The Full Cost of Electricity (FCe-)

FCe-

Household Energy Costs for Texans
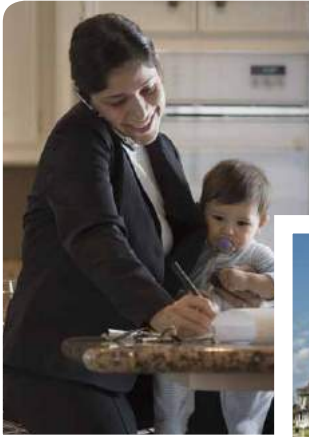
PART OF A SERIES OF WHITE PAPERS

TEXAS

The University of Texas at Austin

THE FULL COST OF ELECTRICITY is an interdisciplinary initiative of the Energy Institute of the University of Texas to identify and quantify the full-system cost of electric power generation and delivery – from the power plant to the wall socket. The purpose is to inform public policy discourse with comprehensive, rigorous and impartial analysis.

The generation of electric power and the infrastructure that delivers it is in the midst of dramatic and rapid change. Since 2000, declining renewable energy costs, stringent emissions standards, low-priced natural gas (post-2008), competitive electricity markets, and a host of technological innovations promise to forever change the landscape of an industry that has remained static for decades. Heightened awareness of newfound options available to consumers has injected yet another element to the policy debate surrounding these transformative changes, moving it beyond utility boardrooms and legislative hearing rooms to everyday living rooms.

The Full Cost of Electricity (FCe-) study employs a holistic approach to thoroughly examine the key factors affecting the *total direct and indirect costs* of generating and delivering electricity. As an interdisciplinary project, the FCe- synthesizes the expert analysis and different perspectives of faculty across the UT Austin campus, from engineering, economics, law, and policy.

In addition to producing authoritative white papers that provide comprehensive assessment and analysis of various electric power system options, the study team developed online calculators that allow policymakers and other stakeholders, including the public, to estimate the cost implications of potential policy actions. A framework of the research initiative, and a list of research participants and project sponsors are also available on the Energy Institute website: energy.utexas.edu

All authors abide by the disclosure policies of the University of Texas at Austin. The University of Texas at Austin is committed to transparency and disclosure of all potential conflicts of interest. All UT investigators involved with this research have filed their required financial disclosure forms with the university. Through this process the university has determined that there are neither conflicts of interest nor the appearance of such conflicts.

This paper is one in a series of Full Cost of Electricity white papers that examine particular aspects of the electricity system.

Other white papers produced through the study can be accessed at the University of Texas Energy Institute website:

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Household Energy Costs for Texans

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ABSTRACT:

Data from the Texas State Data Center estimates that 24% of Texas households (2.1 million) have gross household yearly earnings less than $25k per year and that these households spend 12.5% of annual income on home energy costs, as compared with 4% spent by households with earnings greater than $25k. Using the Residential Energy Consumption Survey data from the U.S. Energy Information Administration (EIA), this paper calculates the number of Texas households with an "energy burden" defined as households that spend greater than 8% of gross annual income on home energy. By this new measure, 22% of Texas households are energy-burdened. Using the available EIA data, this paper describes these Texas households through a series of demographic characteristics, including by education and employment level, household ownership, race and ethnicity, and urban/rural residence. The distribution of energy-burdened households provides an important perspective on understanding possible distribution of the Full Cost of Electricity to all citizens, and that costs should not only be represented in total dollars per month or cost per unit (e.g., $/kWh), but also in relation to income and ability to pay.

1 | ELECTRICITY AFFORDABILITY:
Energy and Electricity Expenses relative to Household Income (Texas case study)

Household utility costs are one of four primary factors considered by the U.S Census Bureau in the calculation of the Supplemental Poverty Measure.

In Texas, 2.1 million households (24%) earn less than $25,000 annually, and the Texas State Data Center estimates that these low-income households in the state spend about 12.5% of their annual incomes on home energy costs, versus 4.0 percent for households earning more than $25,000 annually [1]. In 2013, Carlos Olmedo of the University of Texas at Austin completed a study of 343 households in 24 colonias for the State Energy Conservation Office and in cooperation with Power Across Texas[1], a non-profit organization promoting energy literacy in Texas. The study found that these very low-income households spend between 11.6 percent and 28.4 percent of their monthly income on electricity [2, 3].

Despite the widespread burden from household energy costs, this social policy issue is not widely discussed in the United States as it is in many parts of Europe. However, there are numerous programs at the federal, state, and local level designed to address the burden of fuel poverty. While a survey of these programs is beyond the scope of this paper, examples are included here to demonstrate that the impact of the efforts is relatively small.

The Low Income Home Energy Assistance Program (LIHEAP) and Weatherization Assistance Program (WAP) are administered by federal block grants

from U.S. Health and Human Services and the Department of Energy respectively. In Texas, the Texas Department of Housing and Community Affairs (TDHCA) receives these block grants, and the funds are dispersed to sub-recipients, most often Community Action Agencies (CAAs), in all 254 counties in the state. In 2012, there were 12,621 Texas households that benefited from federally funded weatherization, and of these, 5330 were weatherized using one-time funding associated with the American Recovery and Reinvestment Act of 2009 (ARRA) [1].

In 2005, the 79th Texas legislature passed SB 712 requiring transmission and distribution utilities (TDUs) to also provide targeted low-income efficiency programs in amounts determined by the Public Utility Commission. For 2012, this program served approximately 24,000 households in the state. Combining the federally funded efforts with this state mandated one, roughly 36,000 of the 2.1 million low-income households in the state received weatherization assistance to address high energy bills in 2012, a year that was supplemented by additional ARRA funding.

The System Benefit Fund (SBF) is a program that has provided energy relief benefits to large numbers of Texans. The fund was established in the original Texas legislation (SB 7, 1999) that restructured the electricity markets and is financed through fees on electricity bills. Any household in the state that receives Medicaid and SNAP benefits or is at or below 125% of poverty is eligible. However, the fund has most often not

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1 Power Across Texas has since ceased as an organization, but the mission of addressing energy for low-income household continues as the mission of the Texas Energy Poverty Research Institute (TEPRI, http://www.txenergypoverty.org/). TEPRI's mission as a research institute is to acquire and share actionable data that helps meet the needs of the energy poor in Texas.

been used for this intended purpose. In 2003, the state legislature used $185M of the $405M accrued so far to certify the state budget [4]. This type of accounting practice became the routine until 2013, at which time $800M had accumulated in the SBF. In that year the 83rd legislature ended this practice by passing House Bill 7, which called for the disbursement of all accumulated funds to assist with the electricity bills of low-income Texans in the summers of 2013-2016. The discontinuance of the SBF in 2016 will leave a void in assistance to energy burdened Texans. The statistical analysis that follows here looks at the demographic characteristics of these households and at the scale of the challenge of high energy costs. ■

## DESCRIPTION OF DATA: RESIDENTIAL ENERGY CONSUMPTION SURVEY

The Residential Energy Consumption Survey (RECS) is conducted at four year intervals by the U.S. EIA and is designed to estimate energy characteristics, consumption, and expenditure for U.S. households. The most recent data set was sampled in 2009 and released by EIA in January 2013. This file contains 900 variables and an increased sample size from previous years to allow for separate estimation by Census Region, Census Division, 16 individual states, and the remaining states organized as groups. According to supporting U.S. EIA documentation, the sample cases were weighted to represent the full population including residences not in the sample.

Each case's weight represents a measure of the size of the population that case represents. Base sampling weights were calculated for each sampled household as the reciprocal of the probability of being selected for RECS. These base weights have been adjusted to account for survey non-response and to ensure that the RECS weights add up to the Census Bureau estimates for housing units in 2009 [5]. The data evaluated in this paper are the Texas subset of RECS: 991 observations representing 8,527,938 Texas households. While these data were collected in 2009, the average retail electricity price in Texas was clustered around $0.12/kWh in 2009 and 2014 as shown in Figure 1. Thus, the RECS data are expected to be representative of the characteristics of families facing a home energy burden in Texas today.

FIGURE 1:

Average monthly retail price of electricity in Texas and U.S. overall (source: EIA Electricity Data Browser).

Average retail price of electricity, monthly
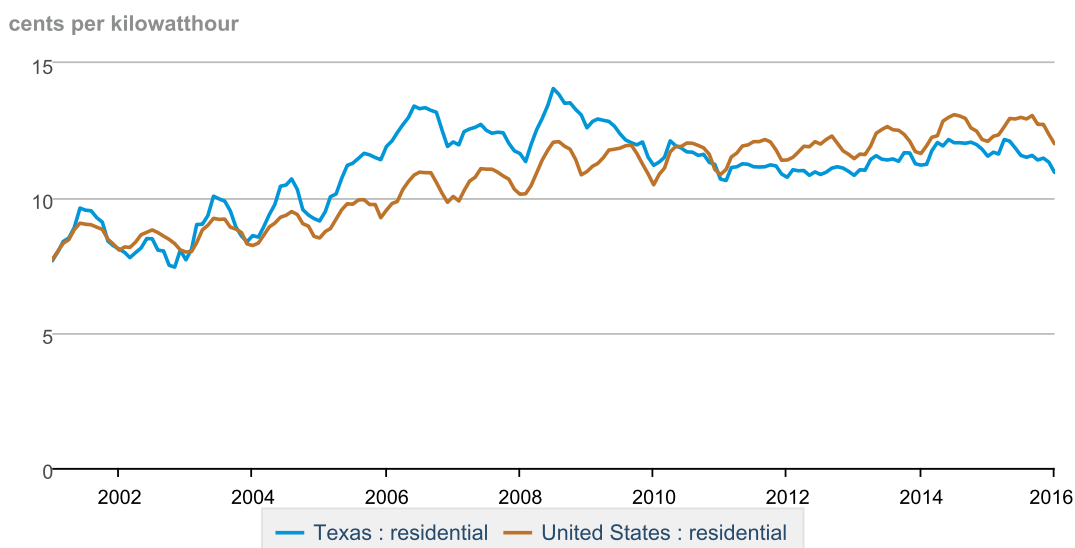
Data source: U.S. Energy Information Administration

OUTCOME VARIABLE – HOUSEHOLD ENERGY BURDEN

This paper defines a poverty statistic, energy burden, measured as home energy expenditures in excess of 8% of gross household income defined as pre-tax, post transfer income that includes transfers from Social Security or TANF but excludes the Earned Income or Child Tax credits.   Many European nations have existing statistical indicators for what is most often labeled as 'fuel poverty.' Prior to 2012, the UK Department of Energy and Climate Change criteria for fuel poverty was a household that would need to spend more than 10% of income to maintain an adequate standard of warmth. Since 2012, this statistic has been redefined as the 'Low Income / High Cost' indicator. Households that meet this standard have 1) fuel costs that are above the national median and 2) were they to spend that amount (10% of income), they would be left with a residual income below the official poverty line [6].

Our definition of energy burden as household energy costs greater than 8% of gross household income is chosen for three principle reasons. First, energy costs are generally lower in the United States than in the UK, and both heating and cooling are necessary for comfort due to the greater geographic diversity. Secondly, the 8% threshold is two times the mean value of 4% paid by households that earn more than $25K annually. Finally, for practical purposes, a sufficient portion of available sample data meets these criteria to allow for a rigorous statistical characterization of energy-burdened households in Texas.

The data evaluated in this paper are the Texas subset of RECS with 991 observations representing 8,527,938 households selected using a multistage area probability sample design, where the universe was broken up into successively smaller, statistically selected areas starting from counties and ending with individual housing units. These data are then benchmarked to occupied housing totals from the U.S. Census Bureau's American Community Survey (ACS), and survey weights are included to indicate the inverse probability of a household being selected in the survey. *In the Texas sample, 22% of households spend more than 8% of household income on energy, and 16% spend more than 10%.* For electricity only, 15% spend more than 8% of household income and 11% spend more than 10%.

Due to the inelasticity of electricity demand, a high degree of collinearity is noted between energy burdened and low-income households, where low-income is defined as household income less than $25K annually. This means, that **although low-income households consume less electricity in total than high-income households, the decrease in electricity demand is much smaller than the decrease in income**. Using the energy burden and low-income definitions, >82% of energy burdened households in the sample are also low-income, and 73% of all low-income households meet the definition of energy burden.

Figures 2-6 summarize the trends of the RECS data in the context of household income. These figures provide some insight before developing a statistical model to understand which demographic variables explain which Texas households are more burdened by spending on household energy and electricity. Electricity composes the vast majority of reported household energy consumption. The RECS data indicate that 377 of 991 (38%) samples reported spending on electricity only (e.g., no other household energy spending), and 48% reported household spending on energy other than electricity at less than 2% of household income. The data indicate that approximately 55% of Texans spend less than 5% of income on household energy, and less than 4% of income on electricity (see Figures 5 and 6).

In addition to the distributions of Figure 2-6, Appendix B indicates average values for income and demographic characteristics. One of the main points in considering the data in Figures 2-6 and Appendix B is that the average rate of electricity ($/kWh) is only one part of the story in thinking about energy costs to low income households. The average rate charged for electricity in 2009 was practically the same (at approximately 0.128 $/kWh) for Texans overall as compared to low-income (<$25K/yr) Texans (Figure 1A) and energy-burdened Texans (Figure 1A).

Probability distribution of the total cost of household energy in Texas in 2009.
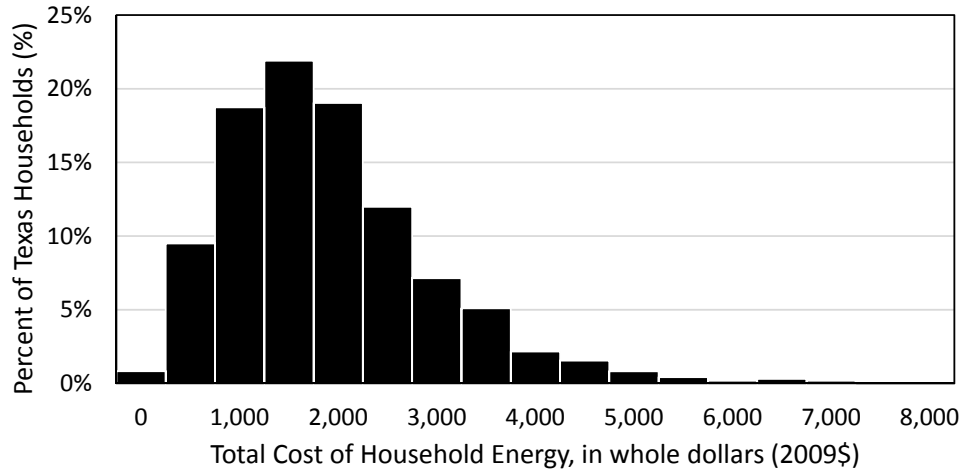
Probability distribution of the total cost of household electricity in Texas in 2009.
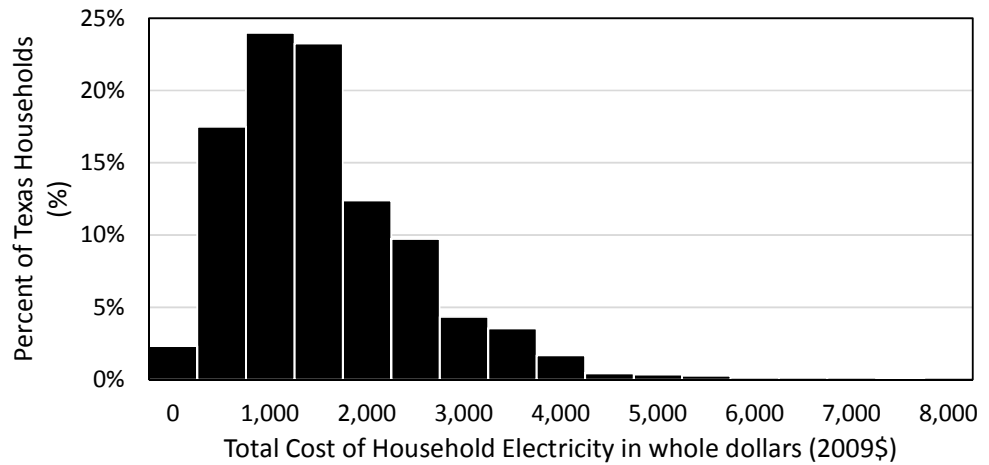
Probability distribution for 2009 gross household income in Texas. The data are plotted to conform to the original RECS data that categorize incomes in increments of $5,000/yr after $10,000/yr. The first four bins show income in increments of $2,500/yr (e.g., 0-2,499; 2,500-4,999, etc.), and each bin afterwards (except for the last two) occurs at intervals of $5,000. The penultimate bin indicates income $100,000-$120,000/yr, and the final bin indicates that 11% of households had gross household income of $120,000 or more.

Probability distribution for fraction of gross household income spent on total household energy. For this calculation, income is assum at the midpoint of the range indicated in the data. Bins ar listed in increments of 1% of income (i.e., the first bin is 0-1% of income, second bin is 1%-2% of income, etc.).
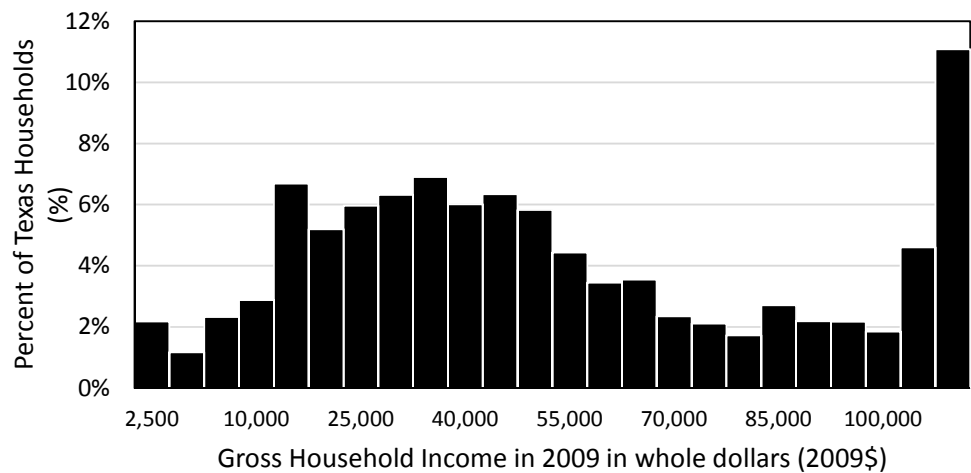
Probability distribution for fraction of gross household income spent on household electricity. For this calculation, income is assumed at the midpoint of the range indicated in the data. Bins are listed in increments of 1% of income (i.e., the first bin is 0-1% of income, second bin is 1%-2% of income, etc.).
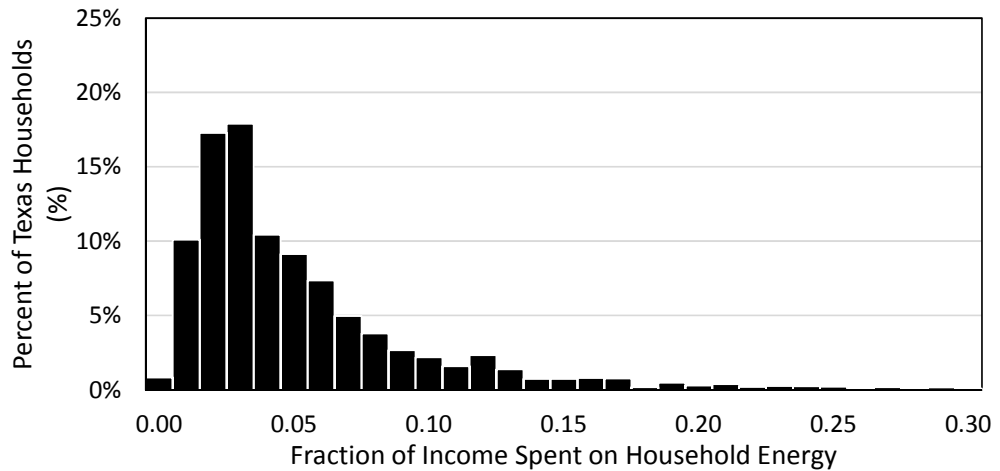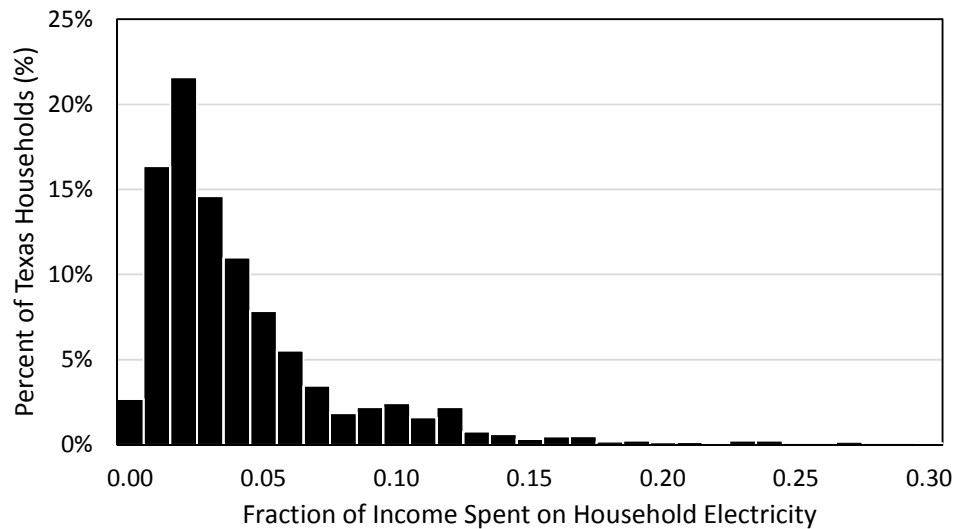

However, when looking at the quantity of electricity consumption, the average Texas household consumes 14,300 kWh/yr, low-income Texans consume around 10,300 kWh/yr, and energy-burdened Texans consume 13,700 kWh/yr. Thus, energy-burdened Texans consume almost the same amount of electricity than does the average Texas household. Part of the explanation is in different consumption patterns for rural versus urban consumption patterns. Rural energy-burdened households consume 17,000 kWh/ yr and urban energy-burdened households only 13,100 kWh/yr. The same pattern, but less severe, exists for low income Texas households – annual electricity consumption is 12,400 kWh/yr and 10,100 kWh/yr for rural and urban, respectively. Future work could determine the contribution of individual factors for lower urban versus rural electricity consumption (less single family unit housing, less time in the home, etc.). ■

3 | STATISTICAL METHODS FOR PREDICTOR VARIABLES OF ENERGY-BURDENED HOUSEHOLDS

The RECS survey uses Fay's method of balanced repeated replication (BRR) for estimating standard errors. BRR incorporates replicate weights to repeatedly estimate the statistic of interest and calculate the differences between these estimates and the full-sample estimate [5]. U.S. EIA references Fay (1989), Heeringa, West, and Berglund (2010), Judkins (1990), Lee and detailed technical Forthofer (2006), Roa and Shao (1999), Rust (1985), and Wolter (2007) for background on the sampling and statistical methods [7-13].

Generally, for BRR, if θ is a population parameter of interest, let:

- $\hat{\theta}$ be the estimate of the full sample for θ

- $\hat{\theta}_r$ be the estimate for the rth replicate subsample using replicate weights, and

- ε be the Fay coefficient such that $0 \leq \varepsilon < 1$.

The variance of $\hat{\theta}$ is estimated by Equation (1):

(1)

$$V(\hat{\theta}) = \frac{1}{R\,(1-\varepsilon)^2} \times \sum_{r=1}^{R}(\hat{\theta}_r - \hat{\theta})^2$$

For the 2009 RECS, R = 244 (the number of replicate subsamples) and ê = 0.5. The formula for calculating the relative standard error (RSE) is:

(2)

$$RSE = \left(\frac{\sqrt{V\hat{\theta}}}{\hat{\theta}}\right) \times 100$$

BINARY LOGIT MODEL AND DATA DIAGNOSTICS

A binary logit model was chosen for purposes of examining the impact of household demographics on the probability of energy burden in Texas households, with energy burden defined as household energy costs greater than 8% of gross household income. A binary logit model is used to predict a two-category response (Energy-burdened or Not Energy-burdened) based on one or more predictor variables. The predictor variables of particular interest to investigate this statistic describe educational attainment, employment and home ownership, race, and urban/rural differences. These variables include ED (Highest education level completed), FTJOB (Full-time employment), OWNRENT (Household is owned versus rented), RACE, SDECSCENT (Latino or Hispanic Descent), and UR1 (Urban/rural). Additional variables add to the predictive strength of the model and are also used to investigate adjacent areas of interest including SPOUSE (Homeowner lives with spouse or partner), GENDER, CIH (Children under 19 in home), SNAP (Public nutritional assistance), AtHome (Household is occupied on a typical weekday), PH65 (Primary householder is age 65 or older), and InvIncome (Household member receives some type of investment income). A third set of variables investigates correlations between energy burden and the adoption of household technologies and controls for associations between Internet (Internet access in home), CWASH (Clothes washer in home), DRYER (Clothes dryer in the home), TV2 (2 or more TVs), and AC (Air conditioning). The last group of variables controls for differences in home size and total energy use between households including whether or not the household has

previously reported taking one of three proactive actions to reduce energy costs (home energy audit, adding insulation, or caulking/weather stripping). Finally, AGE and AGE-squared are included in order to model the non-linear differences in household energy burden across the range of 18 – 85 year old householders in the sample. These data are presented graphically against key demographic characteristics in Figures 1A – 5A of the Appendix. The variables selected for the full binary logit model are shown below as Figure 7.

FIGURE 7:

Variables selected from 2009 RECS Survey for binary logit modeling of "energy burden" in Texas

Variables for Binary Logit Analysis - Energy Burdened Texas Households

Demographic Characteristics
Race - Race of Householder
Sdescent - Householder of Spanish or Latino Descent
Ed - Highest Education Level Completed
Gender - Gender of Primary Householder
Spouse - Lives with Spouse or Partner
UR1 - Urban or Rural Census Household
Age - Age of Primary Householder
Age-Squared - Control for Non-Linearity
CU10 - Children under 10 in Household
CIH - Children under 19 Living in Household
PH65 - Primary Householder 65 or Older

Income Related Characteristics
OwnRent - Household in Owned
FtJob - Primary Householder with Full-Time Job
SNAP - Received Foodstamps or WIC Assistance
AtHome - Household member at home on typical day
InvIncome - Receives investment income
RetirePay - Receives retirement pay

Controls for Home Size and Energy Use
Tsqft - Total sqft of household
Tsft-squared - Control for Non-Linearity
Tbtu - Total usage in thousand BTU, 2009
Tbtu-squared - Control for Non-Linearity
ProA - Proactive action take to improve efficiency

Controls for Home Technologies
AC - Air conditioning used in household
Cwash - Clothes washer used in household
Dryer - Clothes dryer used in household
Internet - Internet access in the household
TV2 - Two or more TVs in household

MEASURE OF MODEL PREDICTIVE PERFORMANCE

The probability of the full model correctly predicting the outcome for household energy burden was evaluated for both weighted and un-weighted data. For the un-weighted sample of 991 observations, the Stata .estat classification command was used and shows that 85% of observations are correctly classified demonstrating the predictive power of the model. For the BRR model, the Stata predict command was used to calculate the predicted probabilities from the model that ENG8 = 1 (Yes) indicates that at least 8% of household income was spent on household energy (ENG = energy spending greater than or equal to 8%). Predicted probabilities > 0.5 were evaluated using a chi-squared test versus the observed data for ENG8. The results, included as Table 1 below, also show that 85% of observations are correctly classified by the BRR model with chi2(1) = 281.17 and Pr = 0.00 meaning that there is zero probability a sample of households like this one occurred randomly and that we can predict with 85% accuracy if a household in energy burdened based on the characteristics described. The interpretation of Table 1 is that 720 samples were predicted to not be energy burdened and were in fact not, and 120 samples were predicted to be energy burdened and in fact were. Thus, 840 samples were correctly predicted out of 991 total samples (840/991 = 85%). The statistical model in effect under predicts the number of energy-burdened households as 17% (164/991) rather than the total from the sample of 23% (227/991).

TABLE 1:

Chi2 (chi squared) test for the BRR model predicted probabilities and observed outcomes for Texas households that are energy burdened (spend ≥8% of household income on energy).

ENERGY BURDENED TEXAS HOUSEHOLD			
Prediction	No	Yes	Total
No	720	107	827
Yes	44	120	164
Total	**764**	**227**	**991**

Pearson chi2(1) = 281.17 Pr = 0.000

Correctly Classified: 85%

Odds-ratios and t-statistics for the nested BRR binary logit model.

Predictor	Description	Odds Ratio	t-statistic
Home Energy Cost > 8% of Income (ENG8) - Texas			
RACE	*Householder's Race*		
Black		1.46	3.80***
Other		1.12	0.52
SDESCENT	*Spanish or Latin Descent*		
Yes		1.47	2.69**
ED	*Educational Attainment*		
SomeCol		0.82	-1.41
Col		0.57	(-3.74)***
Adv		0.20	(-4.45)***
GENDER	*Householder's Gender*		
Male		0.62	(-5.33)***
Spouse	*Married or Lives with Partner*		
Yes		0.34	(-9.10)***
UR1	*Urban or Rural Household*		
Urban		1.17	1.09
AGE	*Age and Age-Squared*	0.97	-1.28
c.AGE#c.AGE		1.0004	1.44
CU10	*Children Under 10 in Home*		
Yes		0.55	(-3.87)***
CIH	*Children in Home*		
Yes		1.16	1.35
PH65	*Primary Householder Over 65*		
Yes		1.54	2.17*
OwnRent	*Householder Owns Home*		
Yes		0.46	(-5.03)***
FTJob	*Householder with Full Time Job*		
Yes		0.25	(-8.15)***
SNAP	*Householder Receives SNAP or WIC*		
Yes		2.60	4.47***
AtHome	*Someone at Home on Typical Workday*		
Yes		1.64	4.31***
InvIncome	*Householder Receives Inv. Income*		
Yes		0.69	(-2.66)**
RetirePay	*Householder Receives Ret. Income*		
Yes		0.52	(-4.09)***
ProA	*Proactive Energy Efficiency*		
Yes		1.08	0.74
AC	*Air Conditioner for Home*		
Yes		0.83	-0.48
Cwash	*Clothes Washer in Home*		
Yes		1.10	0.41
Dryer	*Dryer Used in Home*		
Yes		1.08	0.36
Internet	*Internet Access in Home*		
Yes		0.63	(-3.43)***
TV2	*Two or More TVs in Home*		
Yes		0.63	(-3.81)***

N = 991.   Survey Weighted Households = 8,527,938   * p<0.05, ** p<0.01, *** p<0.001

It is noted here that adding a binary for low-income households improves the prediction of outcomes from 85% to 91% of observations in sample. For the collinearity reasons previously discussed, this variable is excluded in order to study the characteristics of greater interest discussed below. ■

3 | RESULTS OF MODEL FOR PREDICTING ENERGY-BURDENED TEXAS HOUSEHOLDS

The results of the nested BRR logit model are presented in table form as Table 2. The results are listed as an odds-ratio, or the fraction of change in being energy burdened if the given energy predictor is true. For example, for the predictor "SPOUSE", indicating if the household has a married couple (or partners) living together, the odds ratio is 0.34, meaning that a married couple living in the same household has 66% (1-0.34) lower chance of being energy burdened relative to the main income earner living alone.

These data are estimates from a sample of 991 Texas households representing a population of 8,527,938 households in 2009 and calculated through the application of the survey weights described previously. Significant impacts are found on the basis of education, home ownership, race, and employment status. Discussion is presented here along each of the four categories of variables described above.

DEMOGRAPHIC CHARACTERISTICS OF SPECIAL INTEREST

The principal variables of interest for this analysis provide insights into the digital divide by education, race, home ownership, and full-time employment status. The impact of these characteristics on existing poverty statistics are clear from previous studies, and public policies designed to eliminate energy burden along these lines are expected to have positive impacts on American families.

These results show that households where the primary householder is working full-time have 4 times lower odds of experiencing energy burden compared with households working less than full-time. This significance of full-time employment on energy burden is made clear when investigating specific demographic types included as Figure 9. For example, white, rural

households with high school (HS) or less education who are working less than full-time have a 0.344 probability of energy burden compared with their fully employed counterparts who have a 0.148 probability. Black, urban households with HS or less education and working less than full-time have a 0.445 probability of energy burden compared with 0.212 for fully employed householders with otherwise the same demographic characteristics.

Educational attainment for the householder has a pronounced effect on household energy burden with energy burden decreasing with increasing levels of education. These data show that households with a college degree have roughly half the odds of energy burden than those with HS degree or less. Advanced degree holders are shown to have five times lower odds of energy burden than those households who did not attend any college. The average marginal impact of an advanced degree versus HS or less is 16.3 probability points with all other characteristics held equal as shown in Figure 8. For a Hispanic, urban, and full-time worker the probability of energy burden decreases from 0.207 for HS or less education to 0.064 for an advanced degree (see Figure 9).

These data also demonstrate that differences in energy burden are significant by race and Hispanic or Latino origin. Two variables are used in the model to investigate the impact of race. SDESCENT is a binary variable that identifies individuals of Latino or Hispanic descent. This variable is significant (t =2.69) and shows that these households have 1.47 times higher odds of household energy burden than non-Hispanic households. RACE is a categorical variable that identifies households as White, Black, or Other. These data show that black households have 1.46 times higher odds (t = 3.80) of energy burden than white households. No statistically significant difference is found between white households

and those classified here as Other. Finally, the average marginal effect in the sample for both RACE and SDESCENT are found to be 4.8 points higher probability of household energy burden.

CHARACTERISTICS PROVIDING ADDITIONAL POPULATION INSIGHTS

Several additional characteristics are included in the model that both increase the predictive power and offer additional insights into households that are energy burdened in Texas. SPOUSE identifies householders who are currently living with their spouse or partner. This variable is highly significant in this model, and these households are shown to have 3 times lower odds (t = -9.10) of energy burden than single households. Further research may also find that households with higher risk demographic characteristics by income, education, and race have a lower probability of being married or living with a partner. Statistically significant differences in home Internet adoption are also found based on the gender of the householder. Male-headed households are found to have 38% lower odds (t = – 5.33) of energy burden than households identified as female.

Other variables of note in this category include PH65 (Primary householder older than 65), OwnRent (Household is owned versus rented), SNAP (Household received food stamp or WIC benefits), InvIncome (Household receives investment income), RetirePay (Household receives retirement income), and AtHome (Member of the household is home on a typical work day). Each of these variables is statistically significant in the model with OwnRent, InvIncome, and RetirePay correlated with a lower probability of energy burden and PH65, SNAP, and AtHome correlated with a higher probability.

TECHNOLOGY ADOPTION VARIABLES

The third set of variables included in the BRR binary logit model represent technology adoption characteristics of the household. The first three of these, AC (Air conditioner used in home), Cwash (Clothes washer in home), and Dryer (Dryer in home) may be considered either routine or commonplace technologies. For these variables,

no statistically significant difference in adoption is found between energy burdened and non-energy burdened households. In contrast, Internet (Internet access in the home) and TV2 (Two or more TVs in home) are highly significant and correlated with lower odds of energy burden. These findings have important implications for future electricity business models that rely on household level adoption of new energy technologies (fuel cells, microturbines, etc.). That is to say, if energy burdened households spend less to adopt new technologies or electronics, that they might also be unlikely to adopt the new energy technologies.

AGE

The final variable examined in detail here is the impact of age on household energy burden. As in many econometric models, age may be expected to be non-linear with respect to likelihood of household energy burden. For this reason, both age and age-squared are included the BRR logit model. The results in Figure 7 show that neither is statistically significant. Rather, there is a gradually decline in energy burden through middle age and then an increase that slightly steepens with increasing age.

Figures 1A-5A graph the probability of household energy burden versus age for the entire 991 observation sample from primary householder ages 18 through 85. These figures examine key household characteristic of interest by age across full-time employment, home ownership status, educational attainment, marriage or living with partner, and receipt of public assistance and provide useful insights. The probabilities presented in Figures 1A-5A were produced using the Stata margins command for each of the demographic groups described on the y-axis using the average marginal effects. For example, Figure 1A is produced by calculating the predicted probability of energy burden at each age with the FtJob (full time job) variable set to "Yes" first for each observation. These predicted probabilities are averaged across every observation and presented as the data points on the "Yes" line. This is then repeated by setting FtJob in every observation to "No", averaging, and then plotting both curves along with the confidence intervals.

AVERAGE MARGINAL EFFECTS

Average marginal effects across all observations
for BRR binary logit model.

Energy Burden in Texas - Average Marginal Effects

Predictor	Change	From	To	pvalue
RACE				
Black vs White	0.048	0.225	0.273	0.000
Other vs White	0.014	0.225	0.239	0.605
Other vs Black	-0.034	0.273	0.239	0.139
SDESCENT				
Yes vs No	0.048	0.218	0.266	0.009
GENDER				
Male vs. Female	-0.059	0.259	0.200	0.000
SPOUSE				
Yes vs. No	-0.136	0.309	0.173	0.000
EDUCATION				
SomeCol vs HSorLess	-0.026	0.266	0.239	0.164
COL vs HSorLess	-0.070	0.266	0.196	0.000
ADV vs HSorLess	-0.163	0.266	0.102	0.000
COL vs SomeCol	-0.043	0.239	0.196	0.058
ADV vs SomeCol	-0.137	0.239	0.102	0.000
ADV vs COL	-0.094	0.196	0.102	0.004
PH65				
Yes vs No	0.054	0.223	0.277	0.035
Own Household				
Yes vs No	-0.099	0.297	0.197	0.000
Full-time Job				
Yes vs No	-0.185	0.332	0.147	0.000
SNAP				
Yes vs No	0.133	0.214	0.347	0.000
INTERNET				
Yes vs No	-0.058	0.270	0.212	0.001
TV2				
Yes vs No	-0.059	0.278	0.219	0.000

Figure 8 presents the average marginal effects (AME) for the statistically and substantively important variables in the data set. These data are the marginal probabilities averaged over all observations in the sample using the Stata .mchange command written by Long and Freese (2014) [14]. Long and Freese (2014) review arguments in the literature that are both for and against the use of average marginal effects (AME) and marginal effects at the means (MEM). MEM measures the marginal change caused by switching a category from say "low income" to "high income" with all other variables held at their sample means. This may be problematic in data where there are multiple categorical variables because the results are based on assumptions of cases such as the average household has one-half of a child or one-third of a college education. In contrast, AME measures the impact of switching from "low income" to "high income" for each observation in the data and the averages all of these results. For example, Hanmer and Kalkan (2013) argue that AME is preferable to the more commonly used MEM on theoretical grounds, partly because there are often not actual observations in the data that matches the MEM values [15]. The case for AME is made stronger in this data set due to the inclusion of predominantly categorical variables. For this reason, the AME are also used for the margins plots in Figures 1A – 5A.

These data provide supporting insights into the themes previously discussed in this paper. At the AME, there are statistically significant differences found between full-time and less than full-time employments (Figure 1A), householders who own their home and those who do not (Figure 2A), across educational attainment categories (Figure 3A), and between Texans who live with a spouse or partner and those who do not (Figure 4A). On average across the sample, households with full-time employment are 18.5 probability percentage points less likely to experience energy burden, households that own the home are 10 points less likely, and householders who live with a spouse or partner are 13.6 points less likely. Energy burden is again seen by educational attainment, where households with HS education or less have more than 16 percentage points higher probability of energy burden than those with advanced degrees and 7 points higher than those with a college education.

The differences continue on the basis of race and gender. Hispanic or black-headed households are both 4.8 points more likely to experience energy burden, and female-headed households are roughly 6 points more likely. Finally, primary householders sixty-five or older are 5.4 points more likely to experience energy burden. This increase in probability with age is reflected in the margins plot figures in Appendix A and is consistent with many of the current energy assistance programs targeted towards the elderly population. However, as the data have shown, a much broader portion of the Texas population is exposed to the burden of high energy costs.

SAMPLE (IDEAL) DEMOGRAPHIC TYPES

Figure 9 might provide the most complete picture of the disparities of energy burden across the households that have been discussed here. The data are organized into four categories split by full-time (Ftjob) and less than full-time employment and rural (RUR) and urban (URB) status. Figure 9 offers additional insights not only into where energy burden exists but also into what socioeconomic characteristics are shown to close the gaps.

The impact of education is illustrated by the differences in the probability of household energy burden between rural, fully employed Hispanics with advanced degrees and their counterparts with a high school or less education. For these sample demographic types, advanced education decreases the probability of energy burden from 18.6% to 5.6%. The impact of full-time employment is demonstrated by comparing urban, less than fully employed black households with high school or less education with their fully employed counterparts. The less than fully employed households with these characteristics experience a 44.5% probability of energy burden versus 21.2% for their fully employed counterparts. The impact of race is seen comparing energy burden for rural, less than full-time with high school or less education. In this group, white households have a 34.4% rate compared with 41.4% for black households and 40.6% for Hispanic or Latino households. ■

Household Energy Burden by Sample Demographic Type for Texas Households.

Energy-Burdened Texas Households - Sample Demographic Types			
Rural with <Full-time Work	**Probability(ENG8)**	**Lower Limit**	**Upper Limit**
White HS <Ftjob RUR	0.344	0.297	0.390
Black HS <FtJob RUR	0.414	0.359	0.468
HISP HS <FtJob RUR	0.406	0.348	0.464
White SCOL <FtJob RUR	0.309	0.259	0.359
Black SCOL <FtJob RUR	0.376	0.318	0.434
HISP SCOL <FtJob RUR	0.369	0.308	0.429
White ADV <FtJob RUR	0.127	0.074	0.179
Black ADV <FtJob RUR	0.166	0.104	0.228
HISP ADV <FtJob RUR	0.161	0.097	0.225
Urban with <Full-time Work	**Probability(ENG8)**	**Lower Limit**	**Upper Limit**
White HS <FtJob URB	0.373	0.327	0.419
Black HS <FtJob URB	0.445	0.407	0.482
HISP HS <FtJob URB	0.437	0.389	0.484
White SCOL <FtJob URB	0.337	0.280	0.393
Black SCOL <FtJob URB	0.406	0.354	0.459
HISP SCOL <FtJob URB	0.398	0.339	0.457
White ADV <FtJob URB	0.142	0.070	0.214
Black ADV <FtJob URB	0.185	0.103	0.266
HISP ADV <FtJob URB	0.180	0.096	0.263
Rural with Full-time Work	**Probability(ENG8)**	**Lower Limit**	**Upper Limit**
White HS FtJob RUR	0.148	0.114	0.181
Black HS FtJob RUR	0.191	0.140	0.242
HISP HS FtJob RUR	0.186	0.138	0.235
White SCOL FtJob RUR	0.128	0.102	0.153
Black SCOL FtJob RUR	0.167	0.125	0.210
HISP SCOL FtJob RUR	0.163	0.123	0.202
White ADV FtJob RUR	0.042	0.017	0.066
Black ADV FtJob RUR	0.058	0.024	0.091
HISP ADV FtJob RUR	0.056	0.023	0.089
Urban with Full-time Work	**Probability(ENG8)**	**Lower Limit**	**Upper Limit**
White HS FtJob URB	0.165	0.137	0.193
Black HS FtJob URB	0.212	0.173	0.251
HISP HS FtJob URB	0.207	0.168	0.245
White SCOL FtJob URB	0.144	0.120	0.168
Black SCOL FtJob URB	0.186	0.151	0.221
HISP SCOL FtJob URB	0.181	0.148	0.215
White ADV FtJob URB	0.048	0.016	0.080
Black ADV FtJob URB	0.066	0.025	0.107
HISP ADV FtJob URB	0.064	0.023	0.105

SUMMARY

This paper used data from the Energy Information Administration to determine demographic and household characteristics that described the odds of a household spending more than 8% of income on home energy. Various factors had statistically significant descriptive power: race, educational level, gender of head of household, couples living together, home ownership, full time employment, low-income assistance, and internet access.

Approximately the same percentage of Texas households are considered low-income (24% at < $25K/yr) and energy-burdened (22% spending more than 8% of gross household income on household energy). Clearly higher incomes enable families to have more disposable income after

paying for core goods, such as energy. As Texans, we can ask ourselves an important question: "What is an acceptable fraction of energy-burdened households?". Perhaps 22% is too high, and we could develop policies to reduce it to lower level that is acceptable for a developed economy.

Understanding household energy consumption patterns, and the ability of various households to pay for household electricity, is also important for businesses. Businesses need to understand the ability of customers to afford new energy technologies (e.g., distributed photovoltaics), and electricity service providers and utilities are being forced to consider new business models in the face of technological change and stagnant median wages. ■

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APPENDIX A
(Texas RECS study): Predictive Margins

Household energy burden by employment status across Texas households

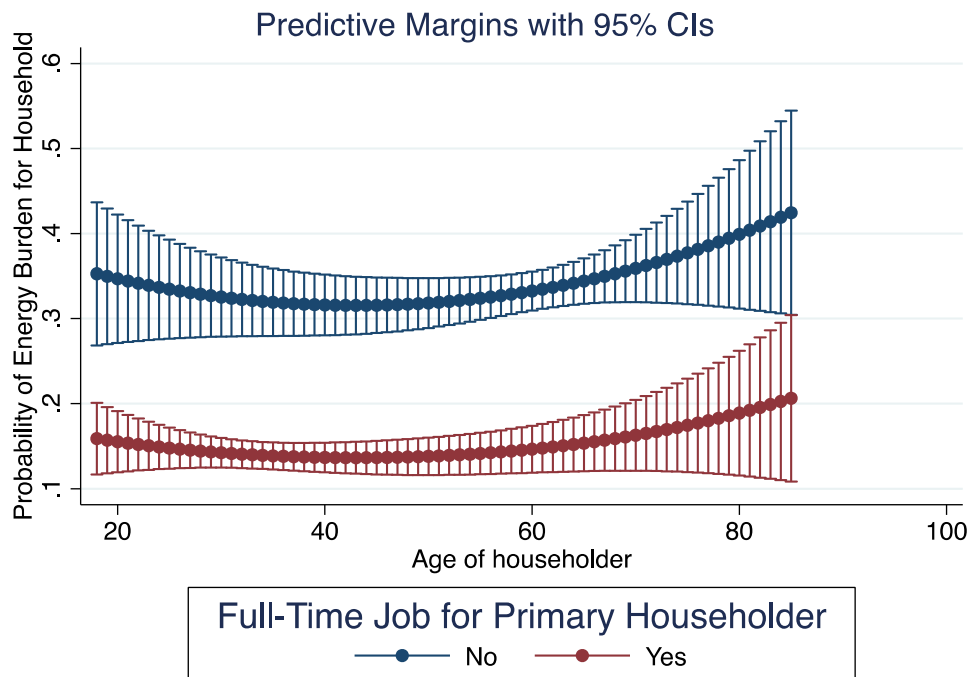### Predictive Margins with 95% CIs

Full-Time Job for Primary Householder
No · Yes

Household energy burden by home ownership status across Texas households

Predictive Margins with 95% CIs

Household is Owned
Rent · Own

Household energy burden by educational attainment across Texas households

Predictive Margins
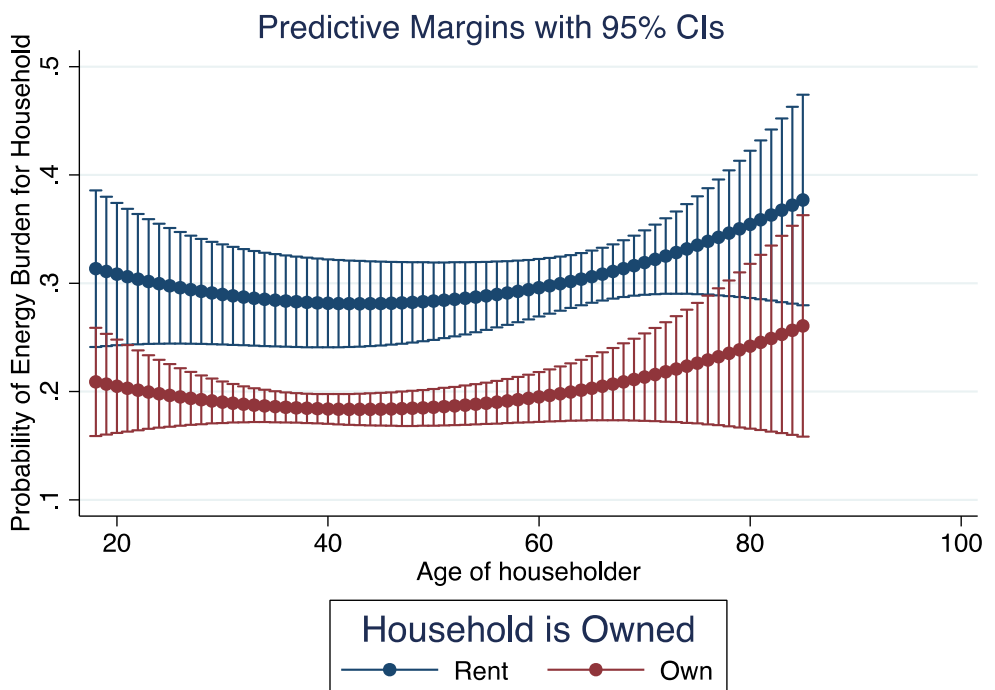
Household energy burden by educational attainment across Texas households
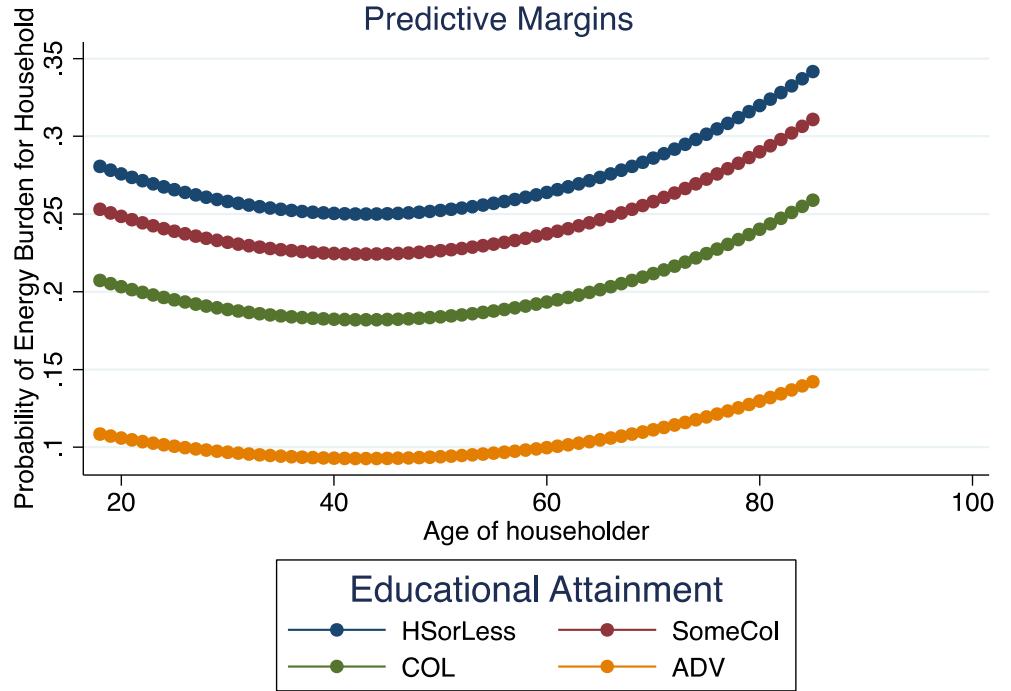
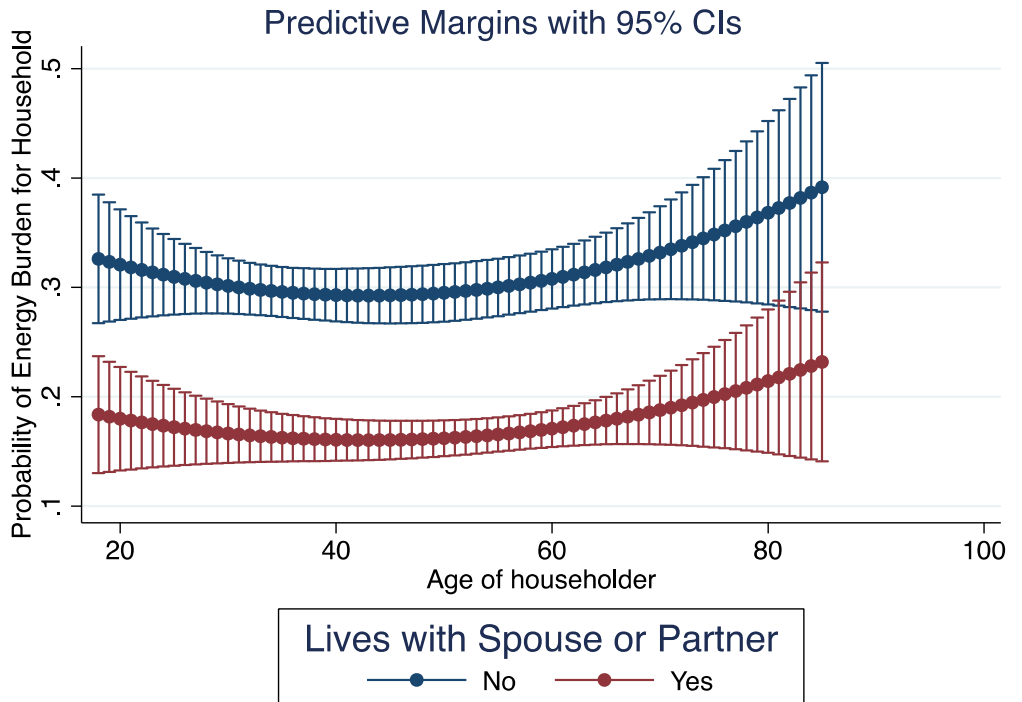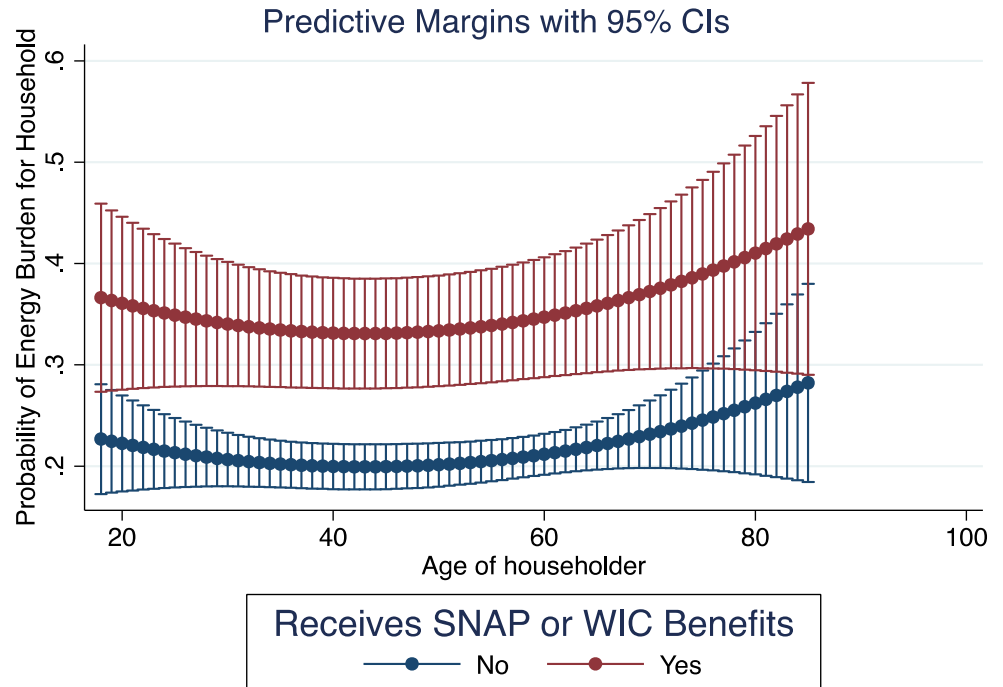Household energy burden by "Lives with Spouse or Partner" across Texas households

Predictive Margins with 95% CIs

Household energy burden by receipt of SNAP or WIC benefits across Texas households

Predictive Margins with 95% CIs

Receives SNAP or WIC Benefits

APPENDIX B
(Texas RECS study): Electricity Rates, Consumption, and Total Household Energy Spending by Demographic

FIGURE 1B:

Average electric rates ($/kWh) for low-income Texas households by demographic. (LI = low income)

How Much Are Texans Paying for Electricity?			
Group	**Households**	**Average Rate**	**Standard Deviation**
All Texans	8,527,938	$0.128	$0.029
Low-Income Texans (<$25k)	2,250,512	$0.127	$0.023
Texans with Income >$25k	6,277,425	$0.129	$0.031
Texans with Income >$75k	2,244,927	$0.129	$0.021
Texans under 150% of Poverty	2,247,265	$0.128	$0.030
LI Rural Texans	207,019	$0.137	$0.022
LI Urban Texans	2,043,492	$0.126	$0.023
LI White Rural Texans	172,219	$0.137	$0.024
LI White Urban Texans	1,463,917	$0.127	$0.024
LI Black Rural Texans	7200	$0.149	1 Observation
LI Black Urban Texans	480,388	$0.127	$0.022
LI Hispanic Rural Texans	66,855	$0.131	$0.033
LI Hispanic Urban Texans	837,661	$0.129	$0.021

FIGURE 2B:

Average electric rates ($/kWh) for energy burdened Texas households by demographic. (EB = energy burdened, spend > 8% of household income on energy)

How Much Are Energy Burdened Texans Paying for Electricity?			
Group	**Households**	**Average Rate**	**Standard Deviation**
All Texans	8,527,938	$0.128	$0.029
All EB Texans	1,993,288	$0.129	$0.022
EB Texans with Income <$25k	1,647,963	$0.127	$0.022
EB Texans with Income >$25k	345,325	$0.136	$0.018
EB Texans with Income >$75k	16,173	$0.140	2 Observations
EB Texans under 150% of Poverty	1,635,368	$0.127	$0.022
EB Rural Texans	273,921	$0.134	$0.020
EB Urban Texans	1,719,367	$0.128	$0.022
EB White Rural Texans	230,713	$0.133	$0.022
EB White Urban Texans	1,237,510	$0.127	$0.022
EB Black Rural Texans	15,608	$0.145	2 Observations
EB Black Urban Texans	416,744	$0.131	$0.021
EB Hispanic Rural Texans	94,681	$0.132	$0.029
EB Hispanic Urban Texans	649,269	$0.129	$0.019

FIGURE 3B:

Annual electricity usage (kWh in 2009) for low-income Texas households by demographic. (LI = low income)

How Much Electricity Are Texans Using?			
Group	**Households**	**KiloWatt Hours**	**Kwh Standard Deviation**
All Texans	8,527,938	14277	7434
Low-Income Texans (<$25k)	2,250,512	10329	4997
Texans with Income >$25k	6,277,425	15692	7653
Texans with Income >$75k	2,244,927	18903	7874
Texans under 150% of Poverty	2,247,265	11816	6803
LI Rural Texans	207,020	12371	7123
LI Urban Texans	2,043,493	10122	4701
LI White Rural Texans	172,219	12608	7797
LI White Urban Texans	1,463,917	9932	4891
LI Black Rural Texans	7201	9455	1 Observation
LI Black Urban Texans	480,388	10632	3951
LI Hispanic Rural Texans	66,855	10440	3315
LI Hispanic Urban Texans	837,661	9191	4686

FIGURE 4B:

Annual electricity usage (kWh in 2009) for energy burdened Texas households by demographic. (EB = energy burdened, spend > 8% of income on energy)

How Much Electricity Are Energy Burdened Texans Using?			
Group	**Households**	**KiloWatt Hours**	**Kwh Standard Deviation**
All Texans	8,527,938	14277	7434
All EB Texans	1,993,288	13678	7623
EB Texans with Income <$25k	1,648,963	11617	4941
EB Texans with Income >$25k	345,325	23515	10180
EB Texans with Income >$75k	16,173	39854	2 Observations
EB Texans under 150% of Poverty	1,635,368	12597	6914
EB Rural Texans	273,921	17025	10995
EB Urban Texans	1,719,367	13145	6830
EB White Rural Texans	230,713	17772	11737
EB White Urban Texans	1,237,510	13187	7143
EB Black Rural Texans	15,609	15476	7880
EB Black Urban Texans	416,744	12966	6318
EB Hispanic Rural Texans	94,681	12253	4879
EB Hispanic Urban Texans	649,269	12342	6036

FIGURE 5B:

Total annual home
energy costs (2009$)
for low-income
Texas households by
demographic.
(LI = low income)

How Much Are Texans Paying for Household Energy?

Group	Households	Energy Dollars	Standard Deviation
All Texans	8,527,938	$2,160	$1,080
Low-Income Texans (<$25k)	2,250,512	$1,591	$727
Texans with Income >$25k	6,277,425	$2,364	$1,113
Texans with Income >$75k	2,244,927	$2,942	$1,227
Texans under 150% of Poverty	2,247,265	$1,777	$892
LI Rural Texans	207,019	$2,019	$1,039
LI Urban Texans	2,043,492	$1,548	$676
LI White Rural Texans	172,219	$1,994	$1,137
LI White Urban Texans	1,463,917	$1,514	$660
LI Black Rural Texans	7200	$1,870	1 Observation
LI Black Urban Texans	480,388	$1,680	$721
LI Hispanic Rural Texans	66,855	$1,521	$487
LI Hispanic Urban Texans	837,661	$1,427	$639

FIGURE 6B:

Total annual home
energy costs (2009$)
for energy burdened
Texas households by
demographic.
(EB = energy
burdened, spend > 8%
of income on energy)

How Much Are EB Texans Paying for Household Energy?

Group	Households	Average Rate	Standard Deviation
All Texans	8,527,938	$2,160	$1,080
All EB Texans	1,993,288	$2,123	$1,132
EB Texans with Income <$25k	1,647,963	$1,796	$722
EB Texans with Income >$25k	345,325	$3,681	$1,412
EB Texans with Income >$75k	16,173	$7,745	2 Observations
EB Texans under 150% of Poverty	1,635,368	$1,918	$929
EB Rural Texans	273,921	$2,582	$1,265
EB Urban Texans	1,719,367	$2,049	$1,095
EB White Rural Texans	230,713	$2,637	$1,366
EB White Urban Texans	1,237,510	$2,043	$1,140
EB Black Rural Texans	15,609	$2,425	2 Observations
EB Black Urban Texans	416,744	$2,090	$1,027
EB Hispanic Rural Texans	94,681	$1,827	$657
EB Hispanic Urban Texans	649,269	$1,923	$906