach is not limited to the price variable as illustrated by equation (3). In Section 5.3, we present a detailed discussion of our price elasticity estimates in comparison with the literature.

The income elasticity estimate is about 0.11 from our GMM estimation. This estimate is well within the range of income elasticity estimates from other studies. For example, Herriges and King (1994) and Barnes et al. (1981) find income elasticity estimates of 0.45 and 0.20, repectively, while Dubin and McFadden (1984) get an estimate of 0.02 and Reiss and White (2005) find no statistically significant income effect.

The remaining parameter estimates in Table 5 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 the number of rooms and household size. Interpreting the remaining housing characteristics is not as straight forward since they appear in interaction terms.

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 two variables ($D_{70}$*House Age). The positive parameter estimates on house age imply that electricity usage increases with household age for those built after 1970.[16] 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. 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, which is useful if much older houses have been renovated. Nevertheless, we fail to find a different age effect for pre-1970 houses than for post-1970 houses.[17]

With respect to appliance holdings, we find all the parameter estimates for appliance-holding have statistically significant values and intuitive signs except for on electric cooking. For instance our demand estimation shows that electricity demand increases when household have electric heating, ACs (window units or central AC), swimming pool, and dryer. All the interaction terms between appliance and weather variables (CDD and HDD) have positive signs, as intuition would suggest. For the house ownership dummy variable, we find a negative, but statistically insignificant effect of home ownership on electricity consumption. One would expect that home owners would be more likely to purchase an energy efficient capital stock, since 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 renters are more likely to have fewer Energy Star appliances than home owners. However, the ownership of energy efficient appliances

[16] We use 1970 as a somewhat arbitrary cut-off point between older construction and newer construction. We 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 $D_{70}$.

[17] Chong (2011) finds that new houses (post-1970) have higher temperature responses than old houses using data from southern California.

may be counteracted by more time spent in the housing unit and/or a greater frequency of appliance usage by house owners, thus obscuring the significance of the ownership effect.

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 ten instruments: quarterly and yearly lagged moving average share of electricity generation from coal, the share from natural gas, the share from hydro plus nuclear, the interaction between the share from coal with lagged coal price, and the interaction between the share from natural gas and lagged natural gas price. The estimation results show that most of the cost shifters are statistically significant. The yearly moving average variables generally have larger effect than those the quarterly variables, indicating that electricity prices are often affected by supply conditions even one year prior to production. We conduct robustness checks on the use of instruments in the following section, together with other sensitivity analysis.

## 5.2 Robustness Checks

Table 6 shows parameter estimates from GMM for three robustness checks. The first one (Robustness #1) is based on one more PSU-state pair than was used in the baseline specification. Recall, in the six PSU-states analyzed in the baseline specification, at least 90% of the residents of in the area are served by the same utility and at least 50% of all customers of the utility are from the PSU-state. In the first robustness check, we remove the second restriction. As a result, Miami, Florida with about 1,600 observations is added to the analysis. The estimate of price elasticity from this specification is -0.975, compared to -0.982 in the baseline specification. Coefficient estimates on household demographics and appliances, except those interacted with weather variables, are very similar between the two specifications as well.

To remove outliers and to obtain better approximation of the average price schedule using a linear function, the baseline specification drops households in the top and bottom 2.5 percent of the electricity expenditure distribution. The second robustness check (Robustness #2) examines the sensitivity of our results to this censoring, in which we drop observations in the top and bottom 10 percent of electricity expenditure. The price elasticity estimate is still very close to that from the baseline specification. Nevertheless, the income elasticity drops from 0.11 to 0.04, suggesting a large effect from the censoring on the estimate of income elasticity. This could be due to the measurement error introduced by censoring in the second moment condition, where average price and quantity among all residential customers at the utility level are used. Another analysis dropping observations in the top and bottom one percent of electricity expenditure, not shown in the table, yields very similar price elasticity estimate as well.

All previous specifications use ten cost shifters as instruments for electricity price to form moment conditions. The third robustness check (Robustness #3) reported in table 6 uses five of the ten lagged cost shifters employed in the baseline model. They are the average share by generation type (coal, natural gas, nuclear and hydro) during the past 12 months, 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. Most of the estimates are very similar to those from the baseline specification. The estimate of price elasticity is -0.942 versus -0.982. All the other coefficient estimates are very similar between the two specifications too.

We conduct several additional robustness checks and all of them yield similar results to those from the baseline estimation. These results are not reported here but are available upon request. One of the robustness checks drops San Francisco in the analysis because its primary utility company PG&E also serves substantial parts of inland California. Since inland California has considerably different climate than coastal San Francisco, as well as significant socio-demographic differences, the average consumption of customers served by PG&E in total may not match up well with the average consumption of customers in San Francisco. Another analysis relaxes baseline model restrictions that require a single utility to cover 90% of the PSU-State and have 50% or more of its customers reside in the PSU-state. For this analysis we retain other criterion in the baseline estimation. The resulting data set has 50,067 observations across 21 unique PSU-states. In an earlier version, we conduct the same analysis for four census regions where we use state-level average price and quantities to construct the second moment conditions. The results are reported at our Resources for the Future (RFF) working paper.

### 5.3 Discussion on Price Elasticity Estimates

Our near unitary price elasticity estimate, though quite robust, is among the larger estimates in the literature, thus a discussion of possible reasons for this result is warranted. Most of other studies that use household-level data, matched with actual rate schedules faced by households, provide significantly less price-elastic demand estimates . For example, using data in 23 large U.S. metropolitan areas from 1972-1973 CEX, Barnes et al. (1981) obtain an estimate of price elasticity 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 during 1984 to 1985, where 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 an average price elasticity of -0.39 across households.[18]

The major difference between our study and the studies discussed directly above is that those studies assume that households respond to marginal prices while we assume households respond to average prices. As illustrated in the next section, this difference can lead to drastically different price elasticity estimates. The question of which price consumers respond to in electricity demand is beyond the scope of this study, but as previously mentioned, there is increasing evidence 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. In addition, three of the four studies discussed above are based on data from

[18]It should be noted that Reiss and White (2005) use an end-use demand estimation model. Thus a household's price elasticity is dependent on its appliance holdings. Correspondingly, Reiss and White (2005) obtain estimations on a range of price elasticities across heterogeneous households. The mean of these price elasticity estimates is -0.39, but a histogram of their estimates show a non-neglible portion of households with price elasticities of -1 or less.

specific geographic locations, while our sample looks at data across several geographically diverse metropolitan areas. These geographic differences in samples may also attribute to the large differences in price elasticity estimates.

The geographic and temporal differences could also attribute to the differences between our estimates and those in Borenstein (2009) and Ito (2011), both of which use very rich household billing data, but also allow households to respond to average price as well as marginal prices. Borenstein (2009) focus on March to May, generally low demand months, from 2000 to 2006 among households served by Southern California Edison which covers a large part of Southern California. The elasticity estimates with respect to average price range from 0 to -0.96 when the estimation does not constrain the elasticity to be the same across months. When it does, the estimates range from -0.18 to -0.41 across three time periods (2000-2002, 2002-2004, and 2004-2006). In addition, the elasticity estimates with respect to marginal price (-0.04 to -0.09) are much smaller in magnitude than those with respect to average price. The study area in Ito (2011) is the territory border of the two utilities and is a small portion of the Orange county, CA with 54,280 customers. The elasticity estimates with respect to average price are about -0.10 to -0.14 across specifications, still larger in magnitude than those with respect to marginal price. It is worth mentioning the elasticity estimates with respect to marginal price in both studies are much smaller than -0.39 from Reiss and White (2005) which covers the whole California, lending support to the idea that regional differences may apply even within California.

## 5.4 Price Elasticities: Average vs. Marginal Price Response

The price elasticities of demand presented here are considerably more elastic than several other recent studies using household level data. While there could be other factors that contribute to the differences in price elasticity estimates across studies (see Dahl 1994), assuming that consumers respond to average prices, as done here, rather than to marginal prices, as is commonly done in the literature, can lead to significant differences in estimates. To further explore this point, we provide a numerical illustration below.

As discussed above, utilities frequently use non-linear price schedules in selling electricity. The non-linearity could be due to an up-front fixed charge, such as a transmission charge, and/or block pricing. The maintained assumption used in most of the literature of electricity demand since Taylor (1975) 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, this could be a rather strong assumption and indeed there is increasing evidence that consumers are more likely to respond to average prices rather than marginal prices. The assumption 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 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 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 charge. Since 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 $\alpha$ can be identified by dividing the difference in quantity consumed between households A and B by the difference in X. In this example, $\alpha$= (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. Given $\alpha = 0.2$, if B and C paid the same price for electricity, then C would consume 4 more units than B. Thus the hypothetical household, B', with the same income level as B, but facing the same marginal price as C, $P_2$= 0.15, would consume four fewer units than C, resulting in 2 units of electricity consumption. Connecting points X, corresponding to $P_2 = 0.15$ and = 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 $\epsilon^{MP} = P_1\beta/Q_B$ = -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 cutoff quantity Q$^*$ = 4.5, average prices paid by the three households are $\bar{P}_A = \bar{P}_B$ =0.10 and $\bar{P}_C$ = 0.1125. Using the same identification strategy as described above, $\alpha$ would again be 0.2 and hypothetical household, B' , facing the same average price of household C, 0.1125, would 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 $\epsilon^{AP}$ = -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.[19] The degree to which the price elasticities will differ is, of course, a function of the data used. Since 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

[19]A similar example, using a decreasing block price schedule would yield the same result with respect to price elasticities as the example described above.

Southern California Edison, Borenstein (2009) is able to estimate elasticities with respect to both marginal prices and average prices. He finds 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.

More generally, the discussion in this section and the comparisons with previous studies in the previous section highlight that further research is warranted to understand the prices to which consumers really respond in electricity demand and to reconcile differences from these studies.

# 6 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 analysis of federal policies that affect electricity prices. To examine this issue, we use simulations to study a federal CO2 emissions regulation similar to that proposed in H.R. 2454 (U.S. Congress 2009), the Waxman-Markey climate bill.

The simulations are conducted using RFF's Haiku electricity market model.[20] Haiku is a deterministic and highly parameterized simulation model of the electricity sector in the forty-eight 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 the EIA. This analysis hinges on the demand side of the Haiku model that 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 from Paul et al. (2009b) that vary by region and season, with a national average of -0.13. We denote this the $\epsilon_L$ case to signify the low elasticity estimates.

The model used in Paul et al. (2009b) is based on state-aggregated data and includes both short-run and long-run elasticity estimates. In the second parameterization, we use a

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

more moderate estimate of -0.4, the $\epsilon_M$ case. This value is in line with the price elasticity estimated in Reiss and White (2005), which is based on marginal price responsiveness from household-level data in California. Nevertheless, we apply this elasticity to all regions covered under the simulation. In our final parameterization, we use the price elasticity estimate from our baseline estimation as the short-run elasticity in the policy simulation. We denote this as the $\epsilon_H$ 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).

The simulation outputs give us average residential electricity prices and consumption and $CO_2$ emissions allowance prices. The model is run over the 2010 to 2035 horizon, with the $CO_2$ emissions policy beginning in 2012 and holding cumulative economy-wide $CO_2$ emissions constant across scenarios.[21] Table 7 shows policy simulation results for four different years (2012, 2016, 2025, and 2035) for each of the parameterization cases. We also show percent changes relative to the Annual Energy Outlook 2010 reference case (U.S. EIA 2010).

The simulation 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 impact 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 $\epsilon_H$ scenario is four percent lower than under

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

the $\epsilon_L$ scenario. This would have a positive welfare impact on households because under an economy-wide 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 7 shows an approximate \$3/MWh difference in electricity prices from the $\epsilon_L$ case to the $\epsilon_H$ 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 $\epsilon_L$ to $\epsilon_H$, 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 about one-third 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 long-run supply curves for electricity production in Haiku are relatively elastic, yield relatively smalls changes in electricity price.

# 7 Conclusion

In this paper, we develop an empirical method to estimate residential electricity demand under the assumption that consumers respond to average prices rather than marginal prices. The method circumvents the need for proprietary individual billing data and instead can be carried out using publicly available data, yet without relying on imputed electricity prices or quantities. We apply the estimation strategy to household-level data from CEX, which includes monthly household electricity expenditures, but not electricity prices or quantities, over the period 2006 - 2008.

We consistently find a price elasticity of electricity demand near -1 across many different specifications. The estimate is at the upper end (in magnitude) among the large set of price elasticity estimates in the the literature, ranging from zero to less than -1. As we show through an numerical illustration, it is not unreasonable for our estimates to be larger than those derived in studies that assume households respond to marginal electricity prices since we explicitly assume that households respond to average electricity prices. As noted above, there are several studies that 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. In addition, the differences in time span and geographic area could be other factors that contribute to the difference, especially from estimates in Borenstein (2009) and Ito (2011). Further research is warranted to understand variations in price elasticities across regions and over time and to reconcile differences across studies.

To put these elasticity estimates into a policy-relevant context, we conduct 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 study, in terms of electricity prices, consumption, and emissions allowance prices, are then compared to outcomes using more conservative estimates of price elasticity from studies assuming marginal-price responsiveness. Not surprisingly, we find that simulations using our elasticity estimates leads to a greater reduction in electricity consumption due to the implementation of the policy and lower emission allowance prices.

Though we believe this study provides a new approach to estimate electricity demand without specific rate structure data, there are several issues left unexplored by this research. First, because we do not have specific bill information, we cannot validate the assumption of average price-responsiveness. This is clearly an important consideration that goes far beyond the current study. In addition, due to 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.

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Table 1: Summary Statistics of Demand Side Variables by Specification

| Variables | Description | Mean | S.D. |
|---|---|---|---|
| Expenditure | Monthly expenditure in $ | 104.79 | 70.16 |
| Avg. Price | Average price in $/MWh | 14.17 | 3.84 |
| Quantity | Imputed quantity in 100 kwh | 6.63 | 1.98 |
| Income | Income in $10,000 | 8.46 | 6.56 |
| # of Rooms | Number of rooms in housing unit | 6.37 | 2.12 |
| Household Size | Number of residents in housing unit | 2.73 | 1.51 |
| House Age | Age of housing unit in years | 45.90 | 31.92 |
| D70 | Equal 1 if unit built before 1970 | 0.51 | 0.50 |
| Resp. Age | Survey respondent age | 50.61 | 15.69 |
| Elec. Heat | Equal 1 if unit has elec. heat | 0.13 | 0.34 |
| Central AC | Equal 1 if unit has central AC | 0.54 | 0.50 |
| Window AC | Equal 1 if unit has window AC | 0.20 | 0.40 |
| Swim Pool | Equal 1 if unit has swim pool | 0.10 | 0.30 |
| Elec. Cook | Equal 1 if unit has elec. stove | 0.33 | 0.47 |
| Dryer | Equal 1 if unit has clothes dryer | 0.83 | 0.40 |
| CDD | Monthly Cooling Degree Days in 100s | 0.75 | 1.21 |
| HDD | Monthly Heating Degree Days in 100s | 3.56 | 3.54 |
| Own House | Equal 1 if housing unit is owned | 0.79 | 0.41 |
| Single House | Equal 1 if housing unit is unattached | 0.62 | 0.49 |

Notes: Summary statistics based on data used in the baseline estimation. Average price and quantity are based on utility-level data from EIA, rather than derived via estimation.

Table 2: List of PSU-states

| PSU-State | General Urban Areas Covered |
|---|---|
| A422-CA* | San Fran.-Oakland-San Jose, CA |
| A424-CA* | San Diego, CA |
| A320-FL | Miami, FL |
| A207-IL* | Chicago, IL |
| A313-MD* | Baltimore, MD |
| A109-NY* | New York, NY |
| A102-PA* | Philadelphia, PA |

Notes: "*"-denotes included in baseline estimation and robustness checks 2 and 3. Robustness check 1 covers all PSU-states listed.

Table 3: Summary Statistics of Cost Shifters by Census Region

| | | Baseline | |
|---|---|---|---|
| Variables | Description | Mean | S.D. |
| % Nat. $\text{Gas}_1$ | % nat. gas gen. over prev. 3 months | 0.21 | 0.20 |
| % Coal $_1$ | % coal gen. over prev. 3 months | 0.33 | 0.27 |
| %(Nuke+Hydro) $_1$ | % (nucl.+hydro) gen. over prev. 3 months | 0.41 | 0.07 |
| % Nat. $\text{Gas}_2$ | % nat. gas gen. over prev. 12 months | 0.20 | 0.19 |
| % $\text{Coal}_2$ | % coal gen. over prev. 12 months | 0.33 | 0.27 |
| % $(\text{Nuke+Hydro})_2$ | % (nucl.+hydro) gen. over prev. 12 mo. | 0.41 | 0.06 |
| $P_1^{NG}$ | Avg. nat. gas price over prev. 3 months | 14.64 | 3.45 |
| $P_1^{C}$ | Avg. coal price over prev. 3 months | 1.76 | 0.18 |
| $P_2^{NG}$ | Avg. nat. gas price over prev. 12 months. | 14.25 | 2.45 |
| $P_2^{C}$ | Avg. coal price over prev. 12 months | 1.69 | 0.15 |

Notes: Summary statistics based on data used in the baseline estimation. The abbreviations "gen." and "prev." stand for "generation" and "previous", respectively. Prices are in $/MBtu for coal and $/thousand feet for natural gas.

Table 4: Monte Carlo Results for Demand Equation

| | True | OLS Results | | GMM Results | |
|---|---|---|---|---|---|
| | Value | Est. | S.E. | Est. | S.E. |
| Panel 1: Upward sloping price schedule(price elas.: -0.3) | | | | | |
| Log(price) | -0.3 | -0.501 | 0.056 | -0.338 | 0.058 |
| Log(income) | 0.2 | 0.232 | 0.003 | 0.202 | 0.005 |
| Log(room number) | 0.4 | 0.471 | 0.009 | 0.404 | 0.012 |
| Log(household size) | 0.3 | 0.360 | 0.005 | 0.303 | 0.008 |
| Electric heat * HDD | 0.1 | 0.119 | 0.002 | 0.101 | 0.003 |
| Central AC * CDD | 0.2 | 0.230 | 0.003 | 0.202 | 0.005 |
| Panel 2: Downward sloping price schedule(price elas.: -0.3) | | | | | |
| Log(price) | -0.3 | -0.658 | 0.0325 | -0.341 | 0.050 |
| Log(income) | 0.2 | 0.1471 | 0.0028 | 0.197 | 0.007 |
| Log(room number) | 0.4 | 0.3129 | 0.007 | 0.396 | 0.016 |
| Log(household size) | 0.3 | 0.2365 | 0.0041 | 0.295 | 0.010 |
| Electric heat * HDD | 0.1 | 0.0812 | 0.0013 | 0.099 | 0.004 |
| Central AC * CDD | 0.2 | 0.1502 | 0.0027 | 0.196 | 0.006 |
| Panel 3: Mixed sloping across PSUs(price elas.: -0.3) | | | | | |
| Log(price) | -0.3 | -0.464 | 0.032 | -0.307 | 0.028 |
| Log(income) | 0.2 | 0.197 | 0.003 | 0.2 | 0.005 |
| Log(room number) | 0.4 | 0.418 | 0.008 | 0.4 | 0.012 |
| Log(household size) | 0.3 | 0.31 | 0.005 | 0.3 | 0.008 |
| Electric heat * HDD | 0.1 | 0.098 | 0.002 | 0.1 | 0.003 |
| Central AC * CDD | 0.2 | 0.184 | 0.003 | 0.199 | 0.005 |

==> Continued on Next Page

| | True | OLS Results | | GMM Results | |
|---|---|---|---|---|---|
| | Value | Est. | S.E. | Est. | S.E. |
| Panel 4: Upward sloping price schedule(price elas.: -1.2) | | | | | |
| Log(price) | -1.2 | -1.058 | 0.051 | -1.187 | 0.070 |
| Log(income) | 0.2 | 0.191 | 0.003 | 0.200 | 0.004 |
| Log(room number) | 0.4 | 0.387 | 0.006 | 0.399 | 0.009 |
| Log(household size) | 0.3 | 0.289 | 0.004 | 0.299 | 0.006 |
| Electric heat * HDD | 0.1 | 0.097 | 0.001 | 0.100 | 0.002 |
| Central AC * CDD | 0.2 | 0.192 | 0.002 | 0.199 | 0.004 |
| Panel 5: Downward sloping price schedule (price elas.: -1.2) | | | | | |
| Log(price) | -1.2 | -1.118 | 0.020 | -1.190 | 0.043 |
| Log(income) | 0.2 | 0.220 | 0.003 | 0.201 | 0.005 |
| Log(room number) | 0.4 | 0.439 | 0.007 | 0.401 | 0.012 |
| Log(household size) | 0.3 | 0.330 | 0.004 | 0.301 | 0.009 |
| Electric heat * HDD | 0.1 | 0.109 | 0.001 | 0.100 | 0.003 |
| Central AC * CDD | 0.2 | 0.220 | 0.003 | 0.200 | 0.006 |
| Panel 6: Mixed sloping across PSUs (price elas.: -1.2) | | | | | |
| Log(price) | -1.2 | -1.145 | 0.019 | -1.193 | 0.016 |
| Log(income) | 0.2 | 0.203 | 0.003 | 0.200 | 0.004 |
| Log(room number) | 0.4 | 0.405 | 0.007 | 0.400 | 0.008 |
| Log(household size) | 0.3 | 0.305 | 0.004 | 0.300 | 0.005 |
| Electric heat * HDD | 0.1 | 0.103 | 0.001 | 0.100 | 0.002 |
| Central AC * CDD | 0.2 | 0.209 | 0.003 | 0.200 | 0.004 |

Notes: Monte Carlo simulations are based on observations from six PSU-states from 2006-2008. Parameters are estimated using both OLS and GMM with 100 runs. Equations include six PSU dummies, two year dummies and 11 month dummies. Other model parameters, not shown here, are all recovered precisely from GMM.

Table 5: Demand Equation Estimates: the Baseline Model

| | OLS | | GMM | |
|---|---|---|---|---|
| | Para. | S.E. | Para. | S.E. |
| Log(price) | **-0.101** | **0.006** | **-0.982** | **0.020** |
| Log(Income) | 0.000 | 0.001 | 0.108 | 0.007 |
| Log(#of rooms) | 0.000 | 0.002 | 0.479 | 0.020 |
| Log(household size) | 0.001 | 0.001 | 0.202 | 0.009 |
| Log(house age) | 0.000 | 0.001 | 0.013 | 0.007 |
| $D_{70}$*Log(house age) | 0.001 | 0.003 | 0.000 | 0.018 |
| $D_{70}$ | -0.002 | 0.005 | -0.038 | 0.031 |
| Log(respondent age) | 0.001 | 0.002 | 0.133 | 0.014 |
| Electric Heat | -0.020 | 0.002 | 0.045 | 0.016 |
| Central AC | -0.002 | 0.002 | 0.077 | 0.012 |
| Window AC | -0.005 | 0.002 | 0.060 | 0.014 |
| Swim Pool | 0.001 | 0.002 | 0.077 | 0.015 |
| Electric Cooking | 0.000 | 0.001 | -0.038 | 0.010 |
| CDD | 0.078 | 0.001 | 0.033 | 0.005 |
| HDD | 0.011 | 0.000 | 0.001 | 0.000 |
| CDD*(Central AC) | 0.003 | 0.001 | -0.005 | 0.006 |
| CDD*(Window AC) | 0.007 | 0.001 | 0.013 | 0.007 |
| HDD*(Electric Heat) | 0.621 | 0.052 | 4.456 | 0.285 |
| CDD*(Swim Pool) | 0.003 | 0.180 | 0.828 | 0.713 |
| Owned House | 0.000 | 0.002 | -0.004 | 0.013 |
| Single House | 0.001 | 0.001 | 0.076 | 0.011 |
| Dryer | 0.002 | 0.002 | 0.146 | 0.013 |

Notes: The number of observations is 16,102 from six PSU-states. The price variable used in OLS is the monthly utility average from EIA. The quantity is the average for the households in the utility service territory. The regression also includes PSU-state dummies, year dummies and month dummies.

Table 6: Demand Equation Estimates: Robustness Checks

| | Robustness 1 | | Robustness 2 | | Robustness 3 | |
|---|---|---|---|---|---|---|
| | Para. | S.E. | Para. | S.E. | Para. | S.E. |
| Log(price) | **-0.976** | **0.008** | **-0.970** | **0.019** | **-0.942** | **0.017** |
| Log(Income) | 0.091 | 0.006 | 0.038 | 0.006 | 0.112 | 0.007 |
| Log(#of rooms) | 0.409 | 0.018 | 0.341 | 0.023 | 0.501 | 0.020 |
| Log(household size) | 0.234 | 0.009 | 0.142 | 0.010 | 0.210 | 0.009 |
| Log(house age) | 0.006 | 0.006 | -0.001 | 0.007 | 0.020 | 0.007 |
| $D_{70}$*Log(house age) | 0.008 | 0.017 | 0.007 | 0.017 | -0.008 | 0.019 |
| $D_{70}$ | -0.019 | 0.031 | -0.050 | 0.030 | -0.031 | 0.033 |
| Log(respondent age) | 0.135 | 0.013 | 0.044 | 0.013 | 0.143 | 0.015 |
| Electric Heat | 0.161 | 0.012 | -0.075 | 0.015 | 0.043 | 0.017 |
| Central AC | 0.133 | 0.013 | 0.046 | 0.011 | 0.102 | 0.013 |
| Window AC | 0.030 | 0.015 | 0.078 | 0.013 | 0.057 | 0.015 |
| Swim Pool | -0.092 | 0.014 | 0.047 | 0.012 | 0.062 | 0.016 |
| Electric Cooking | -0.008 | 0.010 | -0.017 | 0.009 | -0.035 | 0.011 |
| CDD | 0.039 | 0.004 | 0.015 | 0.005 | 0.051 | 0.006 |
| HDD | 0.000 | 0.000 | 0.002 | 0.000 | 0.001 | 0.000 |
| CDD*(Central AC) | -0.041 | 0.004 | 0.026 | 0.005 | -0.025 | 0.006 |
| CDD*(Window AC) | -0.010 | 0.006 | 0.019 | 0.006 | 0.023 | 0.007 |
| HDD*(Electric Heat) | 0.567 | 0.060 | 4.869 | 0.313 | 4.429 | 0.287 |
| CDD*(Swim Pool) | 7.682 | 0.422 | -1.434 | 0.671 | 0.527 | 0.785 |
| Owned House | 0.052 | 0.012 | 0.003 | 0.012 | -0.023 | 0.014 |
| Single House | 0.081 | 0.010 | 0.051 | 0.010 | 0.097 | 0.012 |
| Dryer | 0.154 | 0.012 | 0.126 | 0.013 | 0.162 | 0.014 |
| No. of Observations | 17,759 | | 13,649 | | 16,102 | |

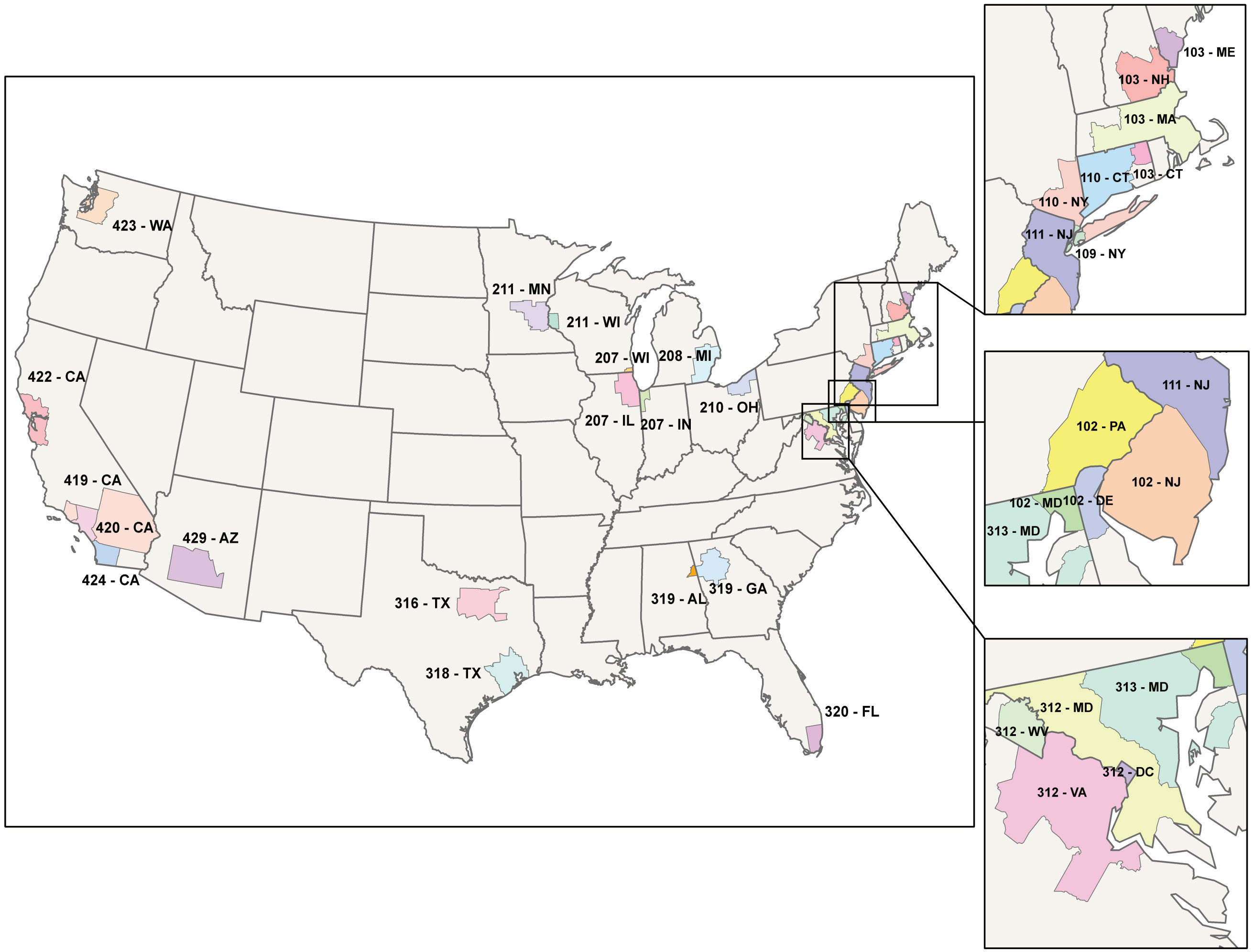
Notes: Estimates are from GMM. All regressions include PSU-state dummies, year dummies and month dummies.

Table 7: National Policy Simulation Results

| | 2012 | | | 2016 | | | 2025 | | | 2035 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\epsilon$ | $P^E$ | $Q$ | $P^A$ | $P^E$ | $Q$ | $P^A$ | $P^E$ | $Q$ | $P^A$ | $P^E$ | $Q$ | $P^A$ |
| $\epsilon_L$ | 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% | |
| $\epsilon_M$ | 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% | |
| $\epsilon_H$ | 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% | |

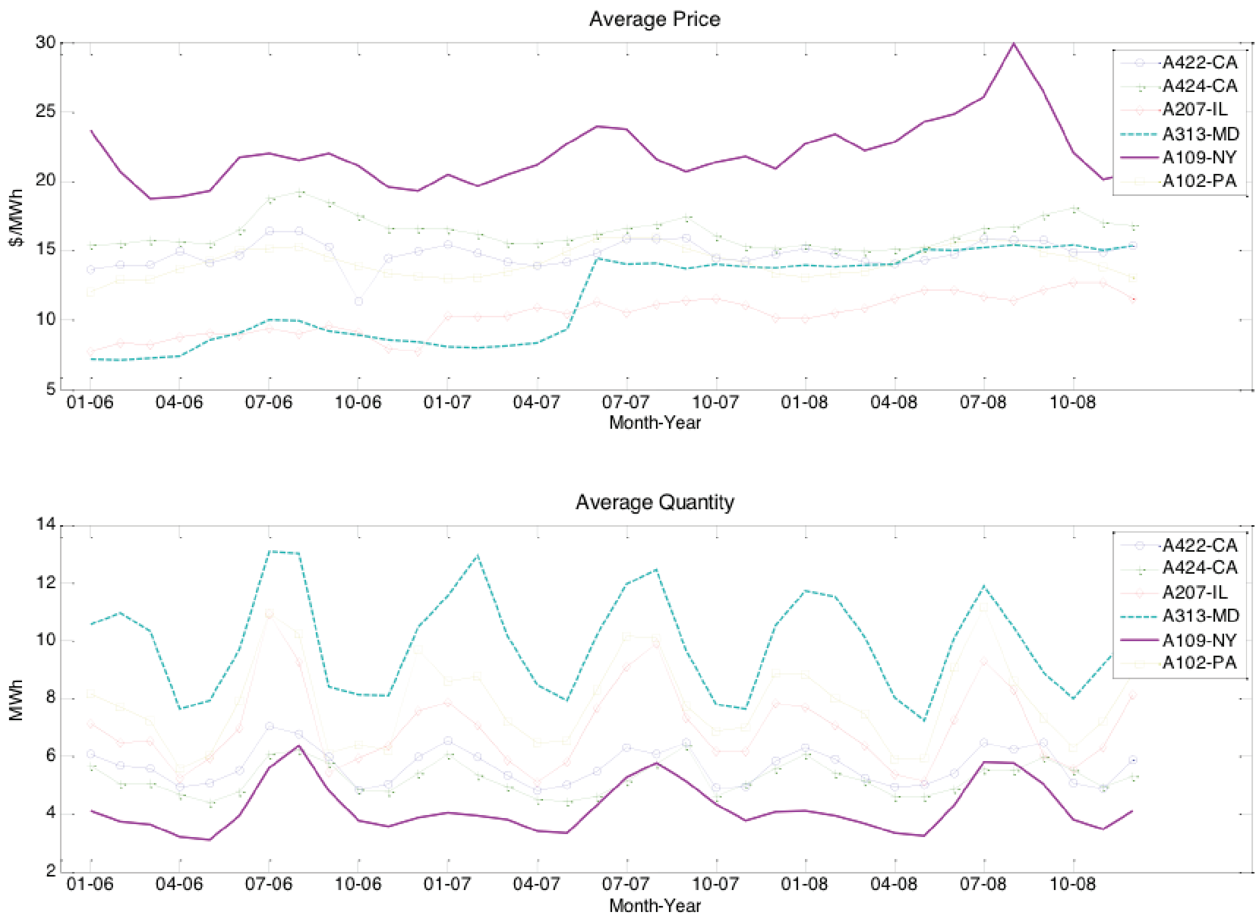
Notes: $P^E$ and $Q$ are the national average residential electricity price (\$/MWh) and national residential quantity consumed (TWh), respectively, for the year given. PA is the allowance price (\$/ton CO2) in the cap-and-trade system for the given year.

Figure 1: Primary Sampling Units



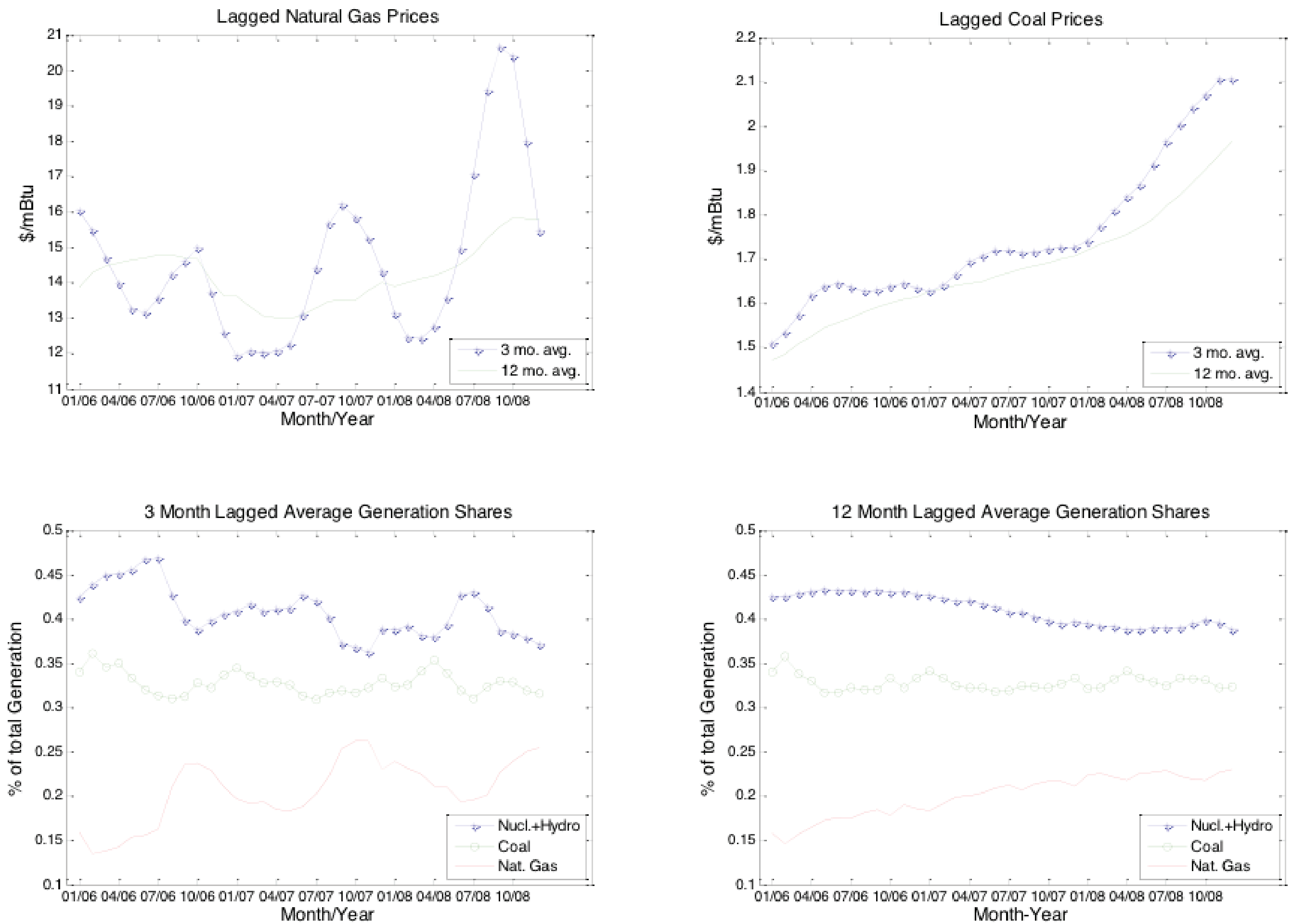

Notes: 37 PSU-state combinations from 21 large PSUs identified in the public CEX data.

Figure 2: Monthly Average Electricity Prices and Quantities



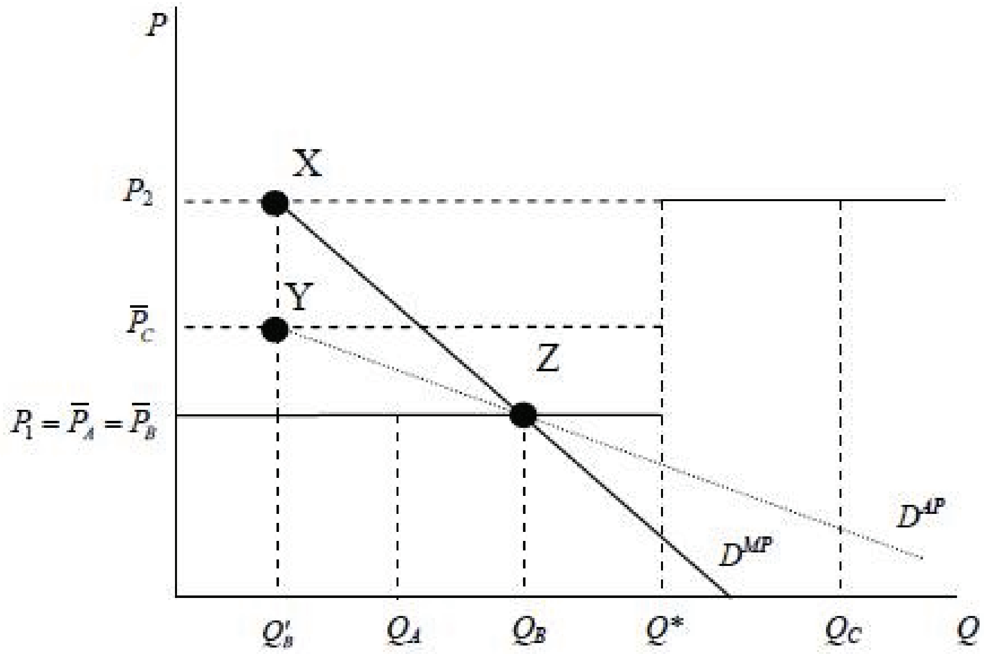

Notes: Monthly averages based on utility-level data of the PSU-states dominant utility.

Figure 3: Average Input Prices and Generation Shares




Notes: For natural gas and coal prices, 3 mo. Avg and 12 mo. Avg. refer to the average prices over the previous three and twelve months, respectively. For all series plotted, averages are across the six PSU-states in the baseline analysis.

Figure 4: Marginal Price versus Average Price Demand Curves




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