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Anna Alberini, Massimo Filippini

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Zurichbergstrasse 18 (ZUE E)
CH-8032 Zurich
www.cepe.ethz.ch

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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Anna **Alberini** and Massimo **Filippini**

Department of Agricultural Economics, University of Maryland, US
and
Centre for Energy Policy and Economics (CEPE), ETH Zurich

Centre for Energy Policy and Economics (CEPE), ETH Zurich
and
Department of Economics, University of Lugano, Switzerland

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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. We estimate a dynamic partial adjustment model using the Kiviet corrected LSDV (1995) and the Blundell-Bond (1998) estimators. In addition to the lagged dependent variable, our equation includes energy prices, income, cooling and heating degree days, and average household size. We find that the short-run own price elasticity of consumption is similar across LDSV, bias-corrected LSDV and the variant of the Blundell-Bond where we instrument for price. The short-run elasticity is the lowest when we use the Blundell-Bond GMM approach that treats the price of electricity as exogenous. The long-term elasticities produced by the Blundell-Bond system GMM methods are largest, and that from the bias-corrected LDSV 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 there is room, in an electricity system mainly based on coal and gas power plants, for discouraging residential electricity consumption and curbing greenhouse gas emissions by imposing a carbon tax.

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 of many individual country governments 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. Economists have suggested several energy policy instruments to reduce energy use in the residential sector: 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.

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.

Several papers have been published that estimate the US residential electricity demand using aggregate data at the state level over the last 30 years. 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)), and use similar controls in the right-hand side of the model. They differ from one another in the specification of the price variable, in the time period covered, and in the estimation procedure. The majority of the studies use average energy prices. Regarding the time period covered, much of this earlier work relies on data from the 1970s and 1980s, and only two recent studies (Bernstein and Griffin, 2006, and Paul et al., 2009) cover the years until 2006. In terms of specification of the model and estimation technique, the majority of the studies employed fixed or random effects models, 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 first-difference 2SLS estimator by Anderson and Hsiao (1982), and the GMM estimator on the first differences by Arellano and Bond (1991)) is Baltagi et. al. (2002), which, however, uses relatively 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.

With these possible limitations, the short-run price elasticity of the residential demand for electricity in the US ranges from -0.20 to -0.35. The estimates of the long-run price elasticity vary more widely, ranging from -0.3 to -0.8. Presumably, the variation in the results, especially in the long-run elasticities, is due to the different econometric approaches and the different periods covered by the samples. From the point of view of policy, 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 two research questions. First, what *are* the 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 certain econometric issues, including the possible endogeneity of lagged consumption and measurement error of the price variable?

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, household size, and HDDs and CDDs, plus state-specific effects. We use the bias-corrected LSDV (LSDVC) estimator proposed by Kiviet (1995) to address the possible endogeneity of lagged consumption in the dynamic panel model. We find that this bias-corrected estimator produces elasticities that are very close to those of the Blundell-Bond (1998) system GMM procedure. However, when we explicitly instrument for price to remedy the measurement error in the price variable, we get larger long-run price elasticities. From an energy policy point of view this latter result implies that there is room for discouraging residential electricity consumption using price increases. Of course, due to the fact that in the US a large amount of electricity is produced using coal power plants, the decrease in the electricity demand will also decrease the level of CO2 emissions.

The remainder of the paper is organized as follows. We briefly review some recent literature in section 2. The data and the different econometric specification and econometric issues are introduced in Section 3. The results of the estimation are presented in Section 4, and a summary and conclusions are presented in section 5.

2. Literature Review

In this section we review recent studies on the estimation of the US residential electricity demand using panel data at the state level.[1] 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

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

relationship between prices and demand differs at the regional level. They adopt a partial adjustment model that includes the 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, 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 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 LDSV 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 LDSV 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 energy price is endogenous due to measurement error. As we explain below, in this paper we explore how the price elasticities are affected by estimation techniques that address these issues.

3. A Model of Electricity Demand

Residential demand for energy is a demand 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), 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:

$$S = S(E, G, CS) \tag{1}$$

[2] For a clear presentation of the household production theory 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%.

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 **Z** and by the weather in the area where the household resides. We denote climate and weather variables as **W**. Formally,

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

The household maximizes utility subject to a budget constraint,

$$Y - P_S \cdot S - X = 0 \tag{3}$$

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:

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

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

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

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

Equations (4)-(6) 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 following static empirical model of electricity demand:

$$\ln E_{it} = \beta_P + \beta_{PE} \ln P_{Eit} + \beta_{PG} \ln P_{Git} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it} + \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \quad (8)$$

where E_{it} is aggregate electricity consumption per capita, Y_{it} is GDP per capita, P_{Eit} is the real average price of electricity, P_{Git} 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. Since energy consumption and the regressors are in logarithms, the coefficients are directly interpreted as demand elasticities.

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,

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

where $0<\lambda<1$.

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 $y_t^* = \alpha \cdot P_E^{\eta} \cdot P_G^{\theta} \cdot \exp(\mathbf{X\gamma})$, where η and θ are the long-term elasticities with respect to the price of electricity and gas, and 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

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

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

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

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 $\ln y_{t-1}$.

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

$$\ln E_{it} = \beta_P + \beta_E \ln E_{it-1} + \beta_{PE} \ln P_{Eit} + \beta_{PG} \ln P_{Git} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it}$$
$$+ \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \qquad (12)$$

where E_{it} is the aggregate electricity and gas consumption per capita, respectively. The price of electricity and gas, and income, are converted to real prices by dividing by the consumer price index (see Bureau of Labor Statistics, 2010).

4. The Data, the Econometric Model, and Estimation Issues

A. The Data

We compiled annual data for all the states in the US from 1995 to 2007. For the purposes of this paper, however, attention is restricted to the contiguous US states (no Alaska and Hawaii), 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 GDP are from the Bureau of Economic Analysis of the US Census Bureau. 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.

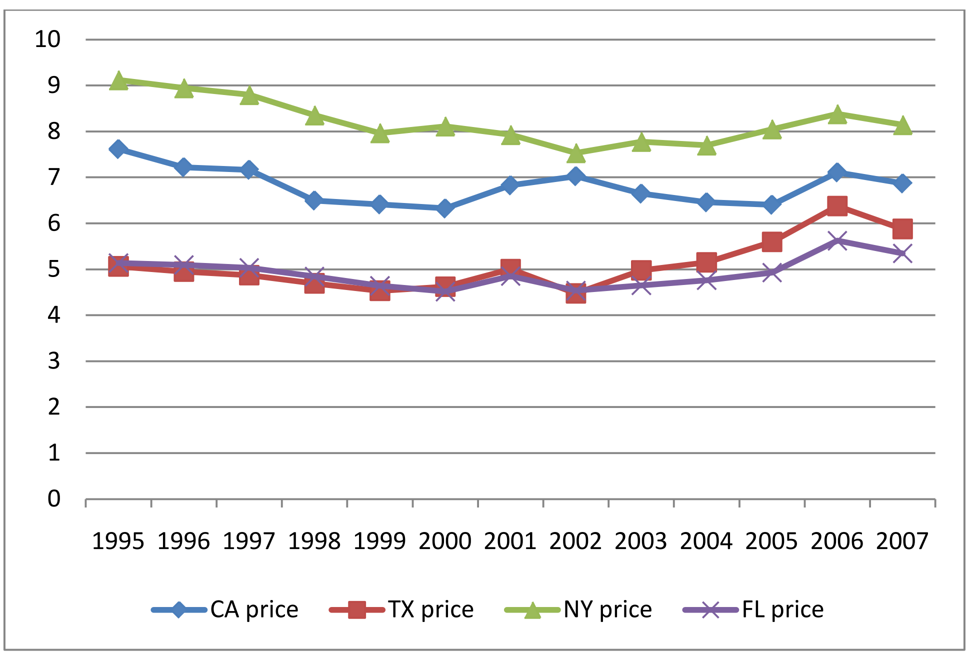
Table 1. Definition of Variables and Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Description
el_kwh	624	25172.22	24043.33	1554	126843	electricity demand, million KWh
Lnel	624	23.49429	1.035496	21.1641	25.56622	log electricity demand in KWh
gas_met	624	99.97596	120.2601	1	568	gas demand, billion m3
price per KWh	624	0.048516	0.012534	0.029797	0.091198	price of electricity per KWh (1982-84 dollars)
price per m3	624	0.005204	0.0015	0.002617	0.010445	price of gas per m3 (1982-84 dollars)
Lnpel	624	-3.0552	0.235832	-3.51334	-2.39473	log price of electricity
Lnpgas	624	-5.29867	0.28396	-5.94557	-4.56167	log price of gas
Popu	624	5863026	6275662	485160	3.64E+07	state population
Lnpop	624	15.11334	1.009303	13.09223	17.40946	log state population
household size	624	2.34673	0.164712	1.888274	2.994109	population/detached houses
Lnhs	624	0.850613	0.069219	0.635663	1.096647	log household size
Income	624	8.88E+07	1.01E+08	6072440	6.46E+08	income of the households in the state (thou. 1982-84 dollars)
Lnic	624	9.583698	0.152811	9.233979	10.17045	log income of the households per capita (in 1982-84 dollars)
Hdd	624	5087.375	1998.374	555	10745	heating degree days (base: 65F)
Cdd	624	1142.109	795.8133	128	3870	cooling degree days (base: 65F)
Lnhdd	624	8.430177	0.509631	6.318968	9.282196	log HDD
Lncdd	624	6.795657	0.728636	4.85203	8.26101	log CDD

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, and within states over time. 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)



B. The Econometric Model

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.

However, 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 $(y_{i,t-1} - \bar{y}_{i,-1})$ 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, it can be shown that the OLS coefficient on the lagged dependent variable is biased upwards, while the LSDV estimator is biased downwards.[4] 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. An alternative approach is to first-difference the data, thus swiping out the state-specific effects:

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

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

where **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).

Arellano and Bond (1991) point out that the latter approach is inefficient and argue that additional instruments can be obtaining by exploiting the orthogonality conditions that exist between the lagged values of $y_{i,t}$ and the disturbances in (13). The Arellano-Bond procedure is 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 sample, 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.

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.

In addition to the possibile "instability" of the GMM estimators 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) is better behaved than the Anderson-Hsiao and the Arellano-Bond estimators.[5]

However, as shown by Hayakawa (2007), the small sample bias of the "system" GMM estimator is smaller than the one of the Arellano-Bond estimator. Therefore, based on this evidence 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.[6] 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.

C. Prices and Measurement Errors

As mentioned, in our first round of estimation we regard the average price of electricity to residential customers, as reported by the EIA, as exogenous. However, since many utilities apply block pricing, the theoretically appropriate measure is block marginal price (Taylor, 1975), which is clearly not available in this case.

There are several reasons why it may be reasonable to use the average price. Shin (1985) argues that households will respond to average price, which is easily calculated from the

[5] 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 panel.

[6] 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.

electricity bill, rather than to actual block marginal price, which is costly to determine.[7] When micro-level data are used, block pricing schemes mean that the block marginal price and the quantity consumed are chosen simultaneously 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 is mitigated by the presence of many different block pricing levels and configurations at different locales. Bernstein and Griffin (2006) and Paul et al. (2009) regard the price of elasticity as exogenous in the demand equation on the grounds that it is set by regulation.

Despite these arguments, we reason that another problem yet may arise because of the way that the EIA calculates the electricity prices used in our regressions—namely measurement error, which makes state-level price and residential electricity econometrically endogenous.[8] Standard econometric theory shows when a regressor is mismeasured, and the measurement error is classical, the estimated regression coefficient is downward biased (Greene, 2007). 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

[7] 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.
[8] For a discussion on the problems generated by measurement error in the data on the estimated price elasticities of the agricultural demand for electricity in the US, see Uri (1994).

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.

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).

4. Estimation Results

Table 2 displays the regression results for the static model. 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	FE—LSDV		RE—GLS	
	Coeff.	T stat	Coeff.	T stat
Intercept	4.1042	10.36	5.1031	12.44
Lnpel	-0.2179	-12.03	-0.2536	-13.25
Lnpgas	0.0486	4.73	0.0583	5.29
Lnic	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	

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 0.82 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.

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

	LSDV		LSDVC		BB-GMM1		BB-GMM2	
	Coeff.	t stat.	Coeff.	t stat.	Coeff.	t stat.	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
dt3	-0.02605	-5.83	-0.0301	-5.76	-0.03667	-5.79	-0.04352	-6.52
dt4	-0.00831	-1.43	-0.00886	-1.21	0.000143	0.01	-0.02003	-1.68
dt5	-0.01571	-2.7	-0.01883	-2.42	-0.01875	-1.99	-0.04026	-3.06
dt6	0.002348	0.37	-0.00103	-0.13	0.006231	0.47	-0.02339	-1.31
dt7	-0.00579	-0.72	-0.01455	-1.35	-0.02173	-1.18	-0.04763	-1.87
dt8	0.011643	1.49	0.003198	0.29	0.013855	0.72	-0.02027	-0.83
dt9	-0.00125	-0.14	-0.01664	-1.42	-0.01375	-0.66	-0.05044	-1.75
dt10	0.016889	1.66	0.002225	0.17	0.006182	0.27	-0.03573	-1.1
dt11	0.044141	3.89	0.027436	1.78	0.023867	0.9	-0.01469	-0.42
dt12	0.02346	1.82	-0.00127	-0.07	-0.02057	-0.78	-0.06262	-1.72
dt13	0.046243	3.85	0.024211	1.49	0.024613	0.91	-0.01721	-0.46
Sargan test (p-value)		0.0000				0.9922		0.1016
Arellano-Bond AR1 test (p-value		0.0000				0.0000		0.0000
Arellano-Bond AR2 test (p-value)		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, 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.

own price elasticity	LSDVC	BB-GMM-1	BB-GMM-2
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

5. Summary and 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 long run price elasticities vary between -0.45 and -0.75.

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 the mere shift towards cleaner sources.

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