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Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities

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Meta-analysis is used to quantitatively summarize previous studies of residential electricity demand to determine if there are factors that systematically affect estimated elasticities. In this study, price and income elasticities of residential demand for electricity from previous studies are used as the dependent variables, with data characteristics, model structure, and estimation technique as independent variables, using both least square estimation of a semi-log model and maximum likelihood estimation of a gamma model. The findings of this research can help better inform public policy makers, regulators, and utilities about the responsiveness of residential electricity consumers to price and income changes.

Key Words: electricity demand, income elasticity, meta-analysis, price elasticity, residential electricity demand

JEL Classifications: Q40, Q41, D12

Many econometric studies of residential electricity demand have been conducted over the years, particularly during the 1970s and early 1980s when energy prices were rising rapidly and concerns about energy conservation increased. Recently, deregulation, record cold winter temperatures, unstable oil prices, and continuing global warming concerns have rekindled interest in understanding the demand for electricity, particularly in predicting the impact of price changes on consumption. Given the variety of energy sources used to generate electricity, understanding consumers' responsiveness to electricity price changes can help municipalities, utility companies, and policy makers predict future energy needs and design pricing and taxation policies.

Many models of electricity demand have been estimated over the years in an effort to better understand the market. These models have varied in numerous ways, using different functional forms and estimation techniques, as well as covering different time periods and different parts of the world. One goal of each of these models was to estimate the residential consumers' price and income elasticities of demand, but the broad spectrum of estimates can create confusion without more detail about the differences in data and analysis techniques utilized. For example, price elasticities reported in the literature range from 0.076 to −2.01 for the short run and −0.07 to −2.5 for the long run.

A recent review by Stanley discusses the process of meta-regression analysis and its usefulness as an analytical tool for economic evaluation in areas where there is wide study-to-study variation in results such as is found with residential electricity demand. Our study utilizes meta-regression analysis to summarize the electricity demand research and determine

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if there are factors that systematically influence estimates of price and income elasticities. Short-run and long-run income and price elasticity estimates reported in previously published research are analyzed. Previous meta-analyses of elasticities include Assmus, Farley, and Lehmann and Tellis of sales marketing elasticities; Espey of gasoline demand; and Espey, Espey, and Shaw of residential water demand analysis. Such studies use meta-analysis to analyze estimates of price and/or income elasticities derived from previous studies and explain differences as a function of cross-study data and analysis differences. Elasticity estimates, rather than the coefficient estimates for price and income, are used as the dependent variables in the meta-analysis because elasticities are unit-free, easily interpreted, and comparable across studies.

Taylor and Bohi also recognized the confusing range of empirical estimates of price and income elasticities of residential electricity demand and sought to explain the variation by categorizing and summarizing many of the energy studies then available. This research, however, differs significantly from theirs in that the influence of study characteristics is estimated quantitatively using regression analysis, rather than simply categorized and discussed qualitatively. Furthermore, the number of studies of electricity demand has increased greatly, with nearly half of the studies included here, and well more than half of the total elasticity estimates, published after Bohi's research.

Data

This study analyzes peer-reviewed journal articles of residential electricity demand. Because time-of-day (TOD) studies are not directly comparable with non-TOD studies, this analysis does not include TOD studies. A search of the literature revealed 36 studies published between 1971 and 2000 covering the time period from 1947 to 1997, providing the basis for this meta-analysis. Many of these studies estimated more than one model with such things as the time period, functional form, and estimation technique varying across models. Among these estimates were five positive short-run price elasticities, four negative short-run income elasticities, and two negative long-run income elasticities—usually the result of small sample sizes and not statistically significant—that were excluded from the meta-analysis. Exclusion of these estimates also aids in estimation of the gamma model as explained in the next section. It is worth noting, however, that comparison of the truncated and untruncated ordinary least squares estimates of the meta-analysis model indicates exclusion does not significantly affect the results. After excluding these estimates, these 36 studies yielded 123 estimates of short-run price elasticity, 125 estimates of long-run price elasticity, 96 estimates of short-run income elasticity, and 126 estimates of long-run income elasticity as shown in Table 1.

For the data set used in this analysis, short-run price elasticity estimates range from -2.01 to -0.004 with a mean of -0.35 and median of -0.28. Long-run price elasticities range from -2.25 to -0.04 with a mean of -0.85 and median of -0.81. Short-run income elasticity estimates range from 0.04 to 3.48 with a mean of 0.28 and median of 0.15. Long-run income elasticities range from 0.02 to 5.74 with a mean of 0.97 and median of 0.92.

Empirical Model

Four models are estimated with the following dependent variables related to residential electricity demand: short-run price elasticity, long-run price elasticity, short-run income elasticity, and long-run income elasticity. Elasticity estimates are used for the dependent variables rather than coefficient estimates for price and income because elasticities are unitless and easy to interpret and compare across studies. Since the variance of the elasticity estimates is rarely reported in the studies reviewed, its use in weighting the estimates in the meta-analysis is precluded.

The short-run price elasticity data are skewed with the greatest density between 0 and -1, the median at -0.28, few observations greater than 0, and the number of obser-

Table 1. Useable Estimates

Author(s)	Year Published	Short-run Price	Long-run Price	Short-run Income	Long-run Income
Acton, Mitchell, and Mowill	1976	14	—	14	—
Anderson	1973	1	2	1	2
Archibald, Finifter, and Moody	1982	2	—	2	—
Barnes, Gillingham, and Hagemann	1981	2	—	2	—
Beenstock, Goldin, and Nabot	1999	—	3	—	3
Beierlein, Dunn, and McConnon	1981	3	3	2	2
Bernard, Bolduc, and Belanger	1996	2	—	2	—
Berndt and Samaniego	1984	4	4	4	4
Branch	1993	1	—	1	—
Dubin and McFadden	1984	5	4	8	4
Garbacz	1984	10	—	10	—
Garcia-Cerrutti	2000	2	2	2	2
Gill and Maddala	1976	7	7	7	7
Halvorsen	1975	—	7	—	7
Halvorsen	1976	2	—	2	—
Henson	1984	19	—	—	—
Herriges and King	1994	3	—	—	5
Hewlett	1977	4	1	4	1
Houthakker, Verleger, and Sheehan	1974	1	1	1	1
Houthakker	1980	14	15	13	14
Hsaio and Mountain	1985	—	—	2	—
Hsing	1995	3	3	3	3
Kokkelenberg and Mount	1993	5	5	5	5
McFadden, Puig, and Kirshner	1978	2	2	1	1
Munley, Taylor, and Formby	1990	3	—	3	—
Murray et al.	1978	3	—	—	3
Parti and Parti	1980	1	—	—	—
Rothman, Hong, and Mount	1994	—	3	—	3
Shin	1985	2	4	2	2
Silk and Joutz	1997	1	1	1	1
Smith	1980	—	54	—	54
Terza	1986	4	—	—	—
Uri	1976	1	1	1	1
Walker	1979	1	—	—	—
Wilder and Willenborg	1975	1	1	1	1
Wilson	1971	—	1	—	—
Total		123	125	96	126

vations tapering off beyond −1. The long-run price elasticity data are similarly skewed, with the median at −0.81 and the number of estimates tapering off beyond −1.5. The income elasticities are also skewed with the distribution on the opposite side of the origin. The gamma distribution is useful for modeling populations with skewed distributions such as those that exist for these elasticity estimates (Mendenhall, Wackerly, and Scheaffer, p. 165). This study includes both generalized least squares (GLS) estimation of a semi-log model using White's heteroscedastic consistent covariance and maximum likelihood estimation of the model assuming a gamma distribution. In estimation of the gamma model, an additional parameter (the shape parameter), is estimated that reflects the degree of skewness.

The gamma distribution is a member of the linear exponential family. Gourieoux, Monfort, and Trognon have shown that this kind of family gives consistent and asymptotically normal estimators of the parameters of the first order moment of the true distribution. Termed pseudo maximum likelihood, this approach involves "maximizing a likelihood associated with a family of probability distributions which does not necessarily contain the true distribution" (Gourieoux, Monfort, and Trognon, p. 681). The calculated standard errors for the estimated parameters of the gamma model are robust to distributional misspecification. Since the gamma distribution is not defined for values less than or equal to zero, actual estimation in this study requires truncation at zero, meaning exclusion of the positive price elasticity estimates and the negative income elasticity estimates, as well as the use of absolute values for price elasticities.

The basic hypothesis of this analysis is that the variation in elasticity estimates arises because of differences in (a) the specification of electricity demand, (b) the nature of the data, (c) the time and location of the study, and/or (d) the econometric estimation technique. These characteristics are described below, with summary statistics presented in Table 2.

Demand Specification

This category covers structural versus reduced-form demand, lag structure, the inclusion or exclusion of potentially significant explanatory variables, and functional form.

Most commonly, electricity demand has been estimated using a reduced-form, double-log static model. However, numerous researchers have estimated a structural model of electricity demand using simultaneous equations to jointly estimate appliance stock demand and electricity use, for example. It has also been common to postulate some lag structure in electricity demand estimation to reflect the fact that some adjustments in usage take time, such as the acquisition of new appliances. The most common lag structure is the use of a lagged dependent variable. Other lag structures have been estimated, but due to the infrequency of these observations, they are grouped together into an "other lags" category for the meta-regression analysis.

Variables commonly included in electricity demand include some measure of appliance stock; the price of substitute fuels; and some measure of temperature, usually heating and cooling degree days. Other variables considered in this analysis were inclusion or exclusion of house size (e.g., square footage) and education level and age of household members, none of which were found to be statistically significant, and therefore are not included in the final model. Household size (number of people) was only found to be significant for long-run income elasticity.

Researchers have also modeled electricity demand using a variety of functional forms including linear, semi-log, and logistic forms. Since no functional form other than double-log and linear was used more than three times, functional form was divided into double-log and non–double-log for estimation of the meta-analysis model.

Data Characteristics

This category includes the measurement of the dependent variable, electricity consumption, as either an aggregate measure or a per household measure, whether cross-sectional, time series, or cross-sectional–time series data were used, and the time interval of the data (either monthly or annual).

The price specification and rate structure are also included. Although most studies use the marginal price of electricity, many use the average price. Other price specifications, such as the Shin price perception model, appeared in the literature, but due to the limited number of observations, only marginal and average price were used in the final meta-analysis. Flat rates, decreasing block rates, and increasing block rates all appeared in the literature, with studies encompassing a variety of these most common.

Time and Location

This category includes information about the setting of each study and the data years ana-

Table 2. Variable Means

Variable	Short-run Price	Long-run Price	Short-run Income	Long-run Income
Elasticity	−0.35	−0.85	0.28	0.97
Demand specification				
Reduced form	0.77	0.85	0.74	0.86
Structural	0.23	0.16	0.26	0.14
Static	0.60	0.56	0.55	0.56
Dynamic	0.40	—	0.45	0.44
Lag dependent variable	—	0.34	—	—
Other lag	—	0.10	—	—
Stock included	0.61	0.13	0.55	0.12
Substitutes included	0.54	0.46	0.68	0.44
Temperature included	—	—	0.76	—
Household size	—	—	—	0.17
Double log model	0.53	0.92	0.58	0.92
Non–double log model	0.47	0.08	0.42	0.08
Data characteristics				
Household level	0.49	—	—	—
Time series	0.11	0.56	0.14	0.56
Cross sectional	0.30	0.11	0.21	0.14
Cross sectional time series	0.59	0.33	0.65	0.30
Monthly	0.41	0.08	0.44	0.06
Annual	0.59	0.92	0.56	0.94
Average	0.36	0.7	0.39	0.71
Marginal	0.64	0.27	0.61	0.29
Increasing block	0.07	—	—	—
Decreasing block	0.39	0.60	0.42	0.58
Time and location				
Aggregate	0.36	0.26	0.50	0.25
Regional	0.64	0.74	0.50	0.75
United States	0.95	0.92	0.92	0.94
Non–United States	0.05	0.08	0.08	0.06
Pre-1972	0.34	0.82	0.40	0.81
1972–1981	0.85	0.82	0.81	0.79
Post-1981	0.11	0.11	0.11	0.15
Publication year	1983	1982	1982	1982
Estimation technique				
Ordinary least squares	0.37	0.08	0.32	0.09
Non–ordinary least squares	0.63	0.92	0.68	0.91

lyzed. Of the electricity demand models analyzed, about one third are estimated using aggregate data encompassing the entire contiguous 48 states. Several analyze regions of the United States such as the Pacific Northwest, whereas others analyze demand in a particular city such as Los Angeles or use data obtained from specific utility companies or service areas such as the Tennessee Valley Authority. All nonaggregate studies are categorized as "regional" studies. Several of the studies included in this analysis modeled the demand for electricity in other countries including Mexico, Costa Rica, Canada, and Israel. The influence of these studies is estimated by including a "non-U.S." dummy variable.

The data years are classified as pre-1972, 1972–1981, and post-1981. These categories are nonexclusive. That is, if the electricity demand study included data from more than one of these time periods, the dummy variable for each included time period would take on a value of one. These time periods are chosen as significant periods of change in energy markets, with OPEC asserting its strength around 1972 and a steady decline of the influence of OPEC and fuel prices after 1981. Publication year was also included to determine if there have been systematic changes in elasticity estimates over time.

Estimation Method

Finally, the estimation technique of each of the studies is considered. Ordinary least squares is the most common technique employed. Other techniques include instrumental variables, two- and three-stage least squares, and error components models. Since none of these techniques was used very frequently, they were all grouped into a non–ordinary least squares (OLS) category.

Other

To determine the influence of individual studies from which multiple elasticity estimates were included, dummy variables were created for each study from which more than 10% of the observations for the meta-analysis were derived. Only Acton, Mitchell, and Mowill (in short-run price and income), Garbacz (short-run income), and Houthakker (long-run price and income) were statistically significant.

In addition to inclusion of study dummy variables as a means of assessing the influence of individual studies, Chow predictive tests and estimation of intrastudy error correlations were also conducted. Similar to the estimation of study dummy variables, the Chow predictive test is estimated for each study from which more than 10% of the observations for the meta-analysis were derived. Since for most studies there are not enough degrees of freedom to run the regression for just that study, the Chow *F*-test statistics were computed using the full data set and the subset of data with a given study excluded (Greene). The only significant results were for Smith in the long-run price elasticity equation and for Houthakker in the long-run income elasticity equation. Results are therefore presented for both the full data set and these significantly different subsets.

Intrastudy error correlations are also estimated for all studies from which more than 10% of the observations for the meta-analysis were derived. Similar to autocorrelation or cross-sectional correlation, OLS would produce unbiased but inefficient estimates in the presence of intrastudy error correlation. For the short-run price elasticity model, intrastudy error correlation estimates were significant for both Acton, Mitchell, and Mowill and Houthakker. For the short-run income elasticity model, correlation estimates were only significant for Acton, Mitchell, and Mowill. Neither long-run model displayed significant intrastudy error correlation. Since standard error correlation corrections depend on normally distributed errors and the skewness of the data in this study suggests nonnormality of errors, rather than attempting to correct for the correlation, regression results for both the full data set and the subset of data omitting the relevant studies are presented.

Results

All of the models were estimated using both the gamma and the GLS specification with White's heteroscedastic consistent covariance and the dependent variable in semi-log form. Results are presented in Tables 3–6. Since several sets of mutually exclusive dummy variables are used, one characteristic from each set of mutually exclusive characteristics is excluded, thus serving as a "base" for comparison. Hence the coefficient estimates shown in Tables 3–6 should be interpreted as deviations from the base model comprised of the omitted variables. This base model used for comparison is a double-log, static, reduced-form OLS model using annual cross-sectional–time series data for the aggregate United States and a marginal price for electricity. All tests of significance are two-sided.

Price Elasticity

Results from the estimation of the gamma and semi-log meta-analysis models for short-run price elasticity are presented in Table 3 and long-run price elasticity in Table 4. Coefficient estimates for short-run price elasticity for the GLS and gamma models are shown both with and without the only significant study dummy variable (Acton, Mitchell, and Mowill) and without the data from Acton, Mitchell, and Mowill and Houthakker, the two studies with significant intrastudy correlation. Coefficient estimates for long-run price elasticity for the GLS and gamma models are shown both with and without the only significant study dummy variable (Houthakker), as well as without the data from Smith, the only study for which the Chow test was significant. There were no significant Chow tests of individual studies for the short-run data, and no studies with significant intrastudy correlation for the long-run data.

In general, the sign and significance of coefficients are consistent across these meta-analysis models for both short-run and long-run price elasticity. However, the gamma model resulted in a significantly higher log-likelihood value than GLS for all but the long-run price elasticity model estimated for the subset of data without Smith. Further, the pseudo R^2, or the squared correlation coefficient between the observed and predicted values, for the gamma models were greater than the adjusted R^2 for the GLS in all cases. Note that in interpreting the coefficients, price elasticity is specified in absolute value; thus a positive coefficient implies a more elastic demand, whereas a negative coefficient implies a less elastic demand.

Demand specification. Although reduced-form models are less cumbersome and easier to estimate, structural equation models are considered to be more accurate as they separate the dynamic features of demand and allow for the identification of the sources of consumption behavior (Bohi). The meta-analysis indicates that there is a statistically significant difference between reduced-form models and structural models in terms of the short-run estimates of the price elasticity, but no significant difference for the long-run estimates.

Taylor pointed out that models that include a lagged dependent variable to capture long-run adjustments impose a fixed relationship between short-run and long-run elasticities, whereas other lag specifications do not necessarily do so. He did not suggest, however, that such models would bias estimates. This meta-analysis finds no significant difference among short-run estimates across various dynamic models, but dynamic models in general are found to produce significantly smaller short-run price elasticity estimates than static models. For the long run, models using a lagged dependent variable produce smaller estimates, but other lag structures do not consistently result in significantly different estimates from static models. This suggests care should be taken in estimating demand using dynamic models to avoid biasing estimates via specification of the lag structure.

Alternatively, one might separately estimate the components that comprise the long-run adjustments to price changes, such as changes in the stock of electricity-using appliances. Since the demand for electricity is a derived demand, it is a function of the demand for services provided by electricity-using appliances. In general, the appliance stock is assumed to be fixed in the short run and variable in the long run. Omission of stock in a long-run model would be expected to result in more elastic estimates of price elasticity, as all of the impact of a change in price would be picked up as a change in consumption, without differentiation between direct changes in consumption and indirect changes due to a change in stock (Anderson). As expected, this meta-analysis did find significantly smaller long-run price elasticity estimates derived from models that included stock. However, short-run models that included stock resulted in significantly larger estimates of price elasticity.

Basic demand theory indicates that there would be a positive cross-price elasticity between electricity consumption and the price of

Table 3. Short-Run Price Elasticity Results

	Full Data Set (n = 123)				Without Intrastudy Error Correlated Data (n = 96)	
	GLS1	GLS2	Gamma1	Gamma2	GLS3	Gamma3
Intercept	51.08	65.80*	45.02	68.99	76.60*	80.77*
Demand specification						
Structural	−0.65***	−0.38*	−0.70***	−0.35	−0.39*	−0.38*
Dynamic	−0.94***	−1.39***	−0.92***	−1.31***	−1.46***	−1.37***
Stock	0.89***	1.03***	0.95***	1.04***	1.07***	1.08***
Substitutes	0.14	0.21	0.18	0.29*	0.17	0.23
Non–double log	0.29	0.62**	0.31	0.73***	0.63**	0.73***
Data characteristics						
Household	0.26	−0.71	0.22	−0.81**	−0.67	−0.70*
Time series	0.96***	0.85**	0.84**	0.70*	0.92**	0.81**
Cross sectional	−0.63**	−0.69***	−0.70***	−0.66***	−1.05***	−1.08***
Monthly consumption	−0.40	−0.03	−0.37*	0.07	−0.20	−0.15
Average price	0.68***	0.63***	0.61***	0.55***	0.55***	0.46***
Increasing block rate	−0.25	−0.14	−0.19	−0.06	−0.10	−0.02
Decreasing block rate	0.62**	0.53**	0.55**	0.47**	0.47*	0.42*
Time and location						
Regional	0.45**	0.63***	0.25	0.44***	0.66***	0.49***
Non–United States	−0.32	−0.50	−0.38	−0.46	−0.65	−0.64*
1972–1981 data	−0.78***	−0.66***	−0.84***	−0.62***	−0.65***	−0.61***
Post-1981 data	−0.79***	−0.41	−0.81**	−0.30	−0.356	−0.24
Publication year	−0.027	−0.034*	−0.024	−0.036*	−0.039*	−0.042*
Estimation technique						
Non–ordinary least squares	0.73***	0.51***	0.64***	0.40**	0.45***	0.33*
Other						
Acton, Mitchell, and Mowill	—	−1.59***	—	−1.76***	—	—
Shape parameter	—	—	3.03***	3.41***	—	3.45***
Log likelihood	−123.47	−119.31	−112.98	−105.14	−95.06	−81.42
Adjusted R^2	0.43	0.46	0.50[a]	0.53[a]	0.43	0.53[a]

substitute fuels. To the extent that the price of substitute fuels is correlated with the price of electricity, the omission of the price of substitutes would bias the estimates of the price elasticity of electricity demand. This analysis indicates the omission of substitutes does not significantly influence short-run price elasticity estimates, but results in significantly lower long-run estimates.

Data characteristics. Use of time series data is generally considered to be a useful means of capturing long-run adjustments, and this study found estimates from time series studies to be significantly more elastic for both the short and the long run. On the other hand, models using cross-sectional data are considered to capture long-run effects if there is significant variation in prices and income. This study finds that cross-sectional studies produced smaller estimates than cross-sectional–time series or time series studies, suggesting that these cross-sectional studies may not have enough variation in price to capture long-run adjustments.

One of the most hotly debated questions in the literature is that of the appropriate price specification. Marginal price is by far the most common choice of researchers, and this price specification is a part of the base model for comparison in each of the meta-analysis models. Economic theory would dictate use of marginal price, but average price is often the only price measure available. Bohi suggests that "elasticity estimates related to marginal price tend to be smaller than those related to average prices." This corresponds to the findings of this meta-analysis for the short run, but there was no significant difference between studies using marginal and average price for the long-run estimates.

Although studies using monthly data are not found to produce significantly different short-run elasticity estimates, they are estimated to produce significantly more elastic long-run estimates than studies using annual data. Monthly data may allow more precise measurement of consumption responses to price changes that are obscured and averaged out through the use of annual data.

Time and location. Bohi suggests that aggregated data tend to produce larger long-run price elasticities, whereas disaggregated data tend to produce slightly larger short-run price elasticities. This study also finds short-run estimates derived from regional-level data to be smaller than those derived from national-level aggregate data, but no significant difference for long-run estimates.

Studies using non-U.S. data estimate the demand for electricity to be less elastic in the short run than those focusing on the U.S., but more elastic in the long run. This suggests that U.S. consumers may be quicker to respond to price changes, but less price sensitive overall in the long run than electricity consumers in other countries.

Results with respect to data years suggest that residential electricity demand was more inelastic in the short run during the energy crises of the 1970s, but not significantly different in the long run compared with either before or after that time. A priori one might expect that the price elasticity prior to 1972 was larger as electricity was arguably less of a necessity then. Rural customers, in particular, relied less on electricity than they do today. In addition, electric appliances such as air conditioners were less common. Over time, more and more appliances that consume electricity became a part of daily life, and consumers increasingly rely on appliances, reducing short-run price elasticity. On the other hand, dramatic improvements in the efficiency of many electric appliances has increased the options for consumers in the long run, perhaps offsetting this effect for long-run estimates.

Other. Finally, the shape parameters are all statistically significant and reflect the skew-

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Table 3. (Continued)

Notes: All t-tests are two-tailed.

[a] Adjusted R^2 is reported for generalized least squares (GLS) models, and the correlation between the observed and predicted values is reported for all gamma models.

* Significant at the .10 level.

** Significant at the .05 level.

*** Significant at the .01 level.

Table 4. Long-Run Price Elasticity Results

	Full Data Set (n = 125)				Alternative Data Set[a] (n = 72)	
	GLS1	GLS2	Gamma1	Gamma2	GLS3	Gamma3
Intercept	99.19***	79.18**	93.49*	61.44	90.44**	82.41*
Demand specification						
Structural	0.21	0.24	0.17	0.21	0.29	0.30
Lag dependent variable	−0.67***	−0.58***	−0.65***	−0.51**	−0.56***	−0.49**
Other lag	−0.53**	−0.31	−0.49	−0.22	−0.45*	−0.36
Stock	−1.11***	−0.98***	−1.12***	−0.99***	−1.07***	−1.04***
Substitutes	1.33***	1.34***	1.29***	1.26***	1.43***	1.38***
Non–double log	0.07	0.25	0.11	0.31	−0.04	−0.05
Data characteristics						
Time series	0.95***	0.86***	0.84***	0.70**	0.77**	0.59*
Cross sectional	−0.51	−0.47	−0.59*	−0.52	−0.49*	−0.53*
Monthly consumption	1.60***	1.52***	1.56***	1.45***	1.75***	1.73***
Average price	−0.15	0.19	−0.02	0.40	−0.17	−0.04
Decreasing block rate	−0.49***	−0.21	−0.51*	−0.15	−0.59***	−0.64**
Time and Location						
Regional	−0.06	−0.08	−0.03	−0.05	−0.10	−0.08
Non–United States	0.99***	0.86**	0.90**	0.75**	1.08***	1.01***
1972–1981 data	0.11	0.05	0.17	0.10	0.07	0.13
Post-1981 data	−0.23	−0.31	−0.25	−0.41	−0.18	−0.19
Publication year	−0.051***	−0.041**	−0.048*	−0.032	−0.046**	−0.043*
Estimation Technique						
Non–ordinary least squares	0.10	0.08	0.08	0.05	0.0001	−0.03
Other						
Houthakker	—	0.52*	—	0.61*	—	—
Shape parameter	—	—	3.88***	3.98***	—	4.71***
Log likelihood	−105.76	−104.81	−97.91	−96.32	−47.39	−48.90
Adjusted R^2	0.21	0.21	0.31[b]	0.31[b]	0.39	0.53[b]

ness of the distributions of short- and long-run elasticities. The mean of the short-run elasticities was much closer to zero with a longer tail, so one would expect to find a smaller shape parameter when compared with the long-run model that had a more normal distribution and a larger shape parameter for comparable models.

Income Elasticity

Results from the estimation of the gamma and GLS meta-analysis models for short-run and long-run income elasticities are presented in Tables 5 and 6. Coefficient estimates for short-run income elasticity for the GLS and gamma models are shown both with and without the only significant study dummy variables (Acton, Mitchell, and Mowill and Garbacz) and without the data from Acton, Mitchell, and Mowill, the only study with significant intrastudy correlation.

Coefficient estimates for long-run income elasticity for the GLS and gamma models are shown both with and without the only significant study dummy variable (Houthakker), as well as without the data from Smith, the only study for which the Chow test was significant. There were no significant Chow tests of individual studies for the short-run data, and no studies with significant intrastudy correlation for the long-run data.

In general, the sign and significance of coefficients are consistent across these meta-analysis models for both short- and long-run income elasticity. However, the gamma model resulted in a significantly higher log-likelihood value than GLS for all meta-analysis model specifications. Further, the pseudo R^2, or the squared correlation coefficient between the observed and predicted values, for the gamma models were greater than the adjusted R^2 for the GLS in all cases.

Demand specification. Structural models do not generally appear to produce different income elasticity estimates for residential electricity demand than reduced-form models. Structural models are often used to obtain consistent estimates when there is correlation between one of the explanatory variables and the error term. Simultaneity bias caused by correlation between income and the error term would tend to bias the estimate of the coefficient on income toward zero. Hence correction for simultaneity bias through use of a structural model would result in a more elastic estimate, as implied by the meta-analysis for the long-run elasticity for the first two gamma models.

Similar to the price models, the short-run estimates of income elasticity from dynamic models were found to be significantly smaller than from static models. There was no significant difference in the long-run estimates, however.

In the estimation of the income elasticity of demand for residential electricity, the inclusion of a measure of appliance stock significantly influences the results. Those models that include some measure of appliance stock estimate the income elasticity of the demand for residential electricity to be significantly lower, in both the short and long run, than those models that exclude stock as a variable. This could be due to the fact that models that include stock do not capture the full long-run influence of income changes on electricity demand, as income influences the level of appliance ownership, which in turn influences electricity consumption. Models that exclude stock, however, exclude a significant explanatory variable in the demand for residential electricity. Rather than excluding stock, long-run elasticity could be calculated by combining the impact of income changes on appliance ownership and direct and indirect changes in

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Table 4. (Continued)

Notes: All t-tests are two-tailed.

[a] Smith is omitted based on a statistically significant Chow test.

[b] Adjusted R^2 is reported for generalized least squares (GLS) models, and the correlation between the observed and predicted values is reported for all gamma models.

* Significant at the .10 level.

** Significant at the .05 level.

*** Significant at the .01 level.

Table 5. Short-Run Income Elasticity Results

	Full Data Set (n = 96)				Without Intrastudy Error Correlated Data (n = 82)	
	GLS1	GLS2	Gamma1	Gamma2	GLS3	Gamma3
Intercept	189.27***	53.77	204.54***	54.41	66.40	84.86
Demand specification						
Structural	−0.37	−0.09	−0.38	−0.16	−0.24	−0.19
Dynamic	−1.12***	−1.35***	−0.90**	−1.29***	−1.10***	−1.06***
Stock	−0.95***	−0.77**	−1.13***	−0.83**	−0.94**	−1.17***
Substitutes	−0.72***	−0.24	−0.72***	−0.17	−1.80***	−1.91***
Temperature	1.16***	1.51***	1.08***	1.45***	1.24***	1.05***
Non–double log	−0.08	−1.24***	−0.37	−1.59***	−0.80**	−1.05**
Data characteristics						
Time series	1.53***	0.77*	1.41***	0.83*	0.49	0.35
Cross sectional	−0.34	−0.15	−0.23	−0.12	−0.31	−0.27
Monthly consumption	−0.22	0.51	−0.02	0.83**	−1.11**	−1.11**
Average price	−0.03	−0.07	−0.05	−0.31	0.05	−0.09
Decreasing block rate	0.20	−0.16	0.01	−0.45	−0.08	−0.29
Time and location						
Regional	0.05	−0.62**	−0.13	−0.73***	−0.50	−0.60**
Non–United States	2.35***	2.50***	2.65***	2.71***	1.36***	1.36**
1972–1981 data	0.58*	0.55	0.86**	0.61**	0.62*	0.80**
Post-1981 data	1.19**	0.39	1.23**	0.21	0.97*	1.12**
Publication year	−0.10***	−0.03	−0.10***	−0.03	−0.03	−0.04
Estimation technique						
Non–ordinary least squares	−0.04	0.14	−0.29	0.01	0.003	−0.11
Other						
Acton, Mitchell, and Mowill	—	1.23***	—	1.07**	—	—
Garbacz	—	−2.46***	—	−2.77***	—	—
Shape parameter	—	—	1.78***	2.32***	—	1.90***
Log likelihood	−119.40	−107.75	−117.37	−102.70	−99.83	−97.08
Adjusted R^2	0.47	0.57	0.54[a]	0.64[a]	0.50	0.58[a]

electricity consumption in a simultaneous equations model.

Inclusion of the price of substitute fuels leads to significantly lower estimates of short-run income elasticity, but does not have a significant impact on long-run estimates. Since one would expect a positive cross-price elasticity between electricity demand and the price of substitutes, this result implies that there may be a positive correlation between income and substitute fuel prices in the short run, but no significant relationship in the long run.

In his electricity demand review, Taylor concluded that temperature was a significant variable in the demand for electricity, yet its exclusion would not be expected to bias price or income elasticity estimates. This study estimates that inclusion of some measure of temperature only influences estimates of short-run income elasticity, resulting in more elastic estimates. Similarly, Taylor determined household size to be a significant variable in estimation of electricity demand. If household size is positively correlated with both consumption and income, its exclusion would positively bias income elasticity estimates. Conversely, its inclusion would result in less elastic estimates, which this study found to be the case for the long run, but not the short run.

Data characteristics. In contrast to the price elasticity estimates, time series data did not produce significantly different long-run income elasticity estimates, but cross-sectional data is estimated to produce significantly more elastic estimates than cross-sectional–time series data in the gamma model. This implies that although cross-sectional data may not have enough price variation to produce long-run price elasticity estimates, there may be enough income variation to produce long-run income elasticity estimates.

Although this meta-analysis estimates that studies using monthly data did not produce significantly different estimates of long-run income elasticity, the short-run model results are inconsistent. The variable indicating use of monthly data in the short-run income elasticity meta-analysis model is the only variable in all models presented in this study that is significant but of opposite sign in different models. In three of the models it is statistically insignificant, whereas in the second gamma model with Acton, Mitchell, and Mowill and Garbacz dummy variables it is positive and significant, and in both models that exclude the Acton, Mitchell, and Mowill data it is negative and significant. Both Garbacz and Acton, Mitchell, and Mowill use monthly data, with the Acton, Mitchell, and Mowill estimates somewhat above the overall mean and Garbacz significantly smaller. Hence it is likely that the separation of Garbacz through the use of a study dummy variable and the heavier weight given to Garbacz in influencing the monthly variable when Acton is omitted biases the meta-analysis results, and that when special treatment or weight is not allotted to Garbacz, estimates from monthly data are probably not significantly different from those using annual data.

Interestingly, decreasing block studies resulted in higher estimates for the long-run income elasticity. This may be because increases in consumption could put households into the next block with a lower price, further increasing consumption, but these results also appear sensitive to how the Houthakker data is treated (whether or not the data is included or a study dummy is included). Unfortunately, there were not enough studies to determine the impact of increasing block rates, although this may change over time as more utilities utilize increasing block rates than in the past.

Time and location. Use of regional as opposed to aggregate U.S. data appears to bias income elasticity estimates downward for the long-run estimates, whereas the short-run estimates appear sensitive to the treatment of the Acton, Mitchell, and Mowill data (inclusion of

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Table 5. (Continued)
Notes: All t-tests are two-tailed.
[a] Adjusted R^2 is reported for generalized least squares (GLS) models, and the correlation between the observed and predicted is reported for all gamma models.
* Significant at the .10 level.
** Significant at the .05 level.
*** Significant at the .01 level.

Table 6. Long-Run Income Elasticity Results

	Full Data Set (n = 126)				Alternative Data Set[a] (n = 112)	
	GLS1	GLS2	Gamma1	Gamma2	GLS3	Gamma3
Intercept	306.81***	194.65***	300.12***	148.03***	193.76***	153.72***
Demand specification						
Structural	0.34	0.33	0.52**	0.42*	0.21	0.29
Dynamic	−0.04	0.04	−0.03	0.10	−0.09	−0.06
Stock	−0.99**	−0.62	−0.90***	−0.51**	−0.63	−0.55***
Substitutes	0.36	0.14	0.41*	0.11	0.20	0.18
Household size	−1.95***	−1.42***	−2.13***	−1.52***	−1.41***	−1.51***
Non–double log	−0.27	−0.30	−0.36	−0.41*	−0.45	−0.58**
Data characteristics						
Time series	0.21	−0.07	−0.01	−0.26	−0.05	−0.20
Cross sectional	0.64	0.60	0.66**	0.67**	0.53	0.60**
Monthly consumption	−0.01	−0.16	−0.07	−0.17	−0.08	−0.05
Average price	−0.22	0.36	−0.03	0.56***	0.34	0.51***
Decreasing block rate	0.29	0.98***	0.18	0.95***	0.91***	0.84***
Time and Location						
Regional	−0.59**	−0.58***	−0.61***	−0.61***	−0.73***	−0.79***
Non–United States	1.89***	1.72***	1.57***	1.43***	1.82***	1.58***
1972–1981 data	0.72**	0.48*	0.87***	0.47*	0.47	0.47**
Post-1981 data	1.86***	1.65***	1.80***	1.26***	1.64***	1.27***
Publication year	−0.16***	−0.10***	−0.15***	−0.07***	−0.10***	−0.08***
Estimation technique						
Non–ordinary least squares	0.43*	0.36*	0.32	0.35*	0.38*	0.37**
Other						
Houthakker	—	1.35***	—	1.48***	—	—
Shape parameter	—	—	4.20***	4.83***	—	5.62***
Log likelihood	−99.86	−92.65	−93.41	−83.93	−74.23	−65.53
Adjusted R^2	0.64	0.67	0.67[b]	0.71[b]	0.71	0.74[b]

the data or a study dummy). The estimated income elasticity for both the short and the long run was found to be significantly higher in studies using data from countries other than the United States, however. Given that these other countries (Mexico, Costa Rica, Israel, Canada) have lower average per capita income than the U.S., this finding contrasts with Lyman's estimate that income elasticity increases as income increases (Taylor). As incomes increase in developing countries, electrification, appliance ownership, and the demand for electricity would increase at a relatively rapid rate. But as electrification approaches 100% and appliance ownership reaches saturation, increases in income may have a smaller impact on total electricity consumption.

On the other hand, differences in income elasticity over time were statistically significant in the long-run meta-analysis model, surprisingly suggesting residential electricity consumers are growing more sensitive to changes in income over time. This may be the result of increased availability of electricity-using appliances and that with generally rising income over time such appliances are being bought at an increasing rate, leading to an even greater increase in electricity use. Publication year was found to be negative and significant, suggesting that over time, income elasticity estimates have become smaller.

Other. Finally, as with the price elasticity models, the shape parameters for the gamma model are all significant and reflect the skewed distribution of the published estimates of income elasticity of residential electricity demand, with the shape parameter in the short-run model indicating a more skewed distribution than for the long-run model.

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Table 6. (Continued)
Notes: All t-tests are two-tailed.
[a] Houthakker is omitted based on statistically significant Chow test.
[b] Adjusted R^2 is reported for generalized least squares (GLS) models, and the correlation between observed and predicted values is reported for all gamma models.
* Significant at the .10 level.
** Significant at the .05 level.
*** Significant at the .01 level.

Conclusions

The results of this meta-analysis could be of potential benefit to anyone interested in modeling the demand for residential electricity. First, it provides a qualitative summary of relevant published work in the area. Yet, it goes beyond the casual categorization of electricity demand estimates by Bohi or the review of Taylor, and formally models the likely effects of different data and methods on empirical results. In addition to noting differences in results across time and approach, some general "rules of thumb" can be inferred about the magnitude of elasticities and systematic factors that influence such estimates, facilitating cross-study comparisons.

Second, the results could be of interest to public utility commissions as a means of understanding the confusing and often contradictory results of previous studies. At present, such commissions, as well as utilities, tend to use a "ballpark" figure of short-run price elasticity in the range of -0.2 to -0.4 (Ruelle). It may not be appropriate to assume that these elasticities are the same for every geographic region. The meta-analysis has revealed subtle differences in elasticities as a function of specific characteristics of previous attempts to model electricity demand. If attempting an original econometric analysis of electricity demand, the modeler should be sensitive to lag structure, data years utilized in the estimation, area of analysis, and rate structure, for example. Extrapolation of results from one place or time period to another may not provide accurate estimates. On the other hand, different variables are more or less important, depending on whether one is interested in long-run or short-run effects.

In the face of a multitude of questions about deregulation, it is important for officials to understand price and income elasticities. Accurately forecasting a change in the quantity demanded that results from a change in price will necessarily require an assumption of the relevant elasticities. This analysis might be used to guide such analysis of electricity demand by policy makers. It could also be used to provide confidence bounds or an adjustment to estimates for researchers faced with less than ideal data—for example, aggregated data or average prices.

As urban expansion continues throughout the United States, it will be increasingly important to know just how much energy will be required to meet the rising demand. Decisions about new sources of electric power, the construction of new power plants, or the creation of new interstate power lines would also need to be based on an accurate understanding of the consumers' responsiveness to price and income changes. The results of this analysis can help analysts understand the implications of different modeling assumptions and data constraints in relation to their estimates of elasticity. If the U.S. is forced to reduce energy use to meet the goals and timetables of the Kyoto or other agreements on global warming, this work may also serve to clarify the effects of a tax increase aimed at lowering consumption of electricity.

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References

Acton, J., B. Mitchell, and R. Mowill. *Residential Demand for Electricity in Los Angeles: An Econometric Study of Disaggregated Data.* Santa Monica, CA: Rand Corporation, Report R-1899-NSF, 1976.

Anderson, K.P. "Residential Demand for Electricity: Econometric Estimates for California and the United States." *Journal of Business* 46,4(1973):526–53.

Archibald, R.B., D.H. Finifter, and C.E. Moody, Jr. "Seasonal Variation in Residential Electricity Demand: Evidence from Survey Data." *Applied Economics* 14(1982):167–81.

Assmus, G., J.U. Farley, and D.R. Lehmann. "How Advertising Affects Sales: Meta-Analysis of Econometric Results." *Journal of Marketing Research* 21(February 1984):65–74.

Barnes, R., R. Gillingham, and R. Hagemann. "The Short-run Residential Demand for Electricity." *The Review of Economics and Statistics* 63(1981):541–51.

Beenstock, M., E. Goldin, and D. Nabot. "The Demand for Electricity in Israel." *Energy Economics* 21(1999):168–83.

Beierlein, J.G., J.W. Dunn, and J.C. McConnon, Jr. "The Demand for Electricity and Natural Gas in the Northeastern United States." *The Review of Economics and Statistics* 63(1981):403–08.

Bernard, J.T., D. Bolduc, and D. Belanger. "Quebec Residential Electricity Demand: A Microeconomic Approach." *Canadian Journal of Economics* 29,1(1996):92–113.

Berndt, E.R., and R. Samaniego. "Residential Electricity Demand in Mexico: A Model Distinguishing Access from Consumption." *Land Economics* 60,3(1984):268–77.

Bohi, D.R. *Analyzing Demand Behavior: A Study of Energy Elasticities.* Baltimore, MD: The Johns Hopkins University Press, 1981.

Branch, E.R. "Short Run Income Elasticity of Demand for Residential Electricity Using Consumer Expenditure Survey Data." *The Energy Journal* 14,4(1993):111–21.

Dubin, J.A., and D.L. McFadden. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica* 52,2(1984):345–62.

Espey, M. "Gasoline Demand Revisited: An International Meta-Analysis of Elasticities." *Energy Economics* 20,3(1998):273–96.

Espey, M., J. Espey, and W.D. Shaw. "Price Elasticity of Residential Demand for Water: A Meta-Analysis." *Water Resources Research* 33,6(1997):1369–74.

Garbacz, C. "A National Micro-Data Based Model of Residential Electricity Demand: New Evidence on Seasonal Variation." *Southern Economic Journal* 3(July 1984):235–49.

Garcia-Cerrutti, L.M. "Estimating Elasticities of Residential Energy Demand From Panel County Data Using Dynamic Random Variables Models with Heteroskedastic and Correlated Error Terms." *Resource and Energy Economics* 22(2000):355–66.

Gill, G.S., and G.S. Maddala. "Residential Demand for Electricity in the TVA Area: An Analysis of Structural Change." *Proceedings of the Business and Economic Statistics Section, Journal of the American Statistical Association,* 1976, pp. 315–419.

Gourieoux, C., A. Monfort, and A. Trognon. "Pseudo-Maximum Likelihood Methods: Theory." *Econometrica* 52,3(1984): 681–719.

Greene, W.H. *Econometric Analysis,* 3rd ed. Upper Saddle River, NJ: Prentice Hall, 1997.

Halvorsen, R. "Residential Demand for Electric

Energy." *Review of Economics and Statistics* 57(1975):12–18.

———. "Demand for Electric Energy in the United States." *Southern Economic Journal* 42(1976):610–25.

Henson, S.E. "Electricity Demand Estimates Under Increasing-Block Rates." *Southern Economic Journal* 51,1(July 1984):147–56.

Herriges, J.A., and K.K. King. "Residential Demand for Electricity Under Inverted Block Rates: Evidence from a Controlled Experiment." *Journal of Business and Economic Statistics* 12,4(1994):419–30.

Hewlett, J.G. "Changing Patterns of Households' Consumption of Energy Commodities." *Proceedings of the American Statistical Association, Business and Economic Statistics Section (Part 1)*, 1977, pp. 99–108.

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

Houthakker, H.S., P.K. Verleger, and D.P. Sheehan. "Dynamic Demand Analyses for Gasoline and Residential Electricity." *American Journal of Agricultural Economics* 56(May 1974):412–18.

Hsiao, C., and D. Mountain. "Estimating the Short-Run Income Elasticity of Demand for Electricity by Using Cross-Sectional Categorized Data." *Journal of the American Statistical Association* 80(1985):259–65.

Hsing, Y. "A Regional Study of the Residential Demand for Electricity: A Comparison of the OLS, CSHTWA, and CSCTWA Models." *The Journal of Economics* 21,1(1995):111–15.

Kokkelenberg, E.C., and T.D. Mount. "Oil Shocks and the Demand for Electricity." *The Energy Journal* 14,2(1993):113–38.

McFadden, D., C. Puig, and D. Kirshner. "Determinants of the Long-Run Demand for Electricity." *Proceedings of the American Statistical Association, Business and Economic Statistics Section (Part 2)*, 1978, pp. 109–17.

Mendenhall, W., D.D. Wackerly, and R.L. Scheaffer. *Mathematical Statistics with Applications*, 4th ed. Boston: PWS-Kent Publishing Co., 1990.

Munley, V.G., L.W. Taylor, and J.P. Formby. "Electricity Demand in Multi-Family, Renter-Occupied Residences." *Southern Economic Journal* 57,1(1990):178–94.

Murray, M.P., R. Spann, L. Pulley, and E. Beauvais. "The Demand for Electricity in Virginia." *Review of Economics and Statistics* 60,4(November 1978):585–600.

Parti, M., and C. Parti. "The Total and Appliance-Specific Conditional Demand for Electricity in the Household Sector." *The Bell Journal of Economics* 11(1980):309–21.

Rothman, D.S., J.H. Hong, and T.D. Mount. "Estimating Consumer Energy Demand Using International Data: Theoretical and Policy Implications." *The Energy Journal* 15,2(1994):67–88.

Ruelle, M. Personal communication. Sierra Pacific Power Company, Reno, NV, April 1998.

Shin, J. "Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand." *The Review of Economics and Statistics* 67,4(November 1985):591–98.

Silk, J.I., and F.L. Joutz. "Short and Long-run Elasticities in U.S. Residential Electricity Demand: A Co-integration Approach." *Energy Economics* 19(1997):493–513.

Smith, V.K. "Estimating the Price Elasticity of U.S. Electricity Demand." *Energy Economics* 2(April 1980):81–85.

Stanley, T.D. "Wheat from Chaff: Meta-Analysis As Quantitative Literature Review." *Journal of Economic Perspectives* 15,3(2001):131–50.

Taylor, L.D. "The Demand for Electricity: A Survey." *The Bell Journal of Economics* 6,1(1975): 74–110.

Tellis, G.J. "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales." *Journal of Marketing Research* 25(November 1988):331–41.

Terza, J.V. "Determinants of Household Electricity Demand: A Two-Stage Probit Approach." *Southern Economic Journal* 53,4(April 1986): 1131–39.

Uri, N.D. "Short-Run Variations in the Demand for Electrical Energy." *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, 1976, pp. 618–21.

Walker, J.M. "The Residential Demand for Electricity." *Resources and Energy* 2(1979):391–96.

Wilder, R.P., and J.F. Willenborg. "Residential Demand for Electricity: A Consumer Panel Approach." *Southern Economic Journal* 42,2(1975):212–17.

Wilson, J.W. "Residential Demand for Electricity." *Quarterly Review of Economics and Business* 11,1(1971):7–22.