University of Nevada, Reno

Measuring price and income elasticities of residential electricity demand: findings from aggregated and disaggregated data

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Measuring price and income elasticities of residential electricity demand: findings from aggregated and disaggregated data

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Abstract

Published estimates of the price elasticity of residential electricity demand range from -0.29 to -0.70, for analyses based on household level data; however, the area level estimates from range from -0.02 to -0.15. A similar pattern has been reported for estimates of the income elasticity of residential demand for electricity. Each published study relied on one type of data set (aggregated or disaggregated) and these datasets cover different time periods and locations. This raises the question: does the pattern generated by the published results reflect systematic differences generated by the use of aggregated vs. disaggregated data, or does the pattern reflect random variations in the study settings? In this research the hypothesis has been tested that the pattern generated by the published results reflects the use of aggregated vs. disaggregated data, by constructing both an individual-level dataset and a county-level dataset for one state (State of Nevada) covering the period from 2005 to 2011. Both datasets have been used to estimate household and utility level price and income elasticities of residential demand for electricity. This research shows the same pattern reported in the published studies: the magnitude of the estimated price elasticity generated by the disaggregated data exceeds the magnitude of the estimate generated by the disaggregated data. However, the magnitudes of the two income elasticities do not follow the same pattern.

Table of Content

Abstract ……………………………………………………………….…………………...i

List of Tables ………………………………………………………….………………...ii

List of Tables ………………………………………………………….……………….iii

List of Figures………………………………………………………………………….iv

Introduction……………………………………………………………………………..1

Literature Review………………………………………………………………………4

Methodology…………………………………………………………………….. .9

Data………………………………………………………………………………..... 18

Empirical results………………………………………………………………………23

Conclusion……………………………………………………………………………..30

Bibliography ……………………………………………………………………...32

List of Tables

Table 1. Comparison with other studies ………………………………………………………….……..…2

Table 2. Variables included in elasticity demand functions using aggregated data……..5

Table 3. Variables included in elasticity demand functions using disaggregated data…8

Table 4. Data summary for income groups ………………………………….…………………….17

Table 5. Geographical specifications of two models……………………..…………….……20

Table 6 Data Summary and its sources …………………………………….…………………..…22

Table 7: LSDV derived coefficients (aggregated approach)……………………………….…24

Table 8: LSDV derived coefficients (disaggregated approach)…………………………..…..25

Table 9. Price and income elasticity estimates for different income levels……….……..…27

Table 10. Price and income elasticity estimates in 2005 and 2011……………………….…29

List of Figures

Figure 1. House heating fuel in 2010 (percentage) ……………………………………..…..10

Figure 2. House heating fuel from 1970 to 2000 (percentage) …………………………………11

Figure 3 Kernel density estimate for monthly electricity consumption in kWh………………….19

Introduction

Estimates of the price and income elasticity of electricity demand inform policy discussions of market deregulation (Reiss et al 2002, Espey, 1998), greenhouse gas emissions and increasing electricity demand in developing countries (Narayan, 2007). Published studies of these elasticities vary in estimation techniques, variable choices, functional forms, level of data aggregation, geographical and chronological specifications. Price elasticity ranges from 0.076 to -2.01 in the short run and -0.107 to -2.5 in the long run (Espey, 1998).

Residential electricity demand models, that use aggregate data, typically include country level electricity consumption, GDP per capita as an income proxy, population and other macroindices such as appliance stock demand to account for the intensity of the electricity usage in the country (Mohamed and Bodger, 2003).

Recent progress in information technologies made it feasible to collect and store household-level data. When utilized as a base for the demand modeling, the microdata often carries information on household size, demographics and behavior patterns, and some data sets contain information regarding the usage of certain appliances and heating devices in the household (US Census PUMA, US EIA RECS). Disaggregate data helps to avoid misspecifications caused by disaggregation bias or approximation of rate data (Deaton and McFadden, 1984), however, this data also rises issues such as heteroscedasticity among households, locality of the research, incompleteness of the survey results. The disadvantage of the aggregated data analysis is the loss of the individual behavior information, which would result in "more precise estimates" (Labandeira et al, 2011, Swan, and Ugursal, 2009).

The estimation of electricity price elasticities shows lower results for aggregate demand and higher ones for the individual household demand. The differences between the elasticity estimates derived from micro or macro data has been addressed multiple times according to the literature review (Halvorsen, 2006, Filippini, 2009, Wiesmann et al, 2011)

Table 1. Comparison with other studies

Study	Country	Time period	Price elasticity	Income elasticity	Type of data	Estimation technique
			Disaggregated data research (bottom-up)			
Filippini and Pachauri	India	1993-1994	(-0.51) to (-0.29)*	0.61 to 0.64*	Microdata (survey)	OLS
M.F.S.R Arthur et al	Mozambique	2002-2003	-0.60	0.69	Microdata (survey)	Deaton's unobservable data method
Tiwari et al	India	1987-1988	-0.70	0.34	Microdata (survey)	Ridge regression (Hoerl and Kennard, 1970)
EIA RECS	USA	1997	(-0.955)	0.102	Household level Microdata	OLS
			Aggregated data research (top-down)			
Alberini, Fillipini	US Sates	1995-2007	(-0.08) to (-0.15)**	0.04 to (-0.09)**	Annual aggregated country observations	Generalized least square method and LSDV for fixed effect estimation
Ziramba	South Africa	1978-2005	(-0.02) (-0.04)***	0.30 0.31***	Annual aggregated country level observations	Bounds testing for cointegration of variables in the long run
Hsiao and Mountain	Ohio State	1960-1980	-	0.17	Aggregated utility annual consumption data	LSDV

*Ranges depending on the season
**Depending on the model
*** long run

The Table 1 summarizes the price and income elasticity coefficients estimated using both aggregated and disaggregated data. It could reflect marginal (Hauthakker, 1951) vs. average (Carter et al 2009) pricing, the level of data aggregation (state or nationwide evidence (Rapanos, 2005) vs. household micro data (Filippini, 2004), as well as geographical and chronological boundaries.

The objectives of this research are:

- To estimate the income and price elasticities using aggregated and disaggregated data collected within one location (State of Nevada) for one time period (2005 to 2011).
- To estimate the household responsiveness on electricity price from different income levels (disaggregated data provides the income variation, suitable for this research).

The most recent similar research, combining aggregated and disaggregated data, was performed by Wiesmann et al in 2011. His findings indicate that income elasticity estimated at the municipal level data (0.2115%*) exceeds the estimated income elasticity using disaggregated household data (0.1282***). The municipal data was collected in 2001, and household surveys were conducted from 2005 to 2006. Electricity price stayed the same for both years and showed no variation, therefore, it was excluded from the equation.

This paper uses data from US Census (disaggregated data) and US EIA (aggregated data) covering the residential electricity demand in the State of Nevada for the period from 2005 to 2011. The log-log equation was a preferred function to describe the relationship between all the components according to goodness-of-fit measurements..

The rest of the paper is organized as follows: the Literature Review presents the overview of publications relevant to the current research; the Data section provides detailed information on variables and their sources. Both models and their specifications are described in the Methodology Section. The Empirical Results Section describes the estimation results and the Conclusion invites to discuss the results.

Literature review

This chapter briefly examines the methods and variables utilized to estimate the residential electricity demand based on the aggregation level. Swan and Ugursal, 1990, summarized the existing literature and noted that the studies can be categorized by the level of data aggregation.

Table 1 shows the results from the past literature on the residential electricity demand.

The difference in coefficients between aggregated data and disaggregated data models is very significant. The reason behind it has been viewed from different standpoints. The absence of micro data to estimate the household behavior forces the researchers to use state or nation level data, which produces the varying results, sometimes much lower than the ones presented from using the disaggregated data. The difference in time and geography also could add to the variance of the results. This paper examines the elasticity coefficients based on the same time interval and place to address the issue.

Aggregate data may produce biased results, if applied to policy analysis on dwelling level (Fell et al, 2011). Therefore, the importance of defining the unbiased elasticity estimates is critical due to social and environmental impact; specifically when policy makers utilize estimates to create policies shaping future energy policies and resource allocation.

1. *Aggregated data approach*

Studies, utilizing aggregated macroeconomic, climate and housing stock characteristics to estimate residential electricity demand, make it possible to detect long-term trends in electricity consumption and compare the results across the regions. Widely available data makes this type of analysis easy to compile, therefore it becomes more common in scientific research. Economic theory indicates, that the models of electricity demand should include the average price of the electricity, the average price of the closest substitute, population, climate characteristics of the area, and the Gross Domestic Product as a measure of the income (Table 2).

Table 2. Variables included in elasticity demand functions using aggregated data

Variable	Description	Author	Methodology
GDP	Income factor influencing consumption	Rapanos, 2005 Alberini and Filippini, 2010	Dynamic panel data OLS model
Heating and cooling degree days	Accounts for differences in geographical areas (base is 65 degrees F)	Holtedahl, 2004 Nakajima et al, 2009	Panel data OLS model
Population and its growth	Population affecting the overall demand or some researchers employ the population growth rate	Majumdar and Parikh, 1996	Two stage model, OLS

2. Engineering or disaggregated data approach

The disaggregated data approach uses data collected at the dwelling level and describes the relationship between household characteristics and electricity consumption. It typically contains cross-sectional data, typically collected over one or two years. There are two classes identified within mentioned models: engineering models and statistical or econometric models (Larsen and Nesbakken, 2002).

2.1. Engineering models

Engineering models focus on technical characteristics of the dwelling. The components of the engineering approach include building envelope information (insulation, roofing, windows, and walls), building type, location, type of heating/cooling system utilized are parts of the equation to estimate the energy needs of the dwelling. Unlike the aggregated data models, this engineering approach can capture the differences in technological changes and behavioral patterns, making possible to create more efficient energy profile of the area.

The disadvantage of the engineering approach is that some of these models require very detailed information on consumer behavior (Capasso model, Capasso et al 1994), or a combination of consumer and dwelling information (Norwegian ERAD model, Larsen, Nesbakken, 2002), which is hard to obtain. In addition, geographically based results are usually applied to improve local energy policies and may not be applicable in different areas due to simple difference in geographical and economic conditions.

2.2. Statistical or econometric model

Conditional Demand Analysis is the most common econometric approach to estimate electricity consumption. The analysis employs dummy variables for various appliances and kitchen characteristics to determine their possible impact on the consumption of the electricity at the dwelling level. Certain physical housing characteristics like number of appliances in the dwelling, number of people living in the dwelling, square footage, type of building and dummy variables to account for level of urbanization differentiate this method from the aggregated estimates of the consumption.

Table 3 shows the common variables utilized for the econometric research.

Table 3. Variables included in elasticity demand functions using disaggregated data

Variable	Description	Author	Methodology used
Household income	Total household income	Baker et al, 1989	Panel data, OLS regression
Persons per household	Number of people living in the dwelling	Fillipini, 2004	OLS regression
Heating and cooling degree days	Accounts for differences in geographical areas (base is 65 degrees F)	Holtedahl, 2004 Nakajima et al, 2009	Panel data OLS regression
Presence of certain appliances	Dummy variable accounting for different household appliances	Larsen & Nesbakken, 2003	Fixed effect GLS panel data
Dwelling size	Physical housing characteristic	Baker et al, 1989	Panel data OLS regression
Geographic characteristics (state, county)	Dummy variable accounting for different area or region	Brown and Logan, 2008	Fixed effects, GLS regression panel data

Methodology

As it was mentioned in the Introduction, this research aims to estimate the price and income elasticities of the residential electricity demand using for one location and one time period, as well as price and income elasticities for households of different income levels. This Chapter shows separate methodologies to estimate these coefficients.

Price and income elasticities for residential electricity demand using aggregated and disaggregated data

This paper estimates a generalized consumer demand function that contains the following components:

Demand = f (Price of the substitute, Price of the complement, Income, Taste preferences),

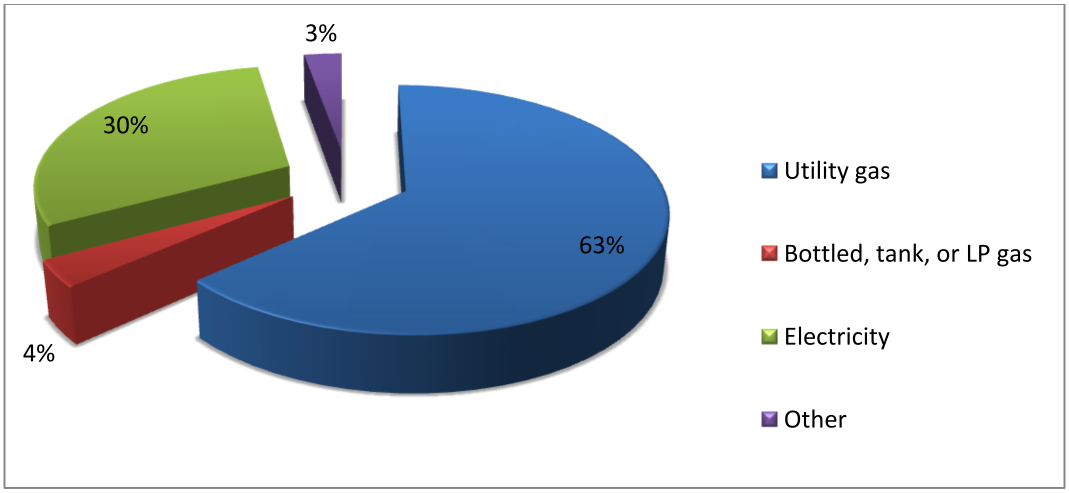
As shown in Figures 1 and 2, natural gas is considered as the closest substitute for the electricity, based on the diversity of the current energy consumption in Nevada. The next substitutes are bottled gas and wood. Due to absence of market price data for those options, we excluded these components from the equation.

Technical factors also impact the supply and demand for electricity, such as:

- Consistent electricity flow depends on the consistent supply from the generators, which in alliance with consumers create a multi-path grid transmitting energy in the area.
- The electricity usage of one participant of the electricity network affects the capacities and characteristics of the rest of the network.
- Inability to store electricity in sufficient volumes makes the electricity storage nearly infeasible, which affects the demand the most in the peak hours (New Zealand Institute for the Study of Competition and Regulation, 2011).

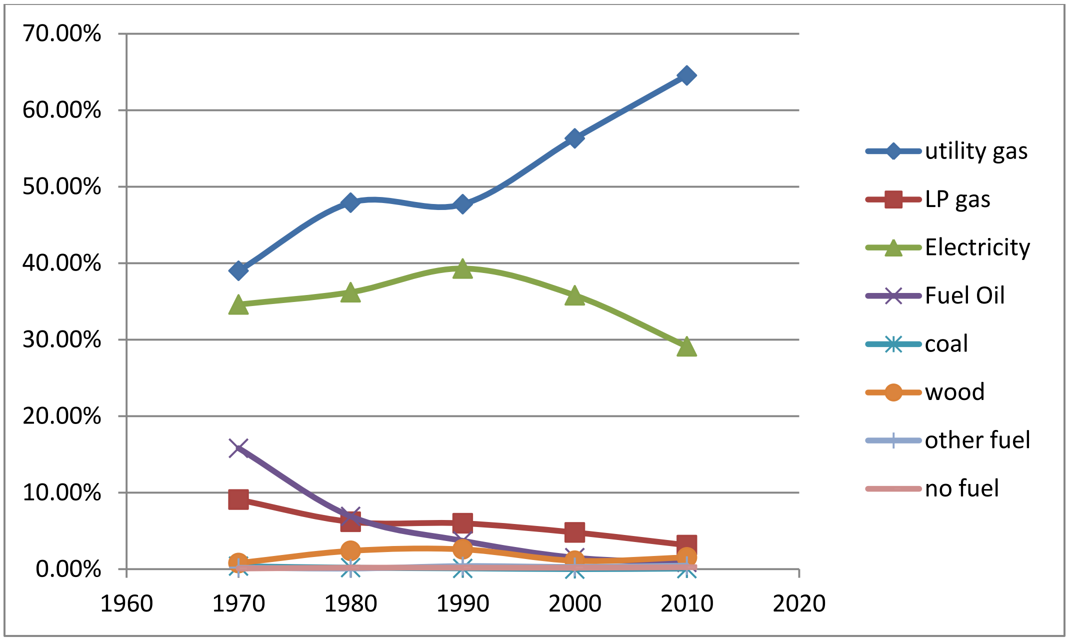
However, this research does not address those issues, focusing only on residential electricity demand characteristics.

Figure 1. House heating fuel in 2010 (percentage)



Source: US Census

Figure 2. House heating fuel from 1970 to 2000 (percentage)



Source: US Census

Appliances and housing characteristics are complements to electricity. Data from the Census contains housing characteristics observations such as building age, size etc, are included in the disaggregated data model. The aggregated model contains specific variables presented by the utility companies for the government reporting.

Tastes and preferences, expressed through the cooling and heating degree-days, reflect the comfort level for the surrounding temperature as a personal choice for each household.

Based on the reviewed literature, there is no clear consensus on what functional form to choose when estimating the residential electricity demand. Numerous studies employed linear and logarithmic forms depending on aggregation level of data. Taking into consideration the non-linear nature of the impacts of electricity and natural gas prices on electricity use the double-log function provided a better fit among all variables of interest.

a. Aggregated data model

The data extracted from the US EIA-826 form is a two-dimensional panel characterized by space and time. In this research, I employed the log-log Least Squares Dummy Variable (LSDV) model to estimate the relationship between determinants and the dependant variable.

$$lnE_{it} = \beta_0 - \beta_1 \, lnP_{E\,it} + \beta_2 \, lnP_{G\,it} + \beta_3 \, lninc_{it} + \beta_4 HDD_{it} + \beta_5 \, CDD_{it} + \varepsilon_{it} \qquad (1)$$

Where:

lnE_{it} – natural log of the average monthly electricity consumption, kWh per customer;

$lnP_{E\,it}$ –natural log of the average residential price of electricity per kWh;

$lnP_{G\,it}$ –natural log of the residential price of utility gas, dollars per 1000 ft^3;

$lninc_{it}$- natural log of the median household income, dollars;

HDD - Heating Degree Days (number of days with temperature cooler than 65 degrees);

CDD - Cooling Degree Days (number of days with temperature warmer than 65 degrees);

i= 1, 2, 3.. N, for each utility company (space variant);

t= 1, 2,…T, for each year from 2005 through 2011 (time variant);

ε_{it}- disturbance error

All monetary values fixed and expressed in 2005 dollars.

Due to the log-log format of the equation, the coefficients will reflect the demand elasticity, therefore no further calculations is necessary.

Standard consumer demand theory predicts the following signs on estimated coefficients:

- Income is expected to have a positive sign since the increase of tends to accelerate the economic activity resulting in higher electricity consumption
- The price elasticity on natural gas prices should have a positive sign; the households driven to maximize their utility will switch some of the load on electric appliances if gas prices go up.
- Heating and cooling degree-days, appointed to determine geographic features of the region, will increase the consumption through furnaces, heaters, coolers, air conditioners, etc; therefore, the impact should have a positive sign.

b. Disaggregated data model

The panel assembled from the US Census data set contains demographic and housing variables describing households and dwellings in Nevada. Fixed effects Least Square Dummy Variable (LSDV) model showed a better fit for the panel data, decreasing the potential of clustered errors.

The disaggregated data model employed the following variables:

$$lnE_{it} = \beta_0 - \beta_1\, lnpe_{it} + \beta_2\, lnpg_{it} + \beta_3\, lninc_{it} + \beta_4 HDD_{it} + \beta_5\, CDD_{it} - Owner + electric\ heat - newer - gas\ heat + unemployed + rms + np + \varepsilon_{it} \quad (2)$$

Where:

lnE_{it}- natural log of the electricity consumption based on respondent's electricity cost and utility rates for the corresponding year, kWh;

$lnpe_{it}$ – natural log of the residential price of electricity, 2005 dollars per kWh;

$lnpg_{it}$ – natural log of the residential price of utility gas, 2005 dollars per 1000 ft^3;

$lninc_{it}$- natural log of the household income, in 2005 dollars;

HDD- Heating Degree Days (number of days with temperature cooler than 65 degrees)

CDD- Cooling Degree Days (number of days with temperature warmer than 65 degrees);

rms- Number of rooms;

np- Number of people in the household;

$Owner$ - Dummy variable to indicate if the dwelling is owned by respondent (otherwise 0);

$electricheat$ – Dummy variable to indicate if the dwelling is heated with electricity (0 otherwise)

$gasheat$ - Dummy variable to indicate if the dwelling is heated with natural gas (0 otherwise)

$newer$- Dummy variable accountable if the dwelling is built after 1985 (0 otherwise)

$unemployed$- Dummy variable indicating the presence of the unemployed household member in the dwelling (0 otherwise)

ε_{it}- error term

i= 1, 2, 3.. N, for each PUMA (space variant);

t= 1, 2,…T, for each year from 2005 through 2011 (time variant);

The logarithmic form of the function will deliver the targeted estimates without any additional calculations.

The following signs are predicted based on the underlying theory:

- Natural gas price elasticity is expected to be positive: increasing gas prices will increase the electric demand. The electricity price elasticity will have a negative sign in this model according to the Law of Demand.
- The coefficients for variables *np* and *rms* will be positive due to a common notion that extra room or person more likely will increase the electricity consumption level.
- Income is one of the main contributors to any consumption. Electricity is considered as a normal good; therefore, the income elasticity is expected to be positive.
- Coefficients for *owner* and *newer* are expected to be negative. Ownership of the house usually leads to renewal of appliances towards more energy efficient, as well as overall improvement of housing conditions (insulation, building materials, etc). Nevertheless, the last decade research showed some positive coefficients associated with the home ownership, concluding that, some owners might develop more relaxed attitude towards energy consumption after improving their appliances and housing features. (Fell et al, 2011). Newer housing dummy indicates that the building codes are upgraded, providing more energy efficient housing. This variable should hold a negative sign.
- The dummy variable *electricheat* indicates whether the dwelling heating system includes the electric furnace only. This should add to the electric consumption, hence the sign is positive.
- The dummy variable *gasheat* indicates the presence of the gas furnace in the dwelling. The sign is negative since the household will consume less electricity to heat the dwelling.

Price and income elasticities of the residential electricity demand based on household income level

The importance of capturing the responsiveness of the households on the price from different income levels is very critical for any policymaker to sustain the acceptable welfare level in the area. To estimate the coefficients for different income levels, I divided households in 7 groups: inc1-inc7 and added each group into disaggregated demand model (2) using their logarithmic equivalent. Table 4 demonstrates the summary statistics for each income group.

Table 4. Data summary for income groups

Variable	Observations	Mean	Std. deviation	Min	Max
inc1	69931	3253.977	6829.341	0	24993.75
inc2	69931	10450.58	17108.22	0	49987.5
inc3	69931	12923.98	25274.62	0	74999
inc4	69931	11017.3	28912.43	0	99975
inc5	69931	12378.74	36707.4	0	149962.5
inc6	69931	4566.881	27508.66	0	199996
inc7	69931	10371.23	61286.22	0	1246781

Data

For the aggregated approach, I assembled a panel data set of annual observations from 2005 through 2011, obtained from US EIA form 861. This form provides utility company level data on annual revenues, customer base and consumption for residential consumers. I also incorporated the average residential electricity price (derived from EIA-861 by dividing firm revenue by firm's customer count) and gas prices (South West Gas pricing schedule). Annual values are used to permit the inclusion of annual degree data obtained from the National Climatic Data Center.

Table 5 provides the breakdown of utility service areas by counties. That makes it possible to introduce each county's macroeconomic indicators to measure income and substitute fuel prices.

Median household income values by county were obtained from the Nevada Department of Employment Training and Rehabilitation. To reflect the substitute energy pricing impact, I added prices from SouthWest Gas Company as a major residential natural gas provider. South West Gas implements only two residential price schedules for Northern and Southern Nevada correspondingly. Table 6 shows the summary statistics for the variables employed in disaggregated and aggregated data research.

For the disaggregated data set empirical analysis, I used household level data, extracted from the US Census American Community Survey from 2005 to 2011. The survey contains responses received from 69931 observations from households residing in Public Use Micro Data Sample Areas from 2005 to 2011. There are 15 PUMA areas in Nevada, geographically shaped to ensure that one hundred thousand people reside in each area (Table 5). The individual survey provided information on household income, number of people in the family, heating fuel and other housing and demographic characteristics. Figure 2 shows the distribution of electricity consumption between 5 to 50 kWh monthly per household.

Figure 3 Kernel density estimate for monthly electricity consumption in kWh

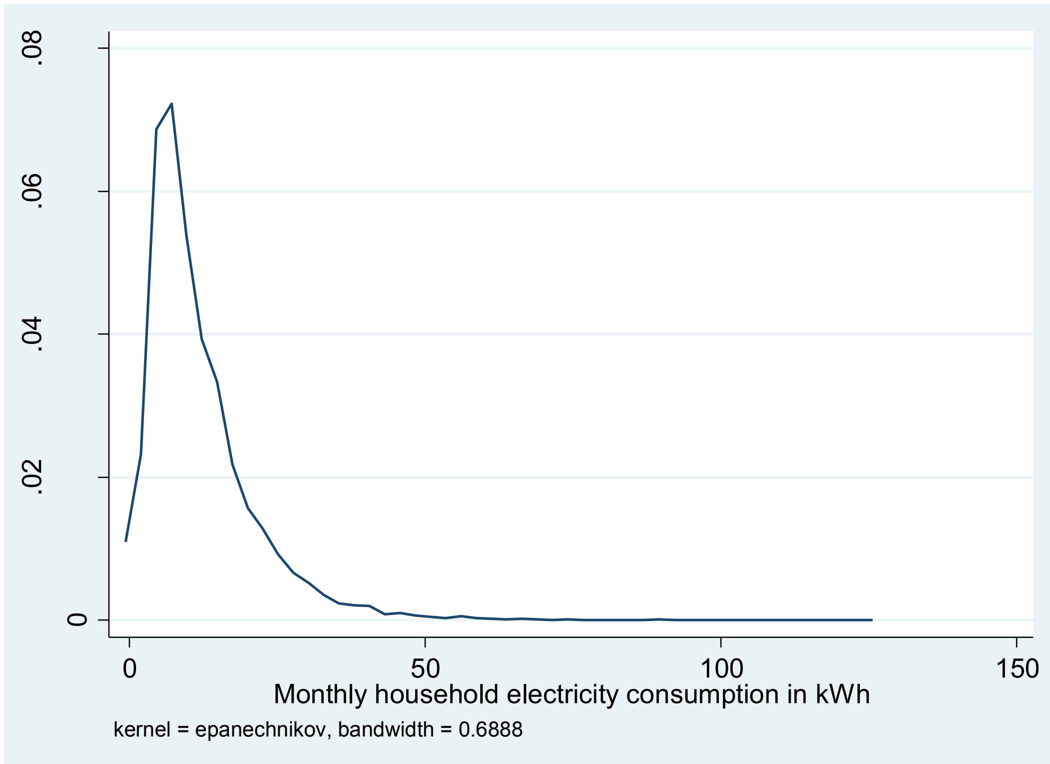


Table 5. Geographical specifications of two models

Northern and Central Nevada

Disaggregated data			Aggregated data		
US Census PUMA Microdata			US Energy Information Administration		
PUMA Code	**County Code**	**Geographical description**	**Util ID**	**Utility name**	**Area of service coverage**
100	031	Washoe Cnty (Sparks City and several CDPs)	17166	Sierra Pacific Power Company	Washoe Cnty
200		Washoe Cnty (City of Reno)			
300	001	Churchill Cnty			
	007	Elko Cnty	22814 20332	Raft River Rural Electric Coop Inc Wells Rural Electric	Elko Cnty
	009	Esmeralda Cnty	19840	Valley Electric Assn	Esmeralda Cnty
	011	Eureka Cnty	20332	Wells Rural Electric	Eureka Cnty
	013	Humboldt Cnty			
	015	Lander Cnty			
	017	Lincoln Cnty			
	021	Mineral Cnty			
	023	Nye Cnty			
	027	Pershing Cnty			
	033	White Pine Cnty	13073	Mt Wheeler Power	White Pine Cnty
400	005	Douglas Cnty	17166	Sierra Pacific Power Company	Douglas, Lyon, Storey Cnties and Carson City
	019	Lyon Cnty			
	029	Carson City			

Southern Nevada

Disaggregated data			Aggregated data		
US Census PUMA Microdata			**US Energy Information Administration**		
PUMA Code	**County Code**	**Geographical description**	**Util ID**	**Utility name**	**Area of service coverage**
501	003	Clark Cnty (Overton, Moapa Valley CDP, part Enterprise and Paradise CDPs)	2008	City of Boulder	Clark County
502	003	Clark Cnty (Sunrise Manor CDP)	13407	Nevada Power Company	Clark County
503	003	Clark Cnty (Whitney CDP, Paradise CDP, Sunrise Manor CDP)	13407		
504	003	Clark Cnty (Paradise CDP)	13407		
505	003	Clark County (City of North Las Vegas)	13407		
506	003	Clark Cnty (Las Vegas and rem. of Clark Cnty)	13407		
507	003	Clark County (Las Vegas City)	13407		Clark County (City of Las Vegas)
508	003	Clark County (Las Vegas City)	13407		
509	003	Clark County (Las Vegas City)	13407		
510	003	Clark County (Spring Valley CDP)	13407		
511	003	Clark County (Henderson City)	13407		Clark County (Henderson City)

Table 6 Data Summary and its sources

Aggregated data

Variable	Observations	Mean	Std. deviation	Min	Max	Source
e	112	12.51539	2.805084	5.965847	16.78572	US EIA
pe	112	9.183036	2.717445	4.48	17.03	US EIA
pg	112	1.146964	0.235956	0.74	1.53	Southwest Gas Corp
income	112	49659.62	7380.323	37291	70125	NV DIETR
hdd	112	4782.759	1807.812	1615	8019	NOAA
cdd	112	1592.5	1195.869	120	4074	NOAA

Disaggregated data

Variable	Observations	Mean	Std. deviation	Min	Max	Source
e	69931	11.76863	9.451468	0.06521	125	US EIA and US Census
pe	69931	11.2374	1.999777	4.48	13.96	US EIA
pg	69931	1.104096	0.22703	0.74	1.53	Southwest Gas Corp
hincp	69931	70129.57	69324.29	1000	1300000	US Census
hdd	69931	3000.079	1801.699	1615	7332	NOAA
cdd	69931	2819.717	1401.473	430	4074	NOAA
owner	69931	0.662339	0.472916	0	1	US Census
newer	69931	0.477313	0.499489	0	1	US Census
unemployed	69931	0.285238	0.451531	0	1	US Census
electricheat	69931	0.293804	0.455507	0	1	US Census
gasheat	69931	0.631394	0.48243	0	1	US Census
np	69931	2.500079	1.468487	1	16	US Census
rms	69931	5.614449	1.965681	1	17	US Census

Empirical results

This Chapter shows the results derived from the aggregated and disaggregated model of the residential electricity demand, as well as results showing the price and income elasticity for different income groups in Nevada.

Elasticity estimates for the aggregate data model are listed in the Table 7. Table 8 shows household responsiveness to price and income changes. The Least Square Dummy Variable regression proved to be a better fit for the data; capturing variations among utility companies and US Census micro data sample areas and time.

Based on the significance of the coefficients in the aggregated data model, the electricity prices, income and weather conditions (cooling degree-days) affect the residential electricity demand the most in the State of Nevada. These coefficients are significant at the 5% significance level and have expected signs. The positive sign for the income elasticity confirms that electricity is a normal good. Compared to the aggregate model, the R^2 for disaggregated model is significantly lower than previous model, it is still within the reasonable range for the individual cross-sectional data (Baek, 2010).

Listed parameters suggest the relatively inelastic demand for residential electricity in Nevada. That suggests that 1% electricity price increase will reduce the electricity consumption by nearly 0.26% for aggregated and 0.8% for disaggregated data. Both estimated coefficients showed high levels of significance (1%).

Income elasticity coefficients are positive in both models: 0.4% for the aggregated data and 0.1% for disaggregated data respectively (both at 1% significance level).

The cooling and heating degree-day coefficients are not showing the expected statistical significance. Similar research according to the literature review shows higher t-values (2.19 for heating degree-days and 0.07 for cooling degree-days) and low estimates (0.03% and 0.08% accordingly) (Baek 2010)

Table 7. LSDV derived coefficients (aggregated approach)[1]

Variable	*Least Squares Dummy Variable*	*t-value*
lnpe	-0.25876***	-4.24
lnpg	-0.25208	-1.32
lninc	0.400513***	3
hdd	0.000335	1
cdd	0.000113*	2.3
City of Boulder	-0.20029	-1.72
City of Caliente	-0.27943***	-11.18
City of Fallon	-0.65477***	-9.01
Lincoln Power Dist No 1	-0.03305	-1.01
Harney Electric Coop	0.115831	1.19
Mt Wheeler Power Inc	0.006108	0.05
Nevada Power Company	-0.23998*	-1.99
Overton Power District 5	-0.05036	-0.7
City of Pioche	-0.20073***	-8.15
Plumas-Sierra Rural Elec	0.055854	0.48
Sierra Pacific Power Co	-0.35615***	-5.04
Valley Electric Assn, Inc	0.067236	0.58
Wells Rural Electric Co	-0.16176	-1.42
Raft River Rural Elec	-0.27357**	-2.94
Penoyer Valley Electric	0.100523*	2.14
2006	-0.01952	-0.97
2007	-0.04634	-1.18
2008	-0.04039	-0.96
2009	-0.04738	-0.76
2010	-0.07824	-0.82
2011	-0.10705	-0.93
Constant	-1.40619	0.98
R sqr=0.9772	*Adj R sqr=0.9702*	*F(26, 85) = 139.89*

[1] *legend: * p<0.05; ** p<0.01; *** p<0.001*
To avoid the dummy variable trap STATA omitted the Alamo Power District and the year 2005 from the regression.

Table 8: LSDV derived coefficients (disaggregated approach)[2]

Variable	***Least Squares Dummy Variable***	***t-value***
lnpe	-0.79677***	-13.81
lnpg	-0.20979	-1.23
lnincome	0.09483***	21.55
hdd	0.0000183	0.42
cdd	-0.0000671	-1.13
owner	0.283444***	33.87
electricheat	0.230895***	15.12
gasheat	0.065034***	4.55
unemployed	0.043839***	5.66
np	0.121365***	47.71
rms	0.119942***	57.36
Puma 200	-0.12581***	-3.85
Puma 300	-0.10777	-1.25
Puma 400	-0.21733***	-8.58
Puma 501	0.337004	1.3
Puma 502	0.200153	0.78
Puma 503	0.318898	1.24
Puma 504	0.18435	0.71
Puma 505	0.28253	1.1
Puma 506	0.314501	1.22
Puma 507	0.293457	1.14
Puma 508	0.403834	1.57
Puma 509	0.151	0.59
Puma 510	0.278725	1.08
Puma 511	0.345136	1.34
Year 2006	0.037787*	2.27
Year 2007	0.024796	0.67
Year 2008	-0.0659	-1.89
Year 2009	-0.09497	-1.72
Year 2010	-0.17401*	-2.03
Year 2011	-0.25283**	-2.36
Constant	1.706004	6.08
R sqr = 0.2426	*Adj R sqr=0.2423*	*F(11, 2168) = 64.67*

[2] *legend: * p<0.05; ** p<0.01; *** p<0.001*
To avoid dummy variable trap, STATA omitted PUMA 100 and the year of 2005.

As noted in the Literature Review, the estimates derived from aggregated data might differ from estimates obtained from less aggregate models, leading to a potential aggregation bias. The income data collected at the dwelling level demonstrates heteroscedastic results among households.

Summarized to the utility level, micro data becomes more compacted. Therefore, the estimates show much lower results than the ones derived from the household demand. Different signs and magnitude of the household price elasticity coefficients may reduce or increase after aggregation depending on the individual household performance, budget, social and demographic reasons, resulting in substantial difference between two models (Garrett, 2002).

Utility level $\beta_1 \, lnP_{E_{it}} = \Sigma\beta_m \, lnP_{E_{it}}$,

where β_m is the coefficient for household *m*, receiving the utility services from utility *i* for year *t*

Taking advantage of the diversity of the US Census data set, I conducted separate regressions to determine the impact the price volatility imposes on different income groups. Table 9 demonstrates the income and price elasticity variation among seven income groups (p-values and t-stats are included).

Table 9. Price and income elasticity estimates for different income levels

Income Level	Price elasticity	t-stats	Income elasticity	t-stats	Count	Percentage
0<25000	-0.8842524***	-17.98	0.0357574***	2.30	15281	21.85%
25000-50000	-0.8588999***	-26.52	0.1869121***	5.69	19719	28.2%
50000-75000	-0.8728454***	-27.16	0.1828295***	3.42	14689	21%
75000-100000	-0.8006088***	-20.00	0.2446507***	2.60	8929	12.77%
100000-150000	-0.8635547***	-21.85	0.2850129***	4.14	7235	10.35%
150000-200000	-0.8757807***	-11.36	-0.0555576	-0.27	1888	2.7%
>200000	-0.841214***	-10.62	0.2305614***	4.01	2190	3.13%
				Total	69931	100%

*legend: * p<0.05; ** p<0.01; *** p<0.001*

The range of the price elasticity (from -0.8 to -0.88) shows that for any income groups the electricity is relatively inelastic. The income elasticity ranging from 0.03% to 0.28% for all income groups indicating that the electricity is a normal good with inelastic demand.

Another focus of this research was to indicate on how the households adjust their electricity consumption within 7-year period. In 2005, Nevada household electricity demand model showed the price elasticity of -0.88% (1% significance level). Same households in 2011 adjusted their consumption equivalent to -0.91%. The economic significance might result in lower range due to time restrictions of micro data: 7 years perhaps are not sufficient for households to adjust their appliances and behaviors towards more significant results. The results for the price and income elasticities are demonstrated in Table 10.

Table 10. Price and income elasticity estimates in 2005 and 2011

Disaggregated data:

Year	Price elasticity	t-stats	Income elasticity	t-stats	R sqr	F statistic
2005	-0.886947***	-19.67	0.2181069***	9.6	0.2704	F(11,9360)=230.67
2011	-0.9116311 ***	-10.33	0.100089***	8.12	0.1988	F(11,9569)=149.85

Aggregated data:

Year	Price elasticity	t-stats	Income elasticity	t-stats	R sqr	F statistic
2005	-0.4683465	-1.81	0.1873507	0.35	0.5422	F(5, 10)=2.25
2011	-0.3944945	--1.70	-0.0486198	-0.08	0.6701	F(5, 10)=4.10

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Conclusion

In this research, I examined aggregate and micro data sets to address two questions:

1) What is the impact of the diaggregated and aggregated variables on the electricity demand within the same geographical and time characteristics?

2) What is the price elasticity of demand for households with different income levels?

Most of the coefficients in both models have signs that are consistent with micro-economic theory. The study also finds that the housing size and household demographic characteristics are very significant drivers of the residential electricity demand. Consideration of these metrics can be valuable for any policymakers when it comes to establishing or revising demand side management related programs.

The main conclusion is that this empirical analysis confirms the significant difference in aggregated and disaggregated estimates for price and income elasticities in Nevada. Price elasticity is -0.26% for aggregated and -0.8% for disaggregated data suggesting inelastic demand for necessity good, the income elasticity estimated at 0.4% for aggregated and 0.1% for disaggregated data respectively.

Estimating elasticities for different income groups showed very close results. The own-price elasticity ranged from -0.8 to -0.88 and income elasticity ranging from 0.03% to 0.28% once again confirming a necessity nature of the electricity as a good. As far as the increase in the consumption when income goes up, the lowest group showed much lower rate compared to the higher income groups. Very important to note, that income has a very significant impact on the overall electricity consumption. Therefore, the policymakers have to take into consideration the income inequalities of the end consumers to increase the efficiency of the policies and guidelines.

In the current research, I find that both angles in estimation of the price and income responsiveness on the State and household level provide valuable information. Difference in estimates suggests the impact of the data aggregation delivering lower estimates for utility data compared to higher results for disaggregated data. The household data also demonstrated some adjustment in price elasticities in 2005 and in 2011: from -0.88 to -0.91. Utility level data showed less statistically significant results.

The electricity plays very important role in economic and technological development of any entity regardless of the level of aggregation. Elasticity values on prices and income can provide some discussion grounds valuable for not only policymakers and environmentalists, but also anyone who is concerned about the future consumption and level of preparedness to meet those expectations.

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