

Response of Residential Electricity Demand to Price: The Effect of Measurement Error

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Abstract

In this paper we present an empirical analysis of the residential demand for electricity using annual aggregate data at the state level for 48 US states from 1995 to 2007. Earlier literature has examined residential energy consumption at the state level using annual or monthly data, focusing on the variation in price elasticities of demand across states or regions, but has failed to recognize or address two major issues. The first is that, when fitting dynamic panel models, the lagged consumption term in the right-hand side of the demand equation is endogenous. This has resulted in potentially inconsistent estimates of the long-run price elasticity of demand. The second is that energy price is likely mismeasured.

To address these issues, we estimate a dynamic partial adjustment model using the Kiviet corrected Least Square Dummy Variables (LSDV) (1995) and the Blundell-Bond (1998) estimators. We find that the long-term elasticities produced by the Blundell-Bond system GMM methods are largest, and that from the bias-corrected LSDV is greater than that from the conventional LSDV. From an energy policy point of view, the results obtained using the Blundell-Bond estimator where we instrument for price imply that a carbon tax or other price-based policy may be effective in discouraging residential electricity consumption and hence curbing greenhouse gas emissions in an electricity system mainly based on coal and gas power plants.

JEL Classification: D, D2, Q, Q4, Q5.

Keywords: residential electricity and gas demand; US states, panel data, dynamic panel data models, partial adjustment model.

1. Introduction

Inducing residential consumers to use electricity more efficiently has been a growing concern for the government in many countries because of climate change, security of supply and an electric power system based on power plants that mainly use nonrenewable resources such as coal and oil. Buildings account for some 30-40% of energy use, and policy instruments are currently in use or are being considered at many locales to help reduce energy use in the residential sector. These include price increases through the introduction of an ecological tax, mandatory energy-saving measures in the construction and renovation of buildings, and subsidies to promote the construction and renovation of energy-saving buildings. These measures would encourage conservation or energy efficiency investments. Both are currently considered important for reducing CO₂ emissions, especially in the US, where coal-fired power plants account for a large share of electricity generation.

The effectiveness of a price policy depends upon the price elasticity of demand for electricity. Underlying this energy pricing policy question is the proper specification and estimation of an electricity demand equation. Much literature in the last 30 years has focused on the use of aggregate nationwide or state-level data to fit energy demand equations and estimate its elasticity with respect to price.

The majority of these studies have used panel data and a dynamic adjustment approach (Halvorsen (1975), Houthakker (1980), Baltagi et. Al. (2002), Kamerschen and Porter (2004), Bernstein and Griffin (2006) and Paul et al. (2009)). Because they use panel data, most of these studies control for unobserved heterogeneity using fixed or random effects, sometimes combined with a simple instrumental variable approach. The short-run price elasticities of the

residential demand for electricity in the US range from -0.20 to -0.35, and the long-run price elasticity vary even more widely, ranging from -0.3 to -0.8.

With the exception of Baltagi et al. (2002), however, most of these studies have failed to recognize and address the possible endogeneity of lagged consumption, which is often included in the right-hand side of the demand equation, and so the estimates of the price elasticity are suspect. Moreover, these studies are generally based on data from the 1970s and the 1980s, and there is no reason to believe that the same responsiveness to price changes observed in periods of rapidly increasing prices (e.g., the 1970s and early 1980s) would hold in periods of stable or decreasing energy prices (Haas and Schipper, 1998).

Despite the potentially serious consequences on the estimated price elasticity, in the literature little attention has been devoted to the possibility that the price of energy might be mismeasured. In two recent studies that use household-level data, Alberini et al. (forthcoming) and Fell et al. (2010) discuss the implications of energy prices that are measured with an error term and implement different approaches to address this problem. Neither exploits the dynamic nature of the data.

We wish to examine how sensitive the price elasticities are to the choice of the econometric estimation technique. From a policy perspective, understanding what drives the different results is important, because the different estimates of the price elasticity imply different conclusions about the effects of electricity pricing policies.

In this paper, we ask three research questions. First, what *are* the current short-run and long-run price elasticities of the residential electricity demand in the US? Second, are the estimates of the elasticity robust to attempts to address a major econometric problem with dynamic adjustment models of electricity demand, namely, the correlation between the lagged

demand and the error term? Third, how are results affected by the possibility that the energy price is mismeasured?

To answer these questions, we use a panel of data documenting annual residential energy demand at the state level in the US for 1995-2007. We estimate a partial adjustment model where the dependent variable is log electricity use per capita in the state (i.e., electricity consumption in the residential sector, divided by population), and the regressors, in addition to the lagged dependent variable, include the log transformations of the price of electricity, the price of the closest substitute (gas), income and other controls.

Holding the time period and the specification the same, we focus on the role of different estimation techniques suited for dynamic panel models. We experiment with bias-corrected least-squares dummy variables and Blundell-Bond GMM estimation, and further instrument for price to address the measurement error. We find that changing the estimation technique alone results in changes in the long-run price elasticity of electricity demand of up to 70%, whereas the short-term estimates can be as far apart as 88% of each other.

The remainder of the paper is organized as follows. We briefly review the literature in section 2. The model is described in section 3. The data are described in section 4. The econometric methods are described in section 5. The estimation results are presented in Section 5. Section 6 concludes.

2. Literature Review

Earlier efforts to study the residential electricity demand in the US using aggregate state-level panels include Halvorsen (1975), Houthakker (1980), Baltagi et. Al. (2002), Kamerschen

and Porter (2004), Bernstein and Griffin (2006) and Paul et al. (2009).¹ Virtually all of these studies include similar controls, such as weather and income, in the right-hand side of the model, but differ for the time period covered by the sample, the specification of the price variable, and the estimation procedure.

Regarding the time period covered, much of this earlier work relies on data from the 1970s and 1980s, and only Bernstein and Griffin (2006), and Paul et al. (2009) cover the years until 2006. The majority of these studies use average energy prices. In terms of specification of the model and estimation technique, fixed or random effects models were used, combined with a simple instrumental variable approach. The only study that uses recent advances in the estimation of dynamic panel data models (e.g., the Anderson and Hsiao, 1982, and Arellano and Bond, 1991, estimators) is Baltagi et. al. (2002), which, however, is based on old data (1970-1990).

The two most recent studies (Bernstein and Griffin, 2006, and Paul et al., 2008) use more recent data and dynamic models, but do not attempt to address the possibility that lagged consumption is endogenous, when included in the right-hand side of the regression equation. Specifically, Bernstein and Griffin (2006) estimate the electricity and gas consumption in the residential sector in the US using a panel of data at the state level from 1977 to 2004. The main goal of their study is to determine whether the relationship between prices and demand differs at the regional level.

They adopt a partial adjustment model that includes the average prices of electricity and gas, one-year lags for each of these variables, and lagged electricity consumption. Controls include per capita income and a climate index. These authors use a log-log functional form,

¹ For a recent exhaustive review on studies estimating the residential electricity demand see Espey and Espey (2004).

state-specific fixed effects, and year effects. When attention is restricted to residential electricity demand, the short- and long-term own price elasticities are -0.243 and -0.32, respectively. Bernstein and Griffin (2006) conclude that residential electricity demand is price-inelastic and that these elasticities are virtually the same as those from studies performed 20 years earlier.

Paul et al. (2008) use monthly average price and electricity demand data at the state level for 1990-2006. They specify partial adjustment models that include state fixed effects, monthly HDDs and CDDs, and daylight hours, among other controls. The price elasticities of demand are allowed to vary across states and regions. When averaged over the nation, the own price elasticity is -0.13 in the short run and -0.36 in the long run, confirming once again that the demand for electricity is price-inelastic.

Paul et al. argue that price is exogenous in the demand equation, but raise the possibility that demand might be serially correlated, in which case lagged demand and the state-specific fixed effects would be correlated, making the LSDV estimator biased and inconsistent. They report that attempts to instrument for lagged electricity demand using past prices (plus all of the exogenous variables) or past prices and past demand (plus all of the exogenous variables) were unsuccessful and resulted in unstable estimates. They therefore report only the LSDV estimation results.

In sum, the two most recent studies on residential energy demand both use the same econometric technique, LSDV, which is based on the “within” variation in all variables. Furthermore, these two studies do not attempt to address two major econometric problems with dynamic adjustment electricity demand models, namely, the correlation between the lagged demand and the error term, and the possibility that the average price of energy at the state level is affected by measurement error.

To our knowledge, the issue of mismeasured energy prices is rarely addressed in the literature. Alberini et al. (forthcoming) instrument for the price of electricity faced by households using state-level averages, which do not exploit the dynamic aspect of the data. They further check what happens to the estimates of the price elasticities when attention is restricted to those households for whom the measurement error is argued to be the smallest. Fell et al. (2010) take an entirely different approach, relying on a structural model that is estimated using GMM and omits prices altogether. As we explain below, in this paper we examine how the price elasticities change when econometric techniques are used that address all of these concerns.

3. The Model

Residential demand for energy is derived from the demand for a warm house, cooked food, hot water, lighting, etc., and can be specified using the basic framework of household production theory.² Households purchase “goods” on the market which serve as inputs to produce the “commodities” that enter in the argument of the household's utility function.³

In the US residential sector, the most important fuels used are electricity (100% of the households) and gas (~60% of the households). Fuel oil (~7% of the households), liquefied petroleum gas (LPG; ~1.5% of the households), and kerosene (~1.5% of the households) are less important. Ignoring the less common fuels, we assume that a household combines electricity, gas and capital equipment to produce a composite energy commodity.

The production function of the composite energy commodity S can be written as:

² See Thomas (1987) and Deaton and Muellbauer (1980). See Flaig (1990) and Filippini (1999) for an application of household production theory to electricity demand analysis.

³ Approximately 45% of the energy used in a household is for appliances and lighting, whereas space heating, water heating and air conditioning account for 30%.

$$S = S(E, G, CS) \quad (1)$$

where E is electricity, G is gas, and CS is the capital stock consisting of appliances. The output of the composite commodity S , namely energy services, is thus determined by the amount of electricity and gas purchased as well as the quantity of the capital stock of appliances.

Energy services S enters in the utility function of the household as an argument, along with aggregate consumption X . The utility function is influenced by household characteristics \mathbf{Z} and by the weather in the area where the household resides. We denote climate and weather variables as \mathbf{W} . Formally,

$$U = U(S(E, G, CS), X; \mathbf{Z}, \mathbf{W}) \quad (2)$$

The household maximizes utility subject to a budget constraint,

$$Y - P_S \cdot S - X = 0 \quad (3)$$

where Y is money income and P_S is price of the composite energy commodity. The price of aggregate consumption X is assumed to be one.

The solution to this optimization problem yields demand functions for E , G , CS and X :

$$E^* = E^*(P_E, P_G, P_{CS}, Y; \mathbf{Z}, \mathbf{W}) \quad (4)$$

$$G^* = G^*(P_E, P_G, P_{CS}, Y; \mathbf{Z}, \mathbf{W}) \quad (5)$$

$$CS^* = CS^*(P_E, P_G, P_{CS}, Y; \mathbf{Z}, \mathbf{W}) \quad (6)$$

$$X^* = X^*(P_E, P_G, P_{CS}, Y; \mathbf{Z}, \mathbf{W}) \quad (7)$$

Equations (4)-(7) describe the long-run equilibrium of the household. This model is static in that it assumes an instantaneous adjustment to new equilibrium values when prices or income change. Specifically, it is assumed that the household can change both the rate of

utilization and the stock of appliances, adjusting them instantaneously and jointly to variations in prices or income, so that the short-run and long-run elasticities are the same.

In this paper attention is restricted to the demand for electricity. Based on equation (4) and on the available data (see section 4) and using a log-log functional form we posit the static empirical model of electricity demand:

$$\ln E_{it} = \beta_i + \beta_{PE} \ln P_{PEit} + \beta_{GE} \ln P_{GEit} + \beta_{INC} \ln INC_{it} + \beta_{HS} \ln HS_{it} + \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \quad (8)$$

where E_{it} is aggregate electricity consumption per capita, INC_{it} is income per capita, P_{PEit} is the real average price of electricity, P_{GEit} is the real average price of gas, HS_{it} is household size, HDD_{it} and CDD_{it} are the heating and cooling degree days in state i in year t , and ε_{it} is the disturbance term.⁴ Since energy consumption and the regressors are in logarithms, the coefficients are directly interpreted as demand elasticities. The β_i terms allow for unobserved state-specific heterogeneity. Depending on the assumptions one is prepared to make about their correlation with the other right-hand side variables in (8), they may be regarded as fixed intercepts (“fixed effects”) or random variables (“random effects”).

Actual electricity consumption may differ from the long-run equilibrium consumption, because the equipment stock cannot adjust easily to the long-run equilibrium. A partial adjustment mechanism allows for this situation. This model assumes that the change in log actual demand between any two periods $t-1$ and t is only some fraction (λ) of the difference between the logarithm of actual demand in period $t-1$ and the logarithm of the long-run equilibrium demand in period t . Formally,

⁴ Functional forms commonly assumed when estimating ad-hoc energy demand models include the linear, semi-log and log-log forms. One of the advantages of the log-log functional form is that the coefficients are directly interpretable as demand elasticities. Xiao et. al. (2007) show in an empirical analysis of residential energy demand that the log-linear model is superior to the linear model.

$$\ln E_t - \ln E_{t-1} = \lambda(\ln E_t^* - \ln E_{t-1}) \quad (9)$$

where $0 < \lambda < 1$, and we have suppressed the i subscript to avoid clutter.

This implies that given an optimum, but unobservable, level of electricity, demand only gradually converges towards the optimum level between any two time periods. Assume that desired energy use (for example, desired electricity consumption) can be expressed as $E_t^* = \alpha \cdot P_E^\eta \cdot P_G^\theta \cdot \exp(\mathbf{X}\boldsymbol{\gamma})$, where η and θ are the long-term elasticities with respect to the price of electricity and gas, and \mathbf{X} is a vector of variables influencing demand for energy, including income, climate, characteristics of the stock of housing, etc. On inserting this expression into (9), we get

$$\ln E_t - \ln E_{t-1} = \lambda \ln \alpha + \lambda \eta \ln P_E + \lambda \theta \ln P_G + \lambda \mathbf{X}\boldsymbol{\gamma} - \lambda \ln E_{t-1}. \quad (10)$$

On re-arranging and appending an econometric error term, we obtain the regression equation:

$$\ln E_t = \lambda \ln \alpha + \lambda \eta \ln P_E + \lambda \theta \ln P_G + \lambda \mathbf{X}\boldsymbol{\gamma} + (1 - \lambda) \ln E_{t-1} + \varepsilon. \quad (11)$$

This expression shows that the short-run elasticities are the regression coefficients on the log prices, whereas the long-run elasticities can be computed by dividing these short-run elasticities (i.e., the coefficients on the log prices) by the estimate of λ . In turn, the latter is easily obtained as 1 minus the coefficient on $\ln E_{t-1}$.

In this paper, the dynamic version of the electricity demand model based on the partial adjustment hypothesis is specified as:

$$\begin{aligned} \ln E_{it} = & \beta_i + \beta_E \ln E_{i,t-1} + \beta_{PE} \ln P_{PEit} + \beta_{GE} \ln P_{GEit} + \beta_{INC} \ln INC_{it} + \beta_{HS} \ln HS_{it} + \\ & + \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it}. \end{aligned} \quad (12)$$

In sum, in the remainder of this paper, we estimate equations (8) and (12), which we interpret as a static and dynamic model, respectively, of electricity consumption for the

representative consumer in the US. The parameters of interest are the short- and long-run elasticities with respect to the price of electricity. Our goal is to see how the estimates of the elasticities change when i) we model unobserved heterogeneity using fixed or random effects, ii) we deploy alternate estimation techniques for the dynamic model, and iii) regard price as mismeasured.

4. The Data

We compiled annual data for all the states in the US (50 states plus the District of Columbia, for a total of 51 units) from 1995 to 2007. For the purposes of this paper, however, attention is restricted to the contiguous US states (Alaska and Hawaii are excluded), and we further drop Rhode Island because of incomplete information. Descriptive statistics for the remaining 48 states are presented in table 1.

Residential electricity consumption figures and prices are provided by the Energy Information Agency. Population and household income are from the Bureau of Economic Analysis of the US Census Bureau.⁵ We obtained heating and cooling degree days from the National Climatic Data Center at NOAA. The typical size of a household is obtained by dividing population by the number of housing units, where the latter variable comes from the US Census Bureau.

⁵ The price of electricity and gas, and income, are converted to real prices by dividing by the consumer price index (Bureau of Labor Statistics, 2010).

Table 1. Definition of Variables and Descriptive Statistics. N=624.

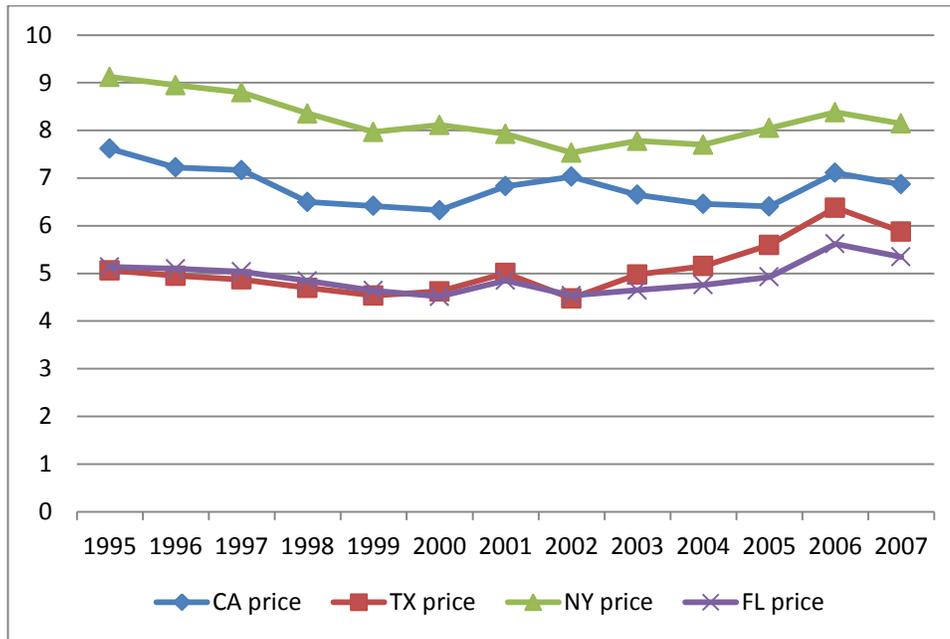
Variable	Label	Mean	Std. Dev.	Min.	Max.
electricity demand per capita, KWh	el_kwh	4537	1209	2147	7086
price of electricity per KWh (1982-84 dollars)	price per KWh	0.048516	0.012534	0.029797	0.091198
price of gas per cubic meter (1982-84 dollars)	price per m ³	0.005204	0.0015	0.002617	0.010445
population/detached houses	household size	2.34673	0.164712	1.888274	2.994109
Income per capita (thou. 1982-84 dollars)	Income per capita	14700	2346	10239	26120
heating degree days (base: 65° F)	HDD	5087.375	1998.374	555	10745
Cooling degree days (base: 65° F)	CDD	1142.109	795.8133	128	3870

Two key variables in the model are the prices of electricity and gas. Regarding the electricity price, the only information available at the state level for the residential sector is the average price, which is calculated by the EIA as the revenue of the utilities coming from the residential sector divided by electricity sales to the residential sector (as documented by the utilities in the EIA Form 861 submitted every year to the agency). The average gas price used in this study is calculated by the EIA as the total sales divided by gas consumption in the residential sector.

We display the price of electricity (in real 1982-1984 dollars) for selected states (California, Texas, New York and Florida, the four largest in terms of population) in Figure 1. Figure 1 shows that electricity prices vary dramatically between states. They also vary within a state over time, but to a much lesser degree. We remind the reader that during our study period, electricity markets were regulated everywhere until about 2000. Several states allowed deregulation starting in or around 2000, but even so, the price and provision of electricity to

residential and other customers is subject to the oversight and approval of the state public utility commission.

Figure 1: Price of electricity in selected states (cents per KWh, 1982-1984)



4. Econometric Specification and Estimation

A. Econometric Techniques

When static energy demand models are estimated using panel data, it is customary to account for unobserved heterogeneity using fixed or random effects. The appropriate estimation techniques are the “within” estimator (also termed LSDV, see Greene, 2007) and GLS (see Baltagi, 1996), respectively. We begin our empirical work with estimating the static model in equation (8) under these two alternate assumptions about the nature of the unobserved heterogeneity.

Next, we turn to dynamic equation (12). Dynamic panel data models that include fixed or random effects are problematic. A major concern is that the lagged dependent variable in the right-hand side might be serially correlated and hence correlated with the error term, which makes the LSDV and GLS estimators (for models with fixed and random effects, respectively) biased and inconsistent, since $(y_{i,t-1} - \bar{y}_{i,-1})$, where $y = \ln E$ and $\bar{y}_{i,-1}$ is the average lagged log consumption within state i , is correlated with $(\varepsilon_{it} - \bar{\varepsilon}_i)$ (see Baltagi, 1995). The bias of the coefficient of the lagged dependent variable vanishes as T gets large, but the LSDV and the GLS estimators remain biased and inconsistent for N large and T small.

Specifically, assuming that the coefficient on the lagged dependent variable is positive, it can be shown that its OLS estimate is biased upwards, while the LSDV estimator is biased downwards.⁶ Therefore, a consistent estimate should lie between the two, which suggests a possible estimation approach.

Kiviet (1995) derives an approximation for the bias of the LSDV estimator when the errors are serially uncorrelated and the regressors are strongly exogenous, and proposes an estimator that is derived by subtracting a consistent estimate of this bias from the LSDV estimator.⁷ An alternative approach is to first-difference the data, thus eliminating the state-specific effects:

$$(13) \quad \Delta y_{it} = \gamma \cdot \Delta y_{i,t-1} + \Delta \mathbf{x}_{it} \boldsymbol{\beta} + \Delta \varepsilon_{it}$$

where \mathbf{x} denotes all exogenous regressors in the right-hand side of equation (12), and to use $y_{i,t-2}$ and $\Delta \mathbf{x}_{it}$ as instruments for $\Delta y_{i,t-1}$ (Anderson and Hsiao, 1981).

⁶ For a discussion on this issue see Nickell (1981) and Harris et al. (2008).

⁷ Since the bias is negative if the true coefficient on the lagged dependent variable is positive, this means that we add a positive quantity to the LSDV estimator.

Arellano and Bond (1991) point out that the latter approach is inefficient and argue that additional instruments can be obtained by exploiting the orthogonality conditions that exist between the lagged values of $y_{i,t}$ and the disturbances in (13).⁸ The Arellano-Bond procedure is a generalized method of moments (GMM) estimator that is implemented in two steps. In practice, the Arellano-Bond estimator has been shown to be biased in small samples, and the bias increases with the number of instruments and orthogonality conditions. Moreover, Arellano and Bond (1991) show that the asymptotic approximation of the standard errors of their two-step GMM estimator is biased downwards, and Judson and Owen (1999) and Arellano and Bond (1991) find that the one-step estimator outperforms the two-step estimator.

In addition to the possible “instability” of the Arellano-Bond estimator with respect to minor changes in the selection of the instruments (see Harris et al., 2008, page 254), one concern is that the above mentioned estimators were developed primarily for situations with large N and small T . In our case, N is modest and should be treated as fixed (since the number of U.S. states does not change), and T is small. Using Monte Carlo simulations, Judson and Owen (1999) show that with balanced dynamic panels characterized by $T \leq 20$, and $N \leq 50$, as is the case here, the Kiviet corrected LSDV (LSDVC) estimator of γ (the coefficient on the lagged dependent variable) outperforms the Anderson-Hsiao and the Arellano-Bond estimators, in the sense that it has lower mean square errors.⁹ They also find that imposing restrictions on the number of lagged dependent variables and exogenous instruments to be used with the Arellano-Bond estimator does not materially reduce the performance of this technique.

⁸ See Baltagi (2008), p. 154, for details on the efficiency issues and chapter 8 for a discussion of the orthogonality conditions.

⁹ With unbalanced panels, by the time T reaches 30, Judson and Owen found the LSDV estimator without bias correction is superior to the Arellano-Bond estimators. Bruno (2005) develops the LSDVC estimator for unbalanced panels.

Under the additional assumption of quasi-stationarity of $y_{i,t}$, $\Delta y_{i,t-1}$ is uncorrelated with ε_{it} . Blundell and Bond (1998) suggest a “system” GMM estimation where one stacks the model in the levels and in the first differences, imposes the cross-equation restrictions that the coefficients entering in the two models be the same, and uses the full set of instruments (corresponding to the full set of orthogonality conditions for both models). Blundell and Bond report that in simulation the “system” GMM estimator is more efficient and stable than the Arellano-Bond procedure. Further, as shown by Hayakawa (2007), the small sample bias of the “system” GMM estimator is smaller than that of the Arellano-Bond estimator. This implies that this econometric approach can also be used with relatively small data sets.

Therefore, based on this discussion and the fact that our dataset has $N=48$ and $T=13$, we estimate our dynamic models using the LSDVC and the Blundell-Bond GMM (BB-GMM) estimators with various restrictions on the number of orthogonality conditions.¹⁰ Moreover, in this first round of estimation, we treat the price of electricity, the price of gas, HDDs, CDDs, population and household size as exogenous variables.

B. Prices and Measurement Errors

As mentioned, we use the average price of electricity to residential customers, as reported by the EIA, and in our first round of estimation we regard it as exogenous. Bernstein and Griffin (2006) and Paul et al. (2009) consider the average price as exogenous on the grounds that it is set by regulation. In what follows, we discuss three issues with the price variable,

¹⁰ A small N constrains the researcher to limit the number of instruments used for estimation. With a small N , it is important to keep the number of instruments less than or equal to the number of groups (or cross-sectional units, which in our case are the states) to improve efficiency and prevent the Sargan test from becoming weak. We use the second lag of the dependent variable as an instrument. We experimented with further lags, but observed a considerable loss of efficiency and rather imprecise estimates. See Cameron and Trivedi (2009) for a discussion of this issue.

namely i) whether average price is the appropriate price variable, ii) whether average price is endogenous or exogenous, and iii) the issue of measurement error.

Regarding i), there is considerable debate in the literature as to whether consumers respond to the marginal price or to the average price, which are different from one another in the presence of fixed fees and/or block pricing.¹¹ When utilities apply block pricing, the theoretically appropriate measure is block marginal price (Taylor, 1975; White and Reiss, 2005), which is clearly not available in this case. However, Shin (1985) argues that households will respond to average price, which is easily calculated from the electricity bill, rather than to actual block marginal price, which is costly to determine.¹² Using household-level data, Borenstein (2008, 2009) and Ito (2010) also support the hypothesis that households tend to respond to average price.

Depending on the nature of the data used, using the average price, however, can create an endogeneity problem. If micro-level data are used, two-part and block pricing schemes mean that the average price depends on the quantity consumed by the household, and are therefore endogenous with one another. At the aggregate level, however, Shin (1985) argues that the potential for the price to be endogenous with consumption—issue ii) above—is mitigated by the presence of many different pricing levels and schemes at different locales.

We are, however, concerned about iii), the issue of measurement error. Our price variable is computed by the U.S. Energy Information Administration (EIA) as the average revenue per kWh of sales by all electric power retailers to a State. For this reason, we are concerned that it

¹¹ Some utilities also use time-of-use rates. It would be interesting to analyze household electricity demand by time-of-use using aggregate data at the state level, but to our knowledge the data needed for this type of analysis are not available for the US. In the literature, there are only few studies that analyze the residential electricity demand by time-of-use using aggregate data. See Filippini (1995, 2010).

¹² Typically the US electric utilities utilize a block rate design. This implies that the marginal price for each household varies with the quantity of electricity consumed, and can vary from season to season, making it difficult for a household to keep track of it.

might be affected by measurement error. For starters, the EIA does sometimes “miss” some retail electricity suppliers. Second, the electric power retailers in a state may apply different tariff structures (block pricing, time-of-use pricing) that are poorly reflected in the data. Third, the EIA data are an ex post annual average, but consumers may make their decisions based on expected prices (Borenstein, 2008, 2009; Ito, 2010).

Standard econometric theory shows when a regressor is mismeasured, and the measurement error is classical (i.e., the measurement error has mean zero and is uncorrelated with the true regressor and with the econometric error term in the regression), the estimated regression coefficient is biased towards zero (Greene, 2007, p. 325). Here, this would make the demand appear to be more inelastic to price than it truly is.

How can one get around the problem of a mismeasured regressor? Suppose it was possible to find *another* measure of price, and that this new measure of price was also affected by measurement error. Let p_{it} be true price, and let observed price be $p_{it}^* = p_{it} + e_{it}$, where e_{it} is a classical measurement error (i.e., a disturbance term with mean zero and constant variance that is uncorrelated with true price and with all other variables in the regression equation). Let r_{it}^* be the additional proxy for price, with $r_{it}^* = p_{it} + u_{it}$, with u_{it} a classical measurement error. It can be shown that the covariance between these two mismeasured price variables is the variance of true price (i.e., $Var(p_{it})$), and this information can be used to correct the bias of the estimated coefficient on mismeasured price (Black and Kniesner, 2003).

Alternatively, r_{it}^* can be used to instrument for p_{it}^* and produce consistent estimates of the coefficient on p_{it}^* . In this paper, we use lagged prices (up to two lags) to instrument for

current prices. In sum, in the dynamic specification we combine instrumental variable estimation for one regressor, price, within the Blundell-Bond estimation of equation (13).¹³

5. Estimation Results

Table 2 displays the regression results for the static model. We account for unobserved heterogeneity by using fixed effects (and the LSDV estimation technique) in column (A) and random effects in column (B). All of the coefficients have the expected signs and are statistically significant. The “within” estimator produces slightly smaller price elasticities, but the GLS and within estimates are close (within 15% of each other). These results are in line with the results from the earlier literature.

Table 2. Estimation results: Static Model.

Dependent variable: log residential electricity consumption per capita	(A) Fixed Effects Model (LSDV)		(B) Random Effects Model (GLS)	
	Coeff.	T stat	Coeff.	T stat
Intercept	4.1042	10.36	5.1031	12.44
Lnpe1	-0.2179	-12.03	-0.2536	-13.25
Lnpgas	0.0486	4.73	0.0583	5.29
Lnice	0.2839	9.35	0.2171	6.83
Lnhs	-0.7476	-7.89	-0.7703	-7.87
LnHDD	0.1472	7.42	0.0948	4.78
LnCDD	0.0799	10.21	0.0864	10.35
sample size	624		624	
R square within	0.7970		0.7918	
R square between	0.0652		0.3401	
R square overall	0.1010		0.3270	

¹³ Our use of past prices as instruments is in contrast with Alberini et al. (forthcoming), where the instrument for individual prices is the state-level average price.

Table 3 displays the regression results for the dynamic model obtained using i) conventional LSDV, ii) LSDVC, iii) a selected variant of the BB-GMM (BB-GMM-1), and iv) a version of the BB-GMM (BB-GMM-2) where we instrument for price, which is endogenous if it is measured with error. Although we expect i) to be biased, we report it in table 4 for comparison purposes.

Most of the coefficients in the LSDV model have the expected signs and are statistically significant. However, as mentioned, due to the correlation between the lagged dependent variable and the error term, we expect the LSDV estimates to be biased and inconsistent.

The majority of the coefficients in the LSDVC model and in the BB-GMM-1 and BB-GMM-2 models have the expected signs and are statistically significant. Moreover, the p-value of the test statistics of serial correlation (for AR1 and AR2 processes) and overidentifying restrictions (Sargan) show that in the two BB-GMM models there is no significant second-order autocorrelation, which is crucial for the validity of the instruments. Furthermore, the p-value of the Sargan test statistic indicates that the null hypothesis that the overidentifying restrictions are valid is not rejected.

The results are comforting in that the coefficients on the price variables and that on the lagged dependent variable (which are used to compute the long-run elasticities) are significant and carry the expected signs in all models. The magnitude of the electricity price coefficients obtained using the LSDV, corrected LSDV, and Blundell-Bond GMM that instruments for electricity prices are relatively similar. This implies that the short-run elasticities will also be similar. It is striking that the Blundell-Bond GMM technique that assumes prices to be

exogenous produces a short-run elasticity that is only half as large as those from the other techniques.

As expected, the coefficient on the lagged dependent variable changes dramatically from one estimation procedure to the next. The LSDVC coefficient on this variable is about 36% larger than its LSDV counterpart. The two Blundell-Bond procedures results in estimated coefficients of 0.81 and 0.79, respectively. These two coefficients are very similar to one another, and represent a 19% increase over the LSDVC estimate, which in turn is larger than the LSDV estimate.

Based on these findings, we expect the long-term elasticities to be largest with Blundell-Bond GMM-2, and indeed this expectation is borne out in the elasticity figures displayed in table 4. Table 4 reports the estimates of the short and long-run own price elasticities, along with standard errors around them, for the consistent estimators of table 3. The estimated short-run own price elasticities vary between -0.08 and -0.15. These values imply that at least in the short-run, raising the price of electricity does not create much of an incentive for customers to decrease electricity consumption. Low as they might be, -0.15 is (in absolute magnitude) 88% larger than -0.08.

Table 3. Dynamic Model. Dependent variable: log residential electricity consumption per capita

	LSDV		LSDVC		BB-GMM1		BB-GMM2	
	Coeff.	t stat.						
intercept	1.858311	4.05			1.258141	1.38	0.483547	0.48
lagged lnelpc	0.49761	15.25	0.682531	19.64	0.811038	18.34	0.791011	23.63
lnpel	-0.15842	-9.85	-0.13812	-8.04	-0.08317	-2.24	-0.15235	-3.55
lnpgas	-0.03068	-2.55	-0.02745	-1.87	0.018566	0.86	0.008243	0.38
lnic	0.063719	1.78	0.052963	1.04	-0.09284	-1.29	0.045463	0.45
lnhs	-0.21625	-2.68	-0.14794	-1.32	0.004938	0.03	-0.2847	-1.7
lnhdd	0.093101	4.68	0.095626	4.56	0.065177	2.89	0.028774	1.4
lncdd	0.072958	10.65	0.076846	9	0.07682	5.91	0.06648	5.48
1997 year dummy	-0.02605	-5.83	-0.0301	-5.76	-0.03667	-5.79	-0.04352	-6.52
1998 year dummy	-0.00831	-1.43	-0.00886	-1.21	0.000143	0.01	-0.02003	-1.68
1999 year dummy	-0.01571	-2.7	-0.01883	-2.42	-0.01875	-1.99	-0.04026	-3.06
2000 year dummy	0.002348	0.37	-0.00103	-0.13	0.006231	0.47	-0.02339	-1.31
2001 year dummy	-0.00579	-0.72	-0.01455	-1.35	-0.02173	-1.18	-0.04763	-1.87
2002 year dummy	0.011643	1.49	0.003198	0.29	0.013855	0.72	-0.02027	-0.83
2003 year dummy	-0.00125	-0.14	-0.01664	-1.42	-0.01375	-0.66	-0.05044	-1.75
2004 year dummy	0.016889	1.66	0.002225	0.17	0.006182	0.27	-0.03573	-1.1
2005 year dummy	0.044141	3.89	0.027436	1.78	0.023867	0.9	-0.01469	-0.42
2006 year dummy	0.02346	1.82	-0.00127	-0.07	-0.02057	-0.78	-0.06262	-1.72
2007 year dummy	0.046243	3.85	0.024211	1.49	0.024613	0.91	-0.01721	-0.46
<i>Sargan test (p-value)</i>		0.0000				0.9922		0.1016
<i>Arellano-Bond AR1 test (p-value)</i>		0.0000				0.0000		0.0000
<i>Arellano-Bond AR2 test (p-value)</i>		0.2204				0.2204		0.1159

Note: BB-GMM-1 instruments for lag electricity up to second lags. BB-GMM-2 treats lag electricity and log price as endogenous. Instruments for lag electricity up to second lags and instruments for the price variable first and second lags. Note: Robust standard errors has been used for the computation of the t-values. Sargan test from Two-Step Estimator.

The story is much less clear-cut for the long-run elasticity. The estimated long-run own electricity price elasticities is approximately -0.43 in the LSDVC and BB-GMM-1 and -0.73 in the BB-GMM-2. The difference is striking (70%), and is mainly due to the fact that the different estimators produce widely different estimates of the coefficient on the lagged demand variable. Because the LSDVC and BB-GMM-1 estimators suffer from the bias determined by the measurement error of the electricity price variable, we regard BB-GMM-2 as the most appropriate estimation technique and its coefficient estimates as the most reliable. For this model, the own price elasticity is high enough that the impact of an increase of the electricity price on electricity consumption is relatively important, at least in the long run, and that a pricing policy holds promise.

Table 4. Short and long-run elasticities implied by the dynamic models.

	LSDVC	BB-GMM-1	BB-GMM-2
own price elasticity			
short run	-0.13812	-0.08317	-0.15235
long run	-0.43508	-0.44219	-0.72898
st err (LR elasticity)	0.127850	0.20996	0.191381

6. Conclusions

In this study, we have examined the demand for electricity in the residential sector in the US. For this purpose, a log-log static and a log-log dynamic model for electricity consumption were estimated using annual state-level data for 48 states over 13 years.

Several estimation techniques are possible for static and dynamic panel data models. Our dataset is characterized by a relatively small N and T, so we must choose the econometric

estimation technique judiciously. We use the LSDVC estimator proposed by Kiviet and the “system” GMM estimator proposed by Blundell and Bond (1998). Moreover, to remedy a possible measurement error in the electricity price variable, which makes state-level price and residential electricity econometrically endogenous, we also used a dynamic specification that combine instrumental variable estimation for one regressor, price, within the Blundell-Bond “system” estimation.

The short-run elasticities vary between -0.08 and -0.15, and the long run price elasticities between -0.45 and -0.75. Changing the estimation technique alone, therefore, changes the estimated elasticities by 70% -88%. Our preferred estimation technique is the Blundell-Bond that instruments for price, because it is stable, efficient and “safe” if the price is mismeasured, as we argue is the case. Neglecting this latter problem would understate the responsiveness to price, and indeed when we instrument for price to correct for the measurement error, the demand is more elastic.

From an energy policy point of view, the results obtained using the version of the BB-GMM (BB-GMM-2), where we instrument for price, imply that there is room for discouraging residential electricity consumption using price increases. Energy price increases may be attained, for example, by raising the tax levied per KWh sold. In an electricity system mainly based on power plants that burn fossil fuels, they may also result from imposing a carbon tax to curb greenhouse gas emissions (National Academy of Sciences, 2010) or follow from the implementation of a cap-and-trade program (US EPA, 2009, 2010; Congressional Budget Office, 2009). In the latter two cases, the reduction in energy consumption would presumably achieve additional reductions in CO₂ and conventional pollutant emissions with respect to those attained with the mere shift towards cleaner sources.

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