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Residential Electricity Access: Objective versus Subjective Measures of Energy Poverty in Texas

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Residential Electricity Access: Objective versus Subjective Measures of Energy Poverty in Texas

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Residential Electricity Access: Objective versus Subjective Measures of Energy Poverty in Texas

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Policymakers in developed countries are increasingly conscious of the pervasiveness of energy poverty, especially in the U.S. where 31% of households experienced energy poverty in 2015. Energy poverty is defined as households that do not have reliable, accessible, and affordable energy services and is especially prevalent among low-income households. The vagueness of this definition has created challenges for policymakers who must estimate the need for energy assistance programs. Historically, in Europe and the U.S., an energy expenditure to income ratio (i.e. objective energy burden) has been used to estimate energy poverty where individuals who spend greater than a certain threshold are energy poor. For instance, in Texas 22% of households spend more than 8% of their income on energy expenditures. However, researchers in Europe have argued that objective energy poverty measures do not capture household, demographic, and health characteristics that have increasingly been identified as drivers of energy poverty. Further they do not account for temporal and spatial variation in residential energy spending, pricing, or consumption patterns. Although survey studies in Europe have used subjective (i.e. stated) measures to identify individuals living in energy poverty, there have been no empirical quantitative analyses comparing energy poverty metrics in the U.S. Using survey data from the Texas Energy Poverty Research Institute this study: (1) compares the household, demographic, financial, and health indicators of objectively measured energy poverty to subjectively measured energy poverty, (2) compares objectively measured energy poverty as well as subjectively measured energy poverty to existing bill assistance eligibility criterion, and (3) analyzes the regional variation in percent of income spent on electricity expenditures. The findings reveal that while objectively and subjectively measured energy poverty are associated with each other, they are driven by different characteristics. The results also indicate regional variation, with individuals in Southwest Texas spending nearly twice as much of their income on their electricity bills as other regions. This study has implications for policymakers who must estimate the need for electricity assistance programs.

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1. Introduction

Energy poverty, fuel poverty, and energy burden are terms used to describe households that do not have reliable, accessible, and affordable energy services for their household or dwelling (Bouzarovski, 2014; Reames, 2016). Energy poverty is used globally to describe this deprivation regardless of end use or type of inadequacy (e.g. affordability or reliability). Energy burden is most commonly used in the U.S. as a proxy for issues that are encompassed by energy poverty, particularly affordability and accessibility. Fuel poverty is used to describe inaccessible household heating in UK and Eastern Europe. In Europe, there is an understanding amongst researchers that energy poverty is a result of a combination of interacting factors including high energy prices, low incomes, inefficient buildings, or individual household practices and needs (Boardman, 2010; Thomson, Bouzarovski, & Snell, 2017).

Energy poverty is especially acute in the U.S. where 31% of households reported that they had challenges paying their bills or keeping their households adequately cool or warm or in 2015 (Berry, Hronis, & Woodward, 2018). In several regions—including Texas, the location of this study— residential electricity prices have increased over the past two decades in conjunction with higher electricity demands in part due to increasingly severe weather (Yun & Steemers, 2009; DOE, 2016; Wible & King, 2016). These trends can create a compounded burden for vulnerable individuals living in older, less energy efficient housing (Valenzuela, et al., 2014). However, in the U.S. there is no formal legislative or regulatory recognition of energy poverty. Further, there is also no consensus on the definition or a metric for energy poverty in the literature in the U.S. In Europe—where energy poverty is formally recognized (Bouzarovski, 2018) and the literature is more developed—there is still not a consensus between policymakers and researchers on a metric for energy poverty (Boardman, 2010; Hills, 2012; Bouzarovski, 2014; Schuessler, 2014; Bouzarovski & Petrova, 2015).

Historically, the percent of income used for energy expenditures has been regarded as an impartial way of determining energy poverty. However, using an expenditure to income ratio as a measure of energy poverty has come under criticism by several scholars (Healy & Clinch, 2004; Harrison & Popke, 2011; Hills, 2012; Bouzarovski, 2014).

Studies have shown that using an expenditure to income ratio is scientifically arbitrary as it does not account for regional and temporal spending factors or differences in types of energy poverty (i.e. chronic versus temporary) (Healy & Clinch, 2004; Buzar, 2007; Moore, 2012; Liddell, Morris, McKenzie, & Rae, 2012). For instance, in much of the early energy poverty literature in the UK, individuals who spend more than 10% of their income on energy were considered energy poor (Boardman, 1991), but spending in the UK has changed over time. When considering regional variation, a study in the U.S. showed that certain cities spend 3% of their income while others spend 12%. Furthermore, many researchers argue that energy poverty should be understood as a combination of factors such as household structure, demographics, household make up (e.g. number of elderly or children in household), and health (Boardman, 2010; Bird & Hernández, 2010; Harrison & Popke, 2011; Reames, 2016; Bouzarovski & Simcock, 2017).

Policymakers and researchers in the U.S. are beginning to take note of the necessity to more effectively coordinate energy poverty relief programs (Bird & Hernández, 2010; Reames, 2016; Wible & King, 2016). In the Texas, the policies and programs meant to ameliorate issues of energy poverty such as weatherization or bill assistance have primarily been inadequate. For instance, according to an 8% expenditure threshold roughly 15% households in Texas are experiencing energy poverty with respect to electricity (Wible & King, 2016). Estimates suggest this is roughly 4 million individuals experiencing household energy poverty with respect to electricity (U.S. Census Bureau, 2019) .Yet Lite-UP Texas, electricity bill assistance program funded by the Texas System Benefit Fund until August 2016, only served roughly 700,000 people (Malewitz, 2016). The Lite-UP program offered low income families a 25-31% discount on their energy bills (Malewitz, 2016). The program was available to individuals who were enrolled in Medicaid, the Supplemental Nutrition Assistance Program (SNAP), or individuals on the Public Utility Commission’s (PUC) list of eligible customers (Public Utility Commission of Texas, 2017).

Before 2017, Retail Electricity Providers (REP) were required to compensate the PUC for maintaining a list of people who were eligible for the Lite-Up program. Individuals on this list were also eligible for consumer protections such as waived fees for late bills and deferred payment plans during the summer. In 2017, the Texas legislature passed Senate Bill 1976 which called on Public Utility Commission to work with Health Services to identify people who are eligible for such protections, but not all REPs are required to compensate the PUC (Handy, 2017; Harmon & Prince, 2018). Instead REPs who would like to create assistance programs that mirror

Lite-Up Texas must request this information and compensate the Utility Commission accordingly. However, Senate Bill 1976 explicitly precludes the Public Utility Commission from requiring that retail utility providers develops their own assistance programs (Handy, 2017; Harmon & Prince, 2018).

With this in mind, the identification of customers who need bill assistance programs is pertinent. Additionally, awareness of assistance programs amongst providers and customers must improve. For instance, the Energy Institute at the University of Texas found that in 2012 only 36,000 households received weatherization assistance (Wible & King, 2016). In a survey study done by the Texas Energy Poverty Research Institute (TEPRI), only 11% of respondents were aware of energy efficiency programs and 22% were aware of bill assistance programs (Harmon & Prince, 2018).

In order for Texas and other states to create policy programs that are more effectively targeted and implemented, a more concrete and coherent understanding of energy poverty must be developed. While most research has focused on customer's dwelling place and structure (i.e. energy efficiency) (Valenzuela, et al., 2014; Ross & Drehobl, 2016), research has shown that socio-demographic and economic factors are powerful indicators of energy poverty and energy consumption (Yun & Steemers, 2009; Reames, 2016; Wible & King, 2016). Some scholars have concluded that comparing energy poverty metrics may highlight different ways individuals experience energy poverty (e.g. temporary versus chronic) (Healy & Clinch, 2004; Herrero, 2017). Others discuss that comparing energy poverty metrics has led to an increased understanding of the asymmetries that exist in public awareness and policymaker awareness of energy poverty (Bouzarovski, 2014; Bouzarovski & Simcock, 2017).

This study seeks to understand the relationship between characteristics (e.g. household structure, demographics, financial hardship, perceived health) and energy poverty. As the definition of energy poverty is vague, energy poverty is explored through two lenses, those respondents who stated they struggle to pay their electricity bill—i.e. *individuals that are subjectively energy burdened*, and those who are found to be energy burdened based on the percent of their income spent on electricity expenditures— i.e. *individuals that are objectively energy burdened*. In doing so, this study fills the gap in the literature in the U.S. that looks at discrepancies between how utility customers perceive energy poverty (i.e. subjective energy burden) and how scholars have historically understood energy poverty (i.e. objective energy burden).

The second purpose of this study is to assess whether there is a relationship between geographic characteristics and household electricity bill expenditures. As electricity bill spending has historically been used to define energy poverty and used to assess need for relief in the U.S., this study seeks to understand whether researchers should estimate the need for energy poverty relief programs on a regional basis. This is done by analyzing whether the percentage of income respondents spend on their electricity bill (i.e. objective energy burden) differs by region. In doing so, the results of this study address the gap in the U.S. energy poverty literature that question the impartiality of objective energy burden as a metric of energy poverty.

More specifically this study addresses the following research questions:

(1) Are subjective energy burden and objective energy burden capturing different populations (with respect to electricity)? Further, are these metrics capturing individuals who currently qualify for programs meant to ameliorate energy poverty?

(2) What are the drivers of subjective and objective energy burden?

(3) Does the percent of income spent on electricity bills vary across Texas (by region)?

In order to answer these research questions, this research utilizes hypothesis testing as well as parametric statistical modeling to analyze survey data collected in 2018 by the Texas Energy Poverty Research Institute (TEPRI). The results indicate that there is an association between individuals who are subjectively and objectively energy burdened. However, the drivers of subjective energy burden and objective energy burden differ. Interestingly, low-to moderate-income individuals who live in southwest Texas spend nearly twice as much on their electricity bill as other regions. As a result of these geographical differences and differences in drivers, we recommend that policymakers use a combination of metrics when estimating the number of people who need assistance programs.

While this study focuses on electricity, the results have implications for regulators and policymakers who must estimate the need for energy poverty relief programs, spread awareness of these issues, and identify individuals who are most in need of these programs. This study supports existing policy program targeting of assistance programs and literature. However, it also highlights under-explored regions and populations who may need assistance. Further, it demonstrates the need to explore the relationship between energy poverty in the U.S. and other vulnerabilities such as health to create more holistic assistance programs.

2. Literature Review

Brenda Boardman is regarded as one of the first to create a numeric metric of energy poverty for the UK in 1991, defined as a household that spends more than certain percentage of their income on energy (Boardman, 1991). Boardman defines energy poverty in the UK as households who spend more than 10% of their income on energy expenditures. At the time, individuals who spent 5% of their income on energy expenditures represented median spending patterns, and 10% was twice that. This study found that the lowest 30% of income earners spent roughly 10% of their income on energy (Boardman, 1991). Similarly, a U.S. based study used an energy burden threshold of 8% as it is twice the mean energy expenditure in the U.S. (Wible & King, 2016). Since then, Boardman herself and several other researches have critiqued an energy burden threshold's ability to measure energy poverty as it does not account for a number of structural, social, and economic factors (Healy & Clinch, 2004; Boardman, 2010; Moore, 2012; Hills, 2012; Herrero, 2017; Bouzarovski & Simcock, 2017). Further it does not address whether the average expenditure is an acceptable value for a household to spend.

This literature review is organized by focusing first on the causes of energy poverty, followed by discussing critiques of current energy poverty measures, specifically (1) the discrepancies between results using stated versus energy burden measured energy poverty, and (2) the necessity of having a regional or localized energy burden metric. The body of energy poverty literature in the U.S. is not nearly as robust as European literature; as such, the focus of much of this literature review is based in Europe.

First it is important to reiterate differences in energy poverty terminology between the U.S. and Europe. For the purpose of this literature review, fuel poverty, energy poverty, and energy burden are used interchangeably. In Europe fuel poverty has historically described household heating issues. However, since this paper is not focused solely on heating issues (fuel poverty) and because it is focused in U.S., the rest of this paper uses the terms energy poverty and energy burden. Specifically, energy burden is invoked as a measure for energy poverty.

CAUSES AND CONSEQUENCES OF ENERGY POVERTY

Early literature on the causes and lived experience of residential energy poverty in developed countries documents the role of energy prices, appliances and household energy inefficiency, and financial hardship (Boardman, 1991; Healy & Clinch, 2004; Buzar, 2007; Bird

& Hernández, 2010). For instance, much of the energy poverty literature at the turn of the 21st century focused on Eastern European countries who experienced exorbitant energy prices as well as high rates of poverty that coincided with the liberalization of their economies (Fankhauser & Tepic, 2007; Buzar, 2007). More recent literature comparing energy poverty in Europe highlights that less well-off countries such as Portugal and Greece, typically have worse household energy efficiency and higher incidences of energy poverty as compared to wealthier countries like Germany. However, a paper reviewing the existing European literature on causes of energy poverty highlights that not all income poor individuals are also energy poor (Bouzarovski, 2014). Further, a report from the London School of Economics showed that energy poverty is an issue distinct from poverty alone (Hills, 2012). In the U.S., one paper posits that low-to moderate-income (LMI) consumers may be experience increased spending on electricity bills due to impact of environmental constraints, flattening electricity demand, and disruptive technologies on residential rates (Thompson, 2016). The same study highlights the significance of geography, social vulnerability such as racial minority, and health issues in contributing to or being a result of energy poverty (Thompson, 2016).

Qualitative studies that document the lived experience of individuals living in energy poverty often cite issues of poor insulation, appliance efficiency, and poor energy reliability (Bird & Hernández, 2010; Harrison & Popke, 2011). Studies analyzing the prevalence of energy poverty in the EU have shown that leaky roofs and rotten or cracked windows are indicators of energy inefficiency (Healy & Clinch, 2004; Thomson & Snell, 2012; Bouzarovski & Simcock, 2017). Furthermore, when analyzing the likelihood of respondents stating "they're having difficulty paying their energy bill or heating their homes", having a "leaky roof" and "rotten or cracked windows" were significant predictors (Thomson & Snell, 2012; Bouzarovski, 2014). The same study, amongst others, showed that individuals who are renters are more likely to state they are "energy poor" or spend significantly more of their income on their energy bills than owners (Bouzarovski, 2014; Ross & Drehobl, 2016).

In the U.S., low-income renters are underserved by energy efficiency services that are meant to ameliorate issues of energy poverty (Ross & Drehobl, 2016). Well documented issues such as the "split incentive" issues explain this issue in part (Bird & Hernández, 2010; Reames, 2016; Harmon & Prince, 2018). One study showed that household tenure (owned versus rented), whether the home was a mobile home, and age of home were significant predictors of energy inefficiency (Reames, 2016). Research has increasingly shown that health, household make up, and demographic characteristics play an important role in both the causes and consequences of energy poverty (Bouzarovski, 2014; Bouzarovski & Simcock, 2017).

Inadequate heating or cooling services leads to poor health or disabilities making individuals unable to work, thus reducing their disposable income (Harrison & Popke, 2011). Furthermore, energy poverty can lead to stress and mental health issues (Bird & Hernández, 2010; Ross & Drehobl, 2016) which exacerbate other health issues. Individuals with illnesses or disabilities are likely to require medical equipment that makes access to energy services such as electricity critical to their health (Bird & Hernández, 2010). Poor residential heating and cooling has also been shown to lead to health issues such as asthma, heart disease, and poor respiratory health (Bird & Hernández, 2010; Ross & Drehobl, 2016). Young children and infants are especially vulnerable to these health issues (Liddell & Morris, 2010).

Household makeup, especially household size and age of members, has been shown to be related to issues of energy poverty and energy inefficiency. One study showed that the primary household being 65 or older increased the likelihood of experiencing energy burden in Texas (Wible & King, 2016). Additionally, individuals who are older than 65 or retired are more likely to live in energy inefficiency (Reames, 2016), more vulnerable to changes in energy bills, and more vulnerable to health impacts of inadequate services (Ross & Drehobl, 2016). Some survey studies have found that households with young children and single parents are also more likely to respond that they have issues with their energy bills and less likely to be targeted by assistance programs (Healy & Clinch, 2004; Bouzarovski, 2014; Middlemiss & Gillard, 2015).

Finally, socio-demographic characteristics such as race, employment, marital status, and education are tied to energy poverty as a result of financial hardship and social vulnerability (i.e. inability to recover from financial shocks). One study showed that individuals who are widowed or single parents more frequently have issues controlling the temperature in their home (Healy & Clinch, 2004). Unemployed and recently unemployed individuals are also more likely to spend a disproportionately high amount of their income on energy expenditures (Bouzarovski, 2014; Ross & Drehobl, 2016). Similarly, having less than a college degree has been shown as a significant predictor of energy inefficiency (Reames, 2016) and objective burden (Wible & King, 2016). Energy efficiency, health, demographics, and financial hardship are inextricably tied and difficult to measure over time. For example, poor insulation is related to poor performance in school; in turn, poor educational attainment is a predictor of energy inefficiency (Bird & Hernández, 2010; Ross & Drehobl, 2016). As a result, methods for quantifying the prevalence of energy poverty have increasingly been debated by scholars over the past two decades (Healy & Clinch, 2004; Thomson & Snell, 2012; Price, Brazier, & Wang, 2012; Schuessler, 2014).

CRITIQUES OF THE MEASURES OF ENERGY POVERTY

Energy poverty scholars agree that there are two different types of energy poverty metrics: "objective" and "consensual" metrics for energy poverty (Price, Brazier, & Wang, 2012; Herrero, 2017; Thomson, Bouzarovski, & Snell, 2017). A key example of consensual metric is stated energy poverty, in which survey respondents are asked whether they consider themselves energy poor (Price, Brazier, & Wang, 2012). While this metric is straightforward, it is a subjective measure. Survey respondents must be aware of what energy poverty means and perceive themselves as energy poor (Herrero, 2017; Thomson, Bouzarovski, & Snell, 2017).

A key example of an objective measure is threshold where individuals spending more than a certain percentage of their income on energy services are considered energy poor (i.e. objective energy burden). One issue highlighted with objective energy poverty metrics is that they may understate energy poverty as low income individuals change their habits or forgo energy necessities to reduce expenditures (Bird & Hernández, 2010; Harrison & Popke, 2011; Herrero, 2017; Thomson, Bouzarovski, & Snell, 2017). Another criticism is that energy burden does not account for social and economic factors such as economic burden, household makeup, and health (Boardman, 2010; Harrison & Popke, 2011; Hills, 2012; Bouzarovski, 2014).

While objective and subjective (i.e. stated energy poverty) measures are the most widely used energy poverty metrics, there are few studies directly comparing results from both metrics. Most studies comparing the objective and subjective measures of energy poverty show that there is little overlap between the populations each metric identifies. One study in the UK showed that only 6% of respondents who were considered energy poor due to energy burden stated that they were energy poor (Palmer, MacInnes, & Kenway, 2008). In another study in the UK, only 16-17% of individuals who were subjectively fuel poor were considered objectively fuel poor (Fahmy, Gordon, & Patsios, 2011). A third UK study showed only 26% of those who were found to be energy poor by the energy burden threshold metric said they "feel fuel poor" (Price, Brazier, &

Wang, 2012). Notably, no studies exist in the U.S. comparing consensual (i.e. survey stated) and objective (i.e. energy burden) measures of energy poverty, particularly electricity.

Another critique of the using a national energy burden threshold is that it does not account for regional differences in economic characteristics, climate, and diversity in energy end uses (Moore, 2012; Liddell, Morris, McKenzie, & Rae, 2012; Herrero, 2017). In a study reviewing UK's success at identifying energy poverty, one study argued that using the nationwide 10% expenditure threshold skewed the UK's estimate of individuals living in energy poverty because it's twice the median (Liddell, Morris, McKenzie, & Rae, 2012). As such, Moore posits that the results will be skewed in regions where climate is particularly severe or where residents are predominantly low or high income. Similarly, Herrero (2017) and Schuessler (2014) argue that in European literature there is a disproportionate focus on heating (historically natural gas or fossil fuel in home) which skews end use and necessities of regions that have more cooling days (historically electric cooling) (Schuessler, 2014; Herrero, 2017).

To account for regional differences Ross & Drehobl (2016) measured energy burden individually in several major cities in the United States. This study utilizes the median percent of income used for energy expenditures of each individual city as the threshold in which a person was considered energy burdened (Ross & Drehobl, 2016). However, the results of the study were not compared to the potential results if a national or state threshold was used. There are no studies in the U.S. comparing regional energy burden indicator to a statewide or nationwide one.

3. Methods

This study utilizes nonparametric tests, chi-squared test for independence, and random parameter binary probit models to analyze survey data from the Texas Energy Poverty Research Institute (TEPRI). The survey research approach allowed for the collection of a large amount of data (n=2020) relatively quicker than other methods such as interviewing (Babbie, 2011). Specifically, this study focused on the responses to four questions that formed the basis for which respondents were considered subjectively or objectively energy burdened.

SURVEY

The survey was deployed in February 2018 to assess electricity affordability as well as behavioral, demographic, and household characteristics of individuals most susceptible to energy poverty in Texas—i.e. LMI residents (Harmon & Prince, 2018). The survey was deployed in 11 regions covering Texas (Figure 1) and gathered 2,020 valid household responses of which are used in this analysis.

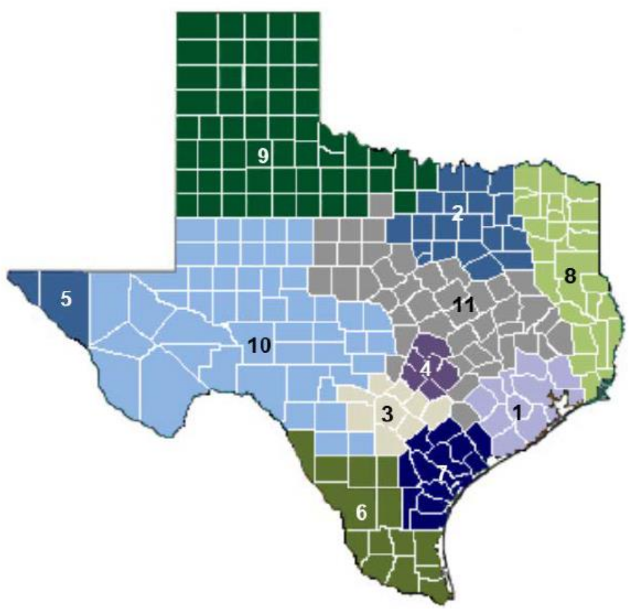

Figure 1. Map of 11 Texas Regions Sampled (Harmon & Prince, 2018)

The survey took approximately 10-15 minutes to complete and used five screener questions to ensure respondents were the age of 18 or above, residents of Texas, and low-to-moderate income ($0-$75,000). The survey questions of interest for this study spanned five categories: energy efficiency, household characteristics, health and insurance, finances, and demographics. These five categories also represent the most cited causes for energy poverty: household structure (e.g. energy efficiency), household makeup, health, financial, and demographic characteristics. The 11 regions and survey sampling methods were based on regional population, electricity market type, and climate. The survey was deployed by Qualtrics (Qualitrics, 2005; Harmon & Prince, 2018). Questions were designed by TEPRI and subject matter experts in order to minimize survey fatigue in respondents and to address the most cited issues in energy poverty and poverty research.

Specific questions of interest for this study were related to subjective and objective burden. For subjective energy burden, the following was asked:

- **Subjective Energy Burden 1**—"Since June 2017, have you had difficulty paying for your electricity bill?" (Response Options: Yes or No)
- **Subjective Energy Burden 2**—"Do your electricity bills cause you great stress or mental comfort?" (Response Options: Yes or No)

To estimate **objective burden**, two questions were used:

- "Please select the dollar amount for your average monthly electricity bill in each season" (Response Options: sliding scale $0−$400 for each of the four seasons)
- "Which of the following best describes your household's annual income in 2017, before taxes?" (Response Options: Less than $10,000 ; $10,000 - $19,999; $20,000 - $29,999; $30,000 - $39,999; $40,000 - $49,999; $50,000 - $59,999; $60,000 - $74,999; $75,000 or more)

From these two questions, the percentage of respondents' income spent on their electricity bill was estimated to discern whether they were objectively energy burdened—i.e. spending greater than a certain percent. First, responses to the questions of how much their electricity bill is in each of the four seasons (e.g. "How much do you spend on your monthly electricity bill in the fall?") were used to estimate respondents' annual electricity bill. As each season lasts three calendar months, the bill amount for each season was multiplied by three and summed in order to estimate the annual electricity bill of each respondent. Then the median of the response to the question “What was your approximate income before taxes in 2017?” was used to estimate the median income of each respondent. For example, if a respondent marked their income was between $20-30,000, $25,000 was used.

Finally, the percentage of income respondents spend on their electricity bill was found by dividing their estimated annual bill by their estimated annual income. The Energy Institute estimated that roughly 55% of Texans spend less than 4% of their income on electricity (Wible & King, 2016). Thus, 8% is roughly twice the median expenditure of Texans. Finally, the threshold of 8% was used for consistency with the Texas Energy Institute. Thus, respondents who spend more than 8% of their income on electricity bill are considered “objectively energy burdened”.

NONPARAMETRIC TESTS

To assess whether the spending threshold at which to consider respondents objectively energy burdened differed by region in Texas, the Kruskal-Wallis test was used (Washington, Karlaftis, & Mannering, 2011) (see Table 1 # 1). The Dunn Test was used to compare spending in each region—e.g. objective energy burden in Region 1 as compared to objective energy burden in Region 2. The Dunn Test identified how specific regions differed in electricity bill spending. First, for a given region, the median percent of income spent on energy was determined. Then this median was multiplied by two to determine the threshold at which an individual in a given region would be considered objectively energy burdened. For example, in Texas as a whole, 8% is the threshold for being considered objectively energy burdened because the median energy expenditure is roughly 4% of a household’s income. Utilizing twice the median as a burden threshold is debated in the literature (Boardman, 1991; Schuessler, 2014). However, one study demonstrates how, especially when the percentage of income individuals spend on energy bills is highly skewed, the median is more representative of customers’ typical spending (Schuessler, 2014). Thus, twice the median percent spent on electricity is assessed in this study.

CHI- SQUARED ANALYSIS

To assess whether the objective and subjective energy burden(s) were associated, a chi-squared test for independence was applied to the data (see Table 1 #s 2-4). Next, the relationship between the responses to each of the three energy burden metrics and Medicaid enrollment, a current eligibility requirement for energy bill assistance programs, was analyzed (see Table 1 #s 5-7) (Public Utility Commission of Texas, 2017; TDHCA, 2019). Notably, participants' response to "Please indicate the type health care coverage that best reflects your current plan?" was used to create a Medicaid variable.

Table 1 Statistical Analyses Used in the Study

#	Test	Method
1	• H_0 : The percent of income respondents spend on electricity does not vary by region • Ha : The percent of income respondents spend on electricity varies by region	Kruskal-Wallis Test and Dunn Test
2	• H_0 : Objective Energy Burden is not independent of Subjective Energy Burden 1 • Ha : Objective Energy Burden is independent of Subjective Energy Burden 1	Chi-Squared Test of Independence
3	• H_0 : Objective Energy Burden is not independent of Subjective Energy Burden 2 • Ha : Objective Energy Burden is independent of Subjective Energy Burden 2	Chi-Squared Test of Independence
4	• H_0 : Subjective Energy Burden 1 is not independent of Subjective Energy Burden 2 • Ha : Subjective Energy Burden 1 is independent of Subjective Energy Burden 2	Chi-Squared Test of Independence
5	• H_0 : Objective Energy Burden is not independent of enrollment in Medicaid • Ha : Objective Energy Burden is independent of enrollment in Medicaid	Chi-Squared Test of Independence
6	• H_0 : Subjective Energy Burden 1 is not independent of enrollment in Medicaid • Ha : Subjective Energy Burden 1 is independent of enrollment in Medicaid	Chi-Squared Test of Independence
7	• H_0 : Subjective Energy Burden 2 is not independent of enrollment in Medicaid • Ha : Subjective Energy Burden 2 is independent of enrollment in Medicaid	Chi-Squared Test of Independence
8	What are the statistically significant drivers of Objective Energy Burden?	Random Parameter Binary Probit Model
9	What are the statistically significant drivers of Subjective Energy Burden 1?	Random Parameter Binary Probit Model
10	What are the statistically significant drivers of Subjective Energy Burden 2?	Random Parameter Binary Probit Model

RANDOM PARAMETER BINARY PROBIT MODELS

The three metrics for burden (Subjective Energy Burden 1, Subjective Energy Burden 2, and Objective Energy Burden) were collapsed into binary variables— energy burdened vs not energy burdened.

Table 2. List of Binary Probit Model Dependent Variables

Dependent Variables (1 if true, 0 otherwise)	Percent of Respondents
Subjective Energy Burden 1 — Difficulty paying electricity bill since 2017	34.3%
Subjective Energy Burden 2— Electricity bill causes stress or mental discomfort	41.2%
Objective Energy Burden—Spending more than 8% of income on electricity bill	22.5%

A best fit model was found using the Akaike Information Criterion (AIC). The independent parameters (Table 3) represent financial, household structure, health, household make up, and demographic characteristics. The inclusion of these parameters allowed for identification of the statistically significant drivers of subjective(s) and objective burden.

Table 3. List of Statistically Significant Binary Probit Independent Variables

Independent Variable (1 if true, 0 otherwise)	Percent of Respondents
Financial characteristics	
Pay bills with savings	15.3%
Pay bills with credit card	24.8%
Pay bills by reducing household energy usage	27.3%
Pay bills by leaving other bills unpaid	20.0%
Pay bills with money borrowed from loved ones	19.2%
Pays bills with income	70.0%
Utility bills cause respondent to skip spending on transportation	20.6%
Utility bills cause respondent to skip spending on food	34.9%
Utility bills cause respondent to skip spending on medications	17.4%
Utility bills cause respondent to skip spending on clothing	45.1%
Difficulty with bills-other essentials	40.4%
Household structure characteristics	
Mounted Window AC	16.7%
Unsure when AC was Built	18.3%
AC 6 to 10 years old	18.9%
Mobile Home	8.8%
Large cracks or openings in windows and doors	26.2%
Household Makeup	
Two member household	28.9%
Two member household are older than 65	6.1%
Health	
Temperature in household makes individuals sick	20.0%
Medicare is my insurance	18.3%
My insurance is through my employer	30.5%
Atleast one household member is disabled	25.5%
Demographic characteristics	
Respondent between 35 and 44	18.7%
Respondent between 45 and 54	12.9%
Education level less than a college degree	30.7%
Married	40.4%
Hispanic or Latino	25.9%
Unemployed	11.3%

Equation 1 was used to predict whether a respondent was experiencing energy burden (subjective or objective)

$$Y_i = \beta X_i + \varepsilon_i \; where \; i = 1,2,3 \ldots n \; (1)$$

$$Y = \begin{cases} 1, & Objective\ Burden \geq 8\% \\ 0, & Objective\ Burden < 8\% \end{cases} \text{ OR}$$

$$Y = \begin{cases} 1, & Subjective\ Burden = "Yes" \\ 0, & Subjective\ Burden = "No" \end{cases}$$

, where Y_i is energy burden (the dependent variable— e.g. objective burden), X_i is a vector of explanatory independent variables (e.g. financial characteristics or demographics), β is a vector of estimated parameters, ε_i is a normally distributed error term. All random parameters were normally distributed (Washington, Karlaftis, & Mannering, 2011).

$$\Pr(Energy\ Burden) = \varphi(\frac{\beta_{Energy\ Burden} X_{Energy\ Burden\_n}}{\sigma}) \; (2)$$

Equation 2 indicates the probability that respondents had either outcome (i.e. subjective/objective energy burdened or not) from observation n. Phi (φ) is the standard cumulative normal distribution and sigma (σ) is the sample standard deviation. $\beta_{Energy\ Burden}$ is a vector of parameters for the energy burdened outcome. $X_{Energy\ Burden\_n}$ is a vector of measured parameters that represents a single outcome for a given observation (Washington, Karlaftis, & Mannering, 2011).

$$\Pr(Energy\ Burden) = \int_x \mathrm{P}(Energy\ Burden) * f(\beta|\varphi) * d\beta \; (3)$$

Equation 3 represents how random parameters were incorporated in the equation to reflect heterogeneity of subjective energy burden(s) and objective energy burden across the population where φ is a vector of parameters of a specified density function, $f(\beta|\varphi)$ (Washington, Karlaftis, & Mannering, 2011). Random parameters are included to reflect the heterogenous effect that the parameters have across the population (normally distributed marginal effect for this study).

The random parameter models were estimated using the method of simulated maximum likelihood with the Halton sequence. Using the Halton sequence approach has been shown to generate an efficient way of drawing values of β from $f(\beta|\varphi)$ to compute probabilities and estimate model parameters (Bhat, 2003).

In this study, 500 Halton draws were used to estimate model random parameters. Independent variables were added iteratively while using the Akaike Information Criterion (AIC) to test if the model improved by adding each variable. AIC represents the amount of information lost when using a specific model; a lower AIC indicates a better model (Bozdogan, 1987). Variables were added to each model until the AIC was minimized.

Marginal effects were used to interpret the sign and magnitude of the impact each independent parameter had on the dependent parameter (e.g. objective energy burden). The given values of the marginal effects were the average marginal effect of each parameter across the sample, for a unit change in the independent parameter (Washington, Karlaftis, & Mannering, 2011). A positive marginal effect demonstrates an increase in likelihood that a respondent is experiencing objective or subjective(s) burden.

4. Results

Survey Results

The results show that Subjective Energy Burden 2 categorized the greatest proportion (41%) of individuals as energy poor (Figure 2). Subjective burden 1 categorized 34% of respondents as energy poor. Objective burden categorized 23% respondents as energy poor.

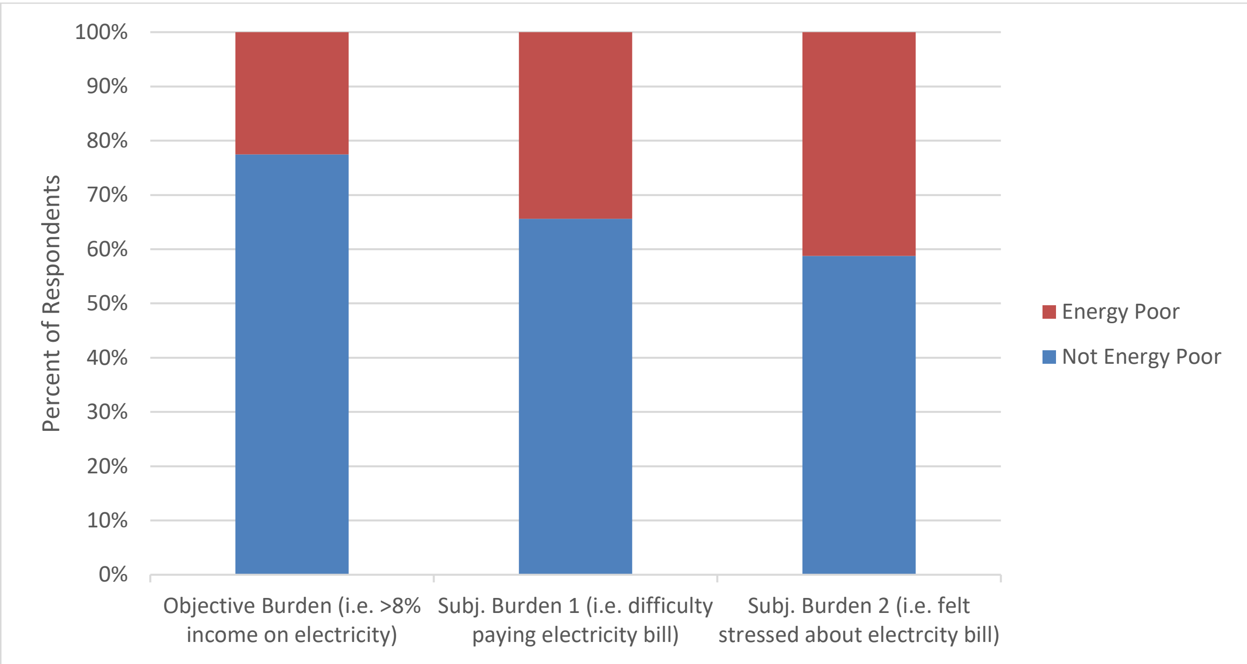

Figure 2. Percentage of Respondents Experiencing Objective and Subjective Energy Burdens

Nonparametric Tests

The median percent respondents spend on their electricity bill in each of the 11 regions in Texas (Figure 1) is shown in (Table 4). The median spending in each region is multiplied by two to obtain the threshold at which a respondent is considered objectively energy burdened in that respective region. For instance, a respondent who spends more than 7.9% of their income on their electricity bill in Region 1 would be considered objectively energy burdened (Table 4). The results indicate the objective energy burden threshold ranges from 6.5% to 13.7%

Table 4. Regional Spending and Objective Energy Burden Threshold

Region	Name	Median Percent of Income Spent on Electricity Bill (%)	Objective Burden Threshold (%)	N
1	Houston Metropolitan	4.0	7.9	385
2	Dallas/Fort-Worth Metroplex	4.2	8.3	385
3	San Antonio Area	4.6	9.3	271
4	Capital Area	3.9	7.8	208
5	West Texas	3.2	6.5	68
6	Southwest Texas	6.8	13.7	97
7	Corpus Christi Metropolitan	5.7	11.3	68
8	East Texas	5.6	11.3	97
9	Texas Panhandle	4.4	8.9	165
10	West/Central Texas	5.0	9.9	208
11	Waco Area	3.9	7.7	68

The results of the Kruskal-Wallis test between objective burden and region was significant (p-value=1.40E-13). Thus, we can reject the null hypothesis that the percent of income that people spend on their electricity bill is independent of the region they live in. The results of the post hoc test, the Dunn test, show that in 31 out of 55 spending comparisons (e.g. compare objective energy burden in Region 1 to Region 5, Region 1 to Region 2) a significant difference (p-value<0.05) was identified. Due to space limitations, the full list of Dunn Test p-values for comparing the percentage of income spent from region to region can be seen in Appendix A.

CHI-SQUARED ANALYSIS

Of the people who were found to be Objectively Energy Burdened, 52% and 54% indicated they were Subjectively Energy Burdened by question 1 and 2 respectively (see Appendix B). The three chi-squared tests of independence run between objective and subjective(s) burden were significant (p-value=0.000). Thus, we reject the null hypothesis that each of the metrics are independent of one another. In other words, objective burden 1 and subjective energy burden 1 are not independent of each other. Objective burden 1 and subjective energy burden 2 are not independent of each other. Finally, subjective energy burden 1 and subjective energy burden 2 are not independent of each other.

The results of the chi-square test of independence between subjective energy burden 1 and Medicaid, as well as for objective energy burden and Medicaid were significant (p-value< 0.1). Thus, we reject the null hypothesis these metrics are independent of Medicaid (Table 1). However, interestingly, the chi squared results between Medicaid use and subjective energy burden 2 (i.e. electricity bill causes stress) are not significant (p-value=0.072). As a result, we cannot reject the null hypothesis that this metric is independent of Medicaid.

RANDOM PARAMETER BINARY PROBIT MODELS

The results for the three random parameter binary probit models are shown in Tables Table 6-Table 9 and descriptive statistics for the significant parameters are shown in Table 3. Table 5 summaries the Pearson product moment correlation coefficients for all three models. The Pearson product coefficient is the correlation between the model's predicted value of objective and subjective energy burden(s) and the actual value as provided by the survey respondent (Greene, 2012). As such, this correlation demonstrates the accuracy of the binary probit models. Results show that all three models had a high accuracy (>0.70).

Table 5 Pearson Product Moment Correlation Coefficient

	Subj. Energy Burden 1	Subj. Energy Burden 2	Obj. Energy Burden
Pearson product moment correlation coefficient	0.820	0.720	0.769

The results of the statistically significant drivers of objective energy burden are shown in Table 6. The results of statistically significant drivers of subjective energy burden 1 and 2 are show in Table 7 and Table 8, respectively. Notably, subjective energy burden 1 and 2 only share two significant health variables and one significant structural variable.

Table 6. Model of the probability of respondents spending more than 8% of their income on their electricity bill (random parameters are normally distributed)

Independent Variables (1 if true, otherwise 0)	Parameter (t-statistic)	Standard deviation (t-statistic)	Marginal Effects
Constant	-1.00 (-8.90)	*fixed*	
Financial characteristics			
Pay bills with income	-0.270 (-2.81)	*fixed*	-0.029
Pay bills with money borrowed from loved ones	0.333 (3.00)	*fixed*	0.035
Pay bills with credit card	-0.538 (-4.46)	0.923	-0.057
Utility bills cause respondent to skip spending on transportation	0.521 (4.70)	0.648	0.055
Household structure characteristics			
Mounted Window AC	.250 (2.04)	1.602	0.027
AC was built 6 to 10 years ago	-0.319 (-2.55)	*fixed*	-0.034
Mobile Home	0.855 (6.22)	*fixed*	0.091
Household Makeup			
Two member household	-0.286 (-2.69)	*fixed*	-0.030
Health			
Temperature in household makes individuals sick	0.331 (2.99)	0.605	0.035
My insurance is through my employer	-1.34 (-8.34)	1.280	-0.142
At least one household member is disabled	0.270 (2.66)	*fixed*	0.029
Demographic characteristics			
Education level less than a college degree	0.590 (6.13)	1.059	0.063
Married	-1.14 (-9.42)	1.117	-0.121
Hispanic or Latino	0.287 (2.70)	1.215	0.030
Unemployed	0.321 (2.34)	0.979	0.034
AIC	1847.000		
Number of observations	2020		

Table 7. Model of the probability of responding "My household has had difficulty paying for the electricity bill since June 2017" (random parameters are normally distributed)

Independent Variables (1 if true, otherwise 0)	Parameter (t-statistic)	Standard deviation (t-statistic)	Marginal Effects
Constant	-1.38 (-15.56)	*fixed*	
Financial characteristics			
Pay bills with Income	-.519 (-5.57)	*fixed*	-0.181
Difficulty with bills-other essentials	2.60 (23.2)	*1.60*	0.907
Household Structure characteristics			
Mounted Window AC	0.255 (2.15)	*fixed*	0.089
Unsure when AC was built	-0.378 (-3.09)	*fixed*	-0.132
Large cracks or openings in windows and doors	0.436 (4.45)	*fixed*	0.152
Household Makeup			
Two member household	-0.403 (-3.72)	0.676	-0.140
Two members of household are older than 65	-1.05 (-3.31)	*fixed*	-0.367
Health			
Atleast one household member is disabled	0.393 (3.86)	*fixed*	0.137
Temperature in household makes individuals sick	0.533 (4.96)	0.854	0.186
Demographic characteristics			
Respondent between 35 and 44	0.322 (2.82)	*fixed*	0.112
AIC	1554		
Number of observations	2020		

Table 8. Model of the probability of responding "Yes, my electricity bills cause stress and mental discomfort."(random parameters are normally distributed)

Independent Variables (1 if true, otherwise 0)	Parameter (t-statistic)	Standard deviation (t-statistic)	Marginal Effects
Constant	-1.52 (-20.6)		
Financial characteristics			
Pay bills with savings	0.400 (3.45)	1.22	0.158
Pay bills with credit card	0.209 (2.31)	0.950	0.083
Pay bills by reducing household energy usage	0.516 (5.82)	0.748	0.203
Pay bills by leaving other bills unpaid	1.12 (10.20)	0.570	0.440
Utility bills cause respondent to skip spending on food	0.683 (7.94)	1.160	0.269
Utility bills cause respondent to skip spending on medications	0.597 (5.36)	*fixed*	0.235
Utility bills cause respondent to skip spending on clothing	0.583 (7.46)	0.46	0.230
Household Structure characteristics			
Large cracks or openings in windows and doors	0.481 (5.54)	*fixed*	0.190
Health			
Temperature in household makes individuals sick	0.868 (8.66)	0.800	0.313
Medicare is my insurance	-0.311 (-2.89)	*fixed*	-0.106
At least one household member is disabled	0.295 (3.15)	*fixed*	0.111
Demographic characteristics			
Respondent between 45 and 54	-0.194 (-1.65)	*fixed*	-0.076
AIC	2062		
Number of observations	2020		

Table 9 below displays the direction of marginal effect results for all three probit models. Notably, were only two variables that were significant in all three models which were parameters related to health—(1) home temperature makes respondent and (2) household has a disabled occupant. In all three models, these health parameters increased the likelihood of experiencing objective/subjective energy burden.

Table 9. Direction of marginal effect for all three models

Independent Variable	Difficulty paying electricity bill (subjective 1)	Electricity bill causes stress (subjective 2)	Spend greater than 8% of income on electricity (objective)
	Influence on the model		
Financial characteristics			
Pay bills with savings	NS	(+)	NS
Pay bills with credit card	NS	(+)	(−)
Pay bills by reducing household energy usage	NS	(+)	NS
Pay bills by leaving other bills unpaid	NS	(+)	NS
Pay bills with money borrowed from loved ones	NS	NS	(+)
Pays bills with income	(−)	NS	(−)
Utility bills cause me to skip spending on transportation	NS	NS	(+)
Utility bills cause me to skip spending on food	NS	(+)	NS
Utility bills cause me to skip spending on medications	NS	(+)	NS
Utility bills cause me to skip spending on clothing	NS	(+)	NS
Difficulty with bills-other essentials	(+)	NS	NS
Household structure characteristics			
Mounted Window AC	(+)	NS	(+)
Unsure when AC was Built	(−)	NS	NS
AC 6 to 10 years old	NS	NS	(−)
Mobile Home	NS	NS	(+)
Large cracks or openings in windows and doors	(+)	(+)	NS
Household Makeup			
Two member household	(−)	NS	(−)
Two member household are older than 65	(−)	NS	NS
Health			
Temperature in household makes individuals sick	(+)	(+)	(+)
Medicare is my insurance	NS	(−)	NS
My insurance is through my employer	NS	NS	(−)
At least one household member is disabled	(+)	(+)	(+)
Demographic characteristics			
Respondent between 35 and 44	(+)	NS	NS
Respondent between 45 and 54	NS	(−)	NS
Education level less than a college degree	NS	NS	(+)
Married	NS	NS	(−)
Hispanic or Latino	NS	NS	(+)
Unemployed	NS	NS	(+)
*NS indicates variable that was not statistically significant			

5. Discussion:

This discussion is organized by research question. Significant explanatory variables that are unique to one model will be discussed under a given model section. Explanatory variables that emerged as statistically significant predictors in more than one model will be discussed in the section comparing multiple models. The results reveal that electricity spending varies by region. The results also reveal that the three models only had two drivers in common, demonstrating that objective energy burden, subjective energy burden 1, subjective energy burden 2 are capturing different ways of experiencing energy poverty. Finally, policy implications including how to use these metrics are discussed.

RESIDENTIAL ELECTRICITY BILL SPENDING BY REGION

The results of the nonparametric tests reveal that, when comparing regions in Texas, there is a significant difference in the amount that individuals spend on their electricity bill. This result indicates that if policymakers use objective burden as a measure of energy poverty, the threshold at which someone is considered objectively burdened should vary regionally. Further, using a statewide threshold at which an individual is considered objectively energy burdened (e.g. spending greater than 8%) would overestimate or underestimate the number of individuals who need energy poverty alleviation programs in particular regions (e.g. bill assistance and weatherization). For instance, in the objective energy burden threshold in Southwest Texas (13.7%) is more than twice that of West Texas is (6.5%). For these reasons, previous work also posits objective energy burden should be measured on a regional basis (Ross & Drehobl, 2016).

Alternatively, the results may indicate that regions with the highest thresholds at which individuals are considered objective burdened (i.e. highest electricity spending) (Region 6, 7, and 8; see Table 4) are in the most need of energy efficiency programs. However, the variation in regional spending may be due to region specific characteristics. Studies posit differences in end use (e.g. heating vs cooling) may drive spending differences (Fahmy, Gordon, & Patsios, 2011), while others argue spending differences are driven by regulated or deregulated market (UT Austin Energy Institute, 2016). For instance, the median spending in Dallas (investor owned utilities) is over 4%, while Austin’s (municipal owned energy utility) spending is less than 3% of household income (Ross & Drehobl, 2016). The complex interpretation of these results indicate that further analysis should be done to assess the reasons for the regional variation in electricity bill spending.

Further, the results demonstrate that objective burden is fickle measure for energy poverty that requires policymakers and researchers to choose a threshold, demonstrating the partiality of "objective" energy burden. For this reason, scholars do not recommend using objective energy burden as a metric (Schuessler, 2014; Herrero, 2017), recommending incorporating regional and temporal factors (Liddell, Morris, McKenzie, & Rae, 2012).

ASSOCIATION BETWEEN OBJECTIVE AND SUBJECTIVE ENERGY BURDEN(S) AND ASSISTANCE CRITERION

The survey results indicate that LMI individuals spend more on their electricity bills than Texans overall. The UT Energy Institute found that roughly 15% of Texas households were objectively burdened (Wible & King, 2016), while the results indicated that 22% of LMI households are objectively burdened. Survey results also reveal that respondents are more likely to have their electricity bills cause stress (i.e. subjective energy burden 2) or have difficulty paying for their electricity bill (i.e. subjective energy burden 1) than they are to spend more than 8% of their income on electricity bills (i.e. objective energy burden). This is contradictory to literature that has shown that individuals are less likely to be subjectively energy burdened than objective energy burdened (Price, Brazier, & Wang, 2012; Herrero, 2017). A previous study revealed that 16% of individuals perceiving themselves as energy poor while 28% were measured to be fuel poor (Price, Brazier, & Wang, 2012).

Similarly, the percentage of individuals who were both subjectively energy burdened (1 or 2) and objectively energy burdened, is relatively high compared to the literature (See Appendix B). A previous study showed 26% of respondents (Price, Brazier, & Wang, 2012) who were experiencing subjective energy burdened were also being objectively energy burdened. However, the results of the current study that show that 52% and 54% of objectively energy burdened individuals are experiencing subjective energy burden 1 and 2, respectively (See Appendix B). Furthermore, hypothesis tests reveal that these three metrics are in fact associated. This is a departure from scholars that have argued that subjective and objective measures do not identify the same individuals (Healy & Clinch, 2004; Price, Brazier, & Wang, 2012).

Critics of subjective indicators have argued that individuals are less likely to state they are "struggling with their energy bill" or "energy poor" for various social reasons. For example, lack of knowledge on energy poverty can lead to fewer individuals identifying themselves as energy poor (Bouzarovski & Simcock, 2017). Additionally, individuals may experience embarrassment in admitting to they need help or hold different interpretations of "inadequate energy services" or "struggling with bills" (Bouzarovski & Simcock, 2017; Herrero, 2017). The results may indicate a difference in social norms and perceptions of self-identifying as having affordability issues in the U.S. compared to Europe.

Alternatively, the higher percentage of individuals (compared to past studies) self-identifying as energy burdened in this study may be due to a difference in language/word choice used to assess subjective energy burden. Past studies explicitly ask survey respondents "do you feel energy poor?" (Healy & Clinch, 2004; Price, Brazier, & Wang, 2012). However, this study asked implicit energy poverty questions, such as asking if respondents "struggle with bills" and "stress about electricity bills". Respondents may have a better understanding of 'difficulty paying for electricity bill" than "energy poor". These results warrant further investigation as it may hold implications for language in future surveys assessing affordability. The complex interpretation of these results indicate further studies should be done regarding perceptions of energy poverty in Texas and awareness of energy assistance programs among customers.

The association between Medicaid and objective burden may indicate that individuals who spend greater than 8% of their income on electricity, are currently eligible for federally funded bill assistance programs (TDHCA, 2019). The same indication can be drawn from the significant results between Medicaid enrollment and subjective energy burden 1. If both metrics are identifying individuals who are eligible for energy bill assistance, they may be provide accurate estimates of the number of individuals who need programs that ameliorate energy poverty. The results reveal that only 14.5% of respondents who are enrolled in Medicaid are experiencing subjective burden 2 (See Appendix C). Further, a respondent's enrollment in Medicaid was not associated with electricity bill causing them stress (i.e. subjective energy burden 2). This result further indicates that compared to the other two metrics, subjective energy burden 2 may not provide an accurate estimation of the number of individuals who need energy assistance programs. Alternatively, these results may reveal that subjective energy burden 2 may simply capture individuals who are not enrolled in Medicaid, but still need some level of assistance. A survey study showed that across LMI groups (e.g. $10-20k or $40-50k) respondents were almost equally likely to state that their electricity bill causes them stress (Harmon & Prince, 2018). As such the results may reveal that there are individuals who do not meet the criteria to enroll in Medicaid but are still experiencing electricity affordability issues.

DRIVERS OF OBJECTIVE ENERGY BURDEN

Notably, the results of the binary probit model for objective energy burden indicate that individuals who are experiencing financial hardship are more likely to spend more than 8% of their income on their electricity bill (i.e. objectively burdened). The statistically significant demographic characteristics indicate that individuals that are more socially vulnerable are more likely to be objectively energy burdened.

For instance, paying for electricity bills with income decreased the likelihood of a respondent being objective energy burdened. This result was not surprising given the association between low income, energy inefficiency, and energy poverty (Ross & Drehobl, 2016; Reames, 2016). As such, it would follow that individuals who have money to pay for electricity bills would, on average, spend less of their income on their electricity bill. Accordingly, it is logical that being unemployed increased the likelihood of a respondent being objectively energy burdened, as unemployed individuals do not have a consistent income. As a result, they will be more likely than their employed counterparts to use a higher percentage of their money to pay essential bills. This result is consistent with previous work in which unemployment emerged as a statistically significant predictor of energy burden (Wible & King, 2016). Additionally, income is an eligibility criteria for federal and state bill assistance programs (TDHCA, 2019; Department of Homeland Security, 2019). These results indicate that income should continue to be a criteria.

Relatedly, the results of the objective burden model show that individuals who are experiencing financial hardship such as their utility bills causing them to skip spending on transportation are more likely to spend more than 8% of their income on their electricity bill. While income is a common criterion for assistance programs, these results indicate that resources—e.g. flyers and brochures—should be targeted at individuals who may seek assistance with transportation—e.g. reduced fare bus pass.

The results also reveal that having employer insurance decreases the likelihood of being objectively energy burdened. As mentioned in the literature review, health issues have repeatedly been shown as both a cause and a result of energy poverty (Liddell & Morris, 2010; Harrison & Popke, 2011). However, we posit that having insurance is tied to both health as well financial stability. Individuals with health insurance are more financially protected from health bills associated with serious accidents or illness (U.S. Centers for Medicare & Medicaid Services, 2018). In a survey study by the Kaiser Foundation, 16% of respondents had declared bankruptcy in the past year as a result of health bills from onetime accidents or sudden illness (Kaiser Family Foundation, 2016). As such, we posit that the reduced financial hardship associated with insurance decreases the likelihood of experiencing energy poverty. Notably, Medicaid enrollment, an eligibility criterion for energy bill assistance programs, did not emerge as a statistically significant driver of objective energy burden. These results may indicate that an individual *not being enrolled* in employer's insurance is a stronger criterion for targeting individuals for energy assistance programs than *being enrolled* in Medicaid. As such, the relationship between insurance provider type (e.g. Medicaid, employer, or private) and energy poverty should be explored further.

Relatedly, the statistically significant demographic characteristics (i.e. marriage, education level, and Hispanic ethnicity) in the objective energy burden model may reveal that social vulnerabilities are characteristic of individuals experiencing energy. While social vulnerability is not as strongly supported by the literature as financial hardship, it has been repeatedly posited as a cause of energy poverty (Bouzarovski, 2014; Reames, 2016; Bouzarovski & Simcock, 2017). Further, the Center for Disease control shows financial hardship and social vulnerability are inextricably tied (Center for Disease Control, 2011). For instance, higher educational attainment is correlated lower financial hardship and lower social vulnerability (Center for Disease Control, 2011; Harmon & Prince, 2018). Respondents who had less than a Bachelor's degree were more likely to be objectively burdened which has been shown as a predictor of objective energy burden (Wible & King, 2016) and energy inefficiency (Reames, 2016).

Similarly, marital status is tied to financial stability and social vulnerability (Michal Grinstein-Weiss, 2004). Results reveal that individuals that are married are less likely to be objectively energy burdened. As mentioned in the literature review, studies have shown that single individuals are more likely to identify themselves as energy poor (Healy & Clinch, 2004; Palmer, MacInnes, & Kenway, 2008). Race is repeatedly shown to be associated with financial stability and social vulnerability (Center for Disease Control, 2011; Rogers & Lange, 2013). These results consistent with previous studies that show Hispanic households are more likely to be objectively burdened (Ross & Drehobl, 2016), and more likely to experience energy inefficiency (Reames, 2016). Future studies should investigate the relationship between energy poverty and social vulnerability.

Notably, living in a mobile home increased the likelihood of a respondent experiencing objective energy burden which may be due to compounding factors of financial hardship, social vulnerability, or household energy inefficiency. Living in a mobile home has not previously been empirically shown as a cause or a result of energy poverty. However, living in a mobile home is associated with financial hardship and social vulnerability (Center for Disease Control, 2011). Furthermore, studies that interviewed low income mobile home residents in Lower Rio Grande Valley region of Texas (Harmon & Prince, 2018) and rural North Carolina (Harrison & Popke, 2011) showed that residents repeatedly discussed not having enough access to social services nearby. Interviewees also repeatedly reported poor insulation in mobile homes (Harrison & Popke, 2011). Notably, living in a mobile home has been shown as a significant predictor of energy inefficiency in low income homes (Reames, 2016). These findings may demonstrate that individuals living in mobile homes are more likely to experience energy poverty. Further, it may demonstrate that weatherization and bill assistance programs should be specifically targeted towards individuals living in mobile homes, especially in rural regions.

DRIVERS OF SUBJECTIVE ENERGY BURDEN(S)

The results reveal that the likelihood of an individual experiencing difficulty pay for electricity bill (i.e. subjective energy burden 1) is influenced by a variety of factors, while the likelihood of an individual being stressed about their electricity bill (i.e. subjective energy burden 2) is primarily driven by financial hardship. Notably, however, results indicate that having difficulty paying for other essential bills increased the likelihood of a respondent experiencing subjective energy burden 1. This result adds to a wealth of literature in both Europe and the U.S. that found that individuals who are living in energy poverty typically experience multiple financial strains at once (Boardman, 1991; Healy & Clinch, 2004; Bird & Hernández, 2010; Ross & Drehobl, 2016). Further these results are supported by the historical integrated targeting of social programs in Texas (Public Utility Commission of Texas, 2017; TDHCA, 2019).

Individuals whose electricity bill causes them stress (i.e. subjective energy burden 2) are primarily experiencing energy poverty as a byproduct of financial hardship and coping by making more severe financial tradeoffs than individuals experiencing objective energy burden or subjective energy burden 1. Individuals who are stressed about their electricity bill are making tradeoffs on essentials such as food, medication, and clothing in order to pay their utility bills. These tradeoffs are some of the most severe tradeoffs documented in energy poverty literature (Bird & Hernández, 2010; Harrison & Popke, 2011; Bouzarovski, 2014). Also, these tradeoffs may imply that targeting individuals who are food insecure or utilizing medical assistance are good energy assistance eligibility criterion. However, to facilitate more studies of these tradeoffs, enrollment in programs like Supplemental Nutrition Assistance Program (SNAP) should be included in survey questions in the future.

Relatedly, the results reveal that individuals who reduce their electricity consumption to pay utility bills are more likely to be stressed about their electricity bill (i.e. subjective energy burden 2). This parameter is much more perceptive than the other tradeoff parameters and challenging to interpret. This result may demonstrate that individuals who reduce their electricity consumption to pay their bill are energy poor. Survey studies have shown that reducing energy consumption in order to pay energy bills is a coping mechanism for energy poverty (Bouzarovski & Simcock, 2017; Herrero, 2017; Harmon & Prince, 2018). Alternatively, such behavior could indicate a respondent's awareness of energy conservation programs as environmentally motivated conservation behavior is associated higher socioeconomic status (Harmon & Prince, 2018). These results warrant further investigation.

COMPARING ALL THREE METRICS

As the three models have only two indicators in common, we posit that the three measures are capturing different experiences of energy poverty. For instance, objective energy burden is capturing energy poverty as a result of structural and social vulnerability while subjective energy burden 2 is capturing energy poverty primarily as a byproduct of financial hardship. This distinction may assist policymakers by using different measures to estimate the need for different assistance programs. For instance, individuals who are only experiencing subjective energy burden 2 may need electricity bill assistance that is variable such as bill discounts during months extreme weather or flexible payment schedules. On the other hand, individuals who are experiencing objective energy burden may need sustained assistance such as energy efficiency programs in addition to a year-round discount on their electricity bill.

Additionally, the distinction in financial trade-offs between measures may also assist policymakers in targeting of assistance programs. For instance, when using objective energy burden as a measure for weatherization programs, individuals may be targeted if they need transportation assistance (e.g. reduced bus fare). Similarly, when using subjective energy burden as a measure for electricity flexible payment plans individuals may be targeted if they utilize food or clothing assistance (e.g. food banks or clothing closets).

Interestingly, the household temperature making household members feel sick and having a disabled household member are the variables that increased the likelihood of a respondent experiencing objective energy burden and subjective energy burden 1 and 2. A respondent's household temperature making household members sick increasing the likelihood of experiencing objective and subjective energy burden(s) is challenging to interpret as is perceptive. This variable may be capturing other variables such as poor materials, mold, or bacteria used in one's household which was not asked in the survey. Studies have shown that some individuals who are subjectively energy burdened also report having mold, bacteria, and rotting wood in their household and described themselves as ill (Harrison & Popke, 2011; Bouzarovski, 2014).

Previous studies show that having a household member with a disability is associated with energy poverty (Bird & Hernández, 2010; Harrison & Popke, 2011; Bouzarovski, 2014). Disabled and chronically ill individuals face more financial hardship and are more likely to have a life-threatening demand for adequate energy services (Bird & Hernández, 2010; Harrison & Popke, 2011). As a result, disabled or chronically ill individuals are typically prioritized in energy assistance programs in the U.S. (Public Utility Commission of Texas, 2017; TDHCA, 2019). This may demonstrate that all three measures of energy poverty are capturing populations that are historically been the most vulnerable to energy poverty (Healy & Clinch, 2004; Herrero, 2017; Ross & Drehobl, 2016).

Notably, results reveal that respondents that have a window mounted air conditioner (AC) have an increased likelihood of experiencing subjective energy burden 1 and objective energy burden. ACEEE recommends Window AC as a cost effective and relatively energy efficient option for short term renters with one or two rooms (Scheer & Moss, 2019). However, for long term residents with larger dwellings window AC is less energy efficient and less cost effective. The increased likelihood of experiencing subjective energy burden 1 and objective energy burden may indicate that long term residents with dwellings with more than two rooms who have window AC are at a higher risk of energy poverty. At the time of this analysis, data on the length of respondents' tenure was not available, these results warrant further investigation as they may hold implications for energy efficiency program development.

Despite studies demonstrating that recent financial hardship, household size, home ownership, and elderly age are associated with energy poverty, these parameters did not emerge as significant. None of the models had statistically significant recent financial hardship (e.g. recent natural disaster) variables. Studies have shown that subjectively energy burdened individuals are more likely to state they had a recent financial hardship and have posited that subjective energy burden and objective energy burden measure temporary and chronic energy poverty, respectively (Healy & Clinch, 2004; Herrero, 2017). Some energy affordability programs, such as the Comprehensive Energy Assistance Program (TDHCA, 2019) are for emergency one-time aid. The results may indicate objective and subjective (s) energy burden are not good measures by which to estimate the number of people who need such programs.

Household size has been shown to have a U-shaped relationship with objective measures of energy poverty (Healy & Clinch, 2004; Herrero, 2017). In other words, the percentage of income a household uses for energy expenditures decreases with the number of household member at first and then increases. This may indicate that individuals in Texas are energy efficient on a per capita basis. This study faced data limitations in sample representation for larger families (more than 5).

Similarly, ownership status is having been shown as a driver of objective burden previously (Wible & King, 2016). Studies have demonstrated that renters have challenges accessing energy efficiency programs (Ross & Drehobl, 2016; Harmon & Prince, 2018). This result may indicate that in Texas renter status is not the major factor that deters LMI individuals from partaking in energy efficiency programs. A study of LMI Texans showed that both owners and renters did not participate in weatherization programs to improve household energy efficiency due to lack of knowledge of eligibility or where to find these services (Harmon & Prince, 2018). Further analysis is required to assess the degree to which knowledge of weatherization program is a driver of partaking in programs.

Surprisingly, while having two household members that are 65 or older was a statistically significant driver of subjective energy burden 1, it was not for the other two measures of energy poverty. Additionally, respondents who were 65 or older was not a statistically significant variable in regards to being subjectively or objectively energy burdened. This may be in contrast to many policy assistance programs and literature that emphasizes the health and financial significance of protecting the elderly from experiencing energy poverty (Healy & Clinch, 2004; Bird & Hernández, 2010; Liddell, Morris, McKenzie, & Rae, 2012; Ross & Drehobl, 2016). Alternatively, we speculate that due to program historic targeting (Public Utility Commission of Texas, 2017), individuals 65 and older may be more aware of energy assistance programs than younger individuals. It follows that elderly individuals would be more likely to take advantage of such programs, reducing the amount they spend on their electricity bills.

6. Conclusion

This study addresses the gaps in energy poverty literature in the U.S. regarding the statistically significant causes and impacts of energy poverty as well as ways of measuring energy poverty. Specifically, the objectives of this study are threefold: (1) to compare the objective and subjective measures of energy poverty as well as assess whether they identify individuals who are currently eligible for energy bill assistance programs; (2) to assess the statistically significant indicators of objective and subjective energy burden(s); (3) to assess the variability in electricity bill spending by region. This study contributes to a small but growing body of literature that seeks to identify the financial, health, household make-up, household structure, and demographic drivers of energy poverty.

A major contribution of the results of this research is that objective energy burden varies by region in Texas. Another major contribution of the findings is that contrary to the literature, there is a relationship between objective and subjective energy burden. The findings also demonstrate that individuals that are objectively burdened or that difficulty paying for electricity bill (i.e. subjective energy burden 1) are eligible for current assistance programs and provide an accurate measure for identifying individuals who need assistance programs. However, individuals who are stressed about their electricity bill are not necessarily eligible for such programs and subjective energy burden 2 may not provide an accurate measure to identify the number of individuals who need such programs. The characteristics that statistically influenced an individual’s likelihood of being subjectively and objectively burdened were health related. Finally, while objective and subjective energy burdens are related, the findings indicate that they are identifying different ways of experiencing energy poverty.

Notably, subjective measures categorized the greatest number of individuals as energy poor demonstrating that Texans are highly perceptive of energy poverty issues. Contrary to literature that emphasizes program assistance targeting elderly individuals and renters, the findings reveal that mobile home residents are susceptible to spending a high amount of their income on electricity bills and as such, should be a more targeted group for energy efficiency and weatherization programs. Financial hardship tradeoffs on essentials (e.g. food and transportation) are major influencers of both subjective and objective burden. As individuals in Southwest Texas, the Corpus Christi Metro Area, and East Texas (Region 6, 7, and 8) spend considerably more on their electricity bills than individuals in other regions, this may indicate policymakers should focus efforts on improving bill assistance and energy efficiency programs in these regions.

The results of this study address the gap in U.S. literature regarding regional differences in electricity bill spending. Further, the findings show that objective burden is not impartial. As the results reveal there is a relation between objective and subjective energy burden. The results provide a direct antithesis to the body of literature that states that subjective and objective burden are not related. However, the drivers of subjective and objective burden are different and show that the measures of energy poverty cannot be used interchangeably. The results of this research contribute to the small, but growing body of literature that reveal that characteristics such as social vulnerability or changing one's energy consumption behavior may be indicative of energy poverty.

The findings demonstrate that future studies should further assess the relationship between health insurance type (e.g. employer or Medicaid), household health, and energy poverty in the U.S. Assessing this relationship will provide health providers, utility providers, and policymakers with insight on ways to integrate assistance programs and which customers to target. Additionally, future studies should utilize different survey language when assessing subjective energy burden to explicitly assess awareness of energy poverty in the U.S. Additionally, the response options to the subjective energy burden questions (e.g. does your electricity bill cause you stress) were binary. Future studies should utilize a scale (e.g. "I feel energy poor never, sometimes, or always"). This will further help policymakers identify individuals who are experiencing temporary versus chronic energy poverty which is important when creating policy programs.

The findings demonstrate that when estimating need, policymakers should not utilize a a single metric of energy poverty. Regardless, the results indicate that 23% of LMI Texas households are utilizing more than 8% of their income on electricity alone. Additionally, 43% of LMI Texans are stressed about their electricity bills. The results of this study contribute to a growing body of research that demonstrates that LITE-UP Texas, a state funded program that provided discounts for all non-municipal energy customers and required the Utility Commission to maintain a statewide list individuals eligible for bill assistance, need to be reinstated. Further, Texas legislators should revise SB 1976 and explicitly require that either the state or each utility provider offer some form of bill assistance.

As nearly a third of U.S. households may be experiencing energy poverty, the results of this study hold implications for federal, state, and local policymakers and utility providers. In order to improve the estimation of the need for energy assistance programs as well as the success of these programs, the results provide a comprehensive assessment of methods for identifying energy poor individuals. Specifically, the findings offer support for policymakers who need comprehensive methods for assessing energy affordability and need for energy assistance programs at a regional level. The results also demonstrate ways of capturing the need for differing energy assistance programs (e.g. weatherization compared to flexible payment schedules). Finally, and perhaps most importantly, to ensure awareness of these programs the results offer insight into how to target individuals who need differing energy assistance. These insights will allow energy assistance program policymakers to develop more effective budgeting, marketing, and program integration.

Appendix A. Results of Dunn Test Comparing Regional Spending on Electricity Bills (highlighted values indicate statistically significant results)

Comparison Number (total of 55)	Regions Compared			p-value
1	4	-	6	1.23E-08
2	1	-	6	2.21E-08
3	2	-	6	1.32E-06
4	5	-	6	1.4E-06
5	4	-	8	2.39E-05
6	1	-	8	9.61E-05
7	4	-	7	9.77E-05
8	6	-	9	0.00014
9	3	-	6	0.000159
10	5	-	8	0.000246
11	1	-	7	0.00029
12	11	-	6	0.000351
13	5	-	7	0.000365
14	10	-	4	0.000839
15	2	-	8	0.00094
16	2	-	7	0.003
17	10	-	6	0.003
18	1	-	10	0.003
19	10	-	5	0.006
20	3	-	4	0.007
21	11	-	8	0.017
22	8	-	9	0.017
23	11	-	7	0.019
24	7	-	9	0.021

Comparison Number (total of 55)	Regions Compared			p-value
25	3	-	8	0.024
26	3	-	5	0.024
27	1	-	3	0.027
28	3	-	7	0.030
29	10	-	2	0.041
30	4	-	9	0.047
31	5	-	9	0.070
32	2	-	4	0.097
33	10	-	7	0.134
34	10	-	8	0.134
35	2	-	5	0.137
36	1	-	9	0.158
37	10	-	11	0.191
38	2	-	3	0.225
39	6	-	8	0.245
40	10	-	9	0.272
41	11	-	5	0.276
42	1	-	2	0.324
43	1	-	5	0.341
44	11	-	4	0.341
45	6	-	7	0.347
46	11	-	3	0.408
47	1	-	4	0.412
48	10	-	3	0.419
49	2	-	9	0.528
50	1	-	11	0.630

Comparison Number (total of 55)	Regions Compared			p-value
51	11	-	9	0.632
52	4	-	5	0.669
53	3	-	9	0.675
54	7	-	8	0.884
55	11	-	2	0.935

Appendix B. Contingency Tables: Objective and Subjective Energy Burden(s)

	Objectively Energy Burdened		
	<8%	≥8%	*Total*
Subjective Energy Burden 1			
No difficulty paying for electricity bill	1110 (71%)	217	*1327*
Yes, difficulty paying for electricity bill	455	238 (52%)	*693*
Total	*1565*	*455*	

Note: 52% of objectively energy burdened are also experiencing subjective energy burden 1

	Objectively Energy Burdened		
	<8%	≥8%	*Total*
Subjective Energy Burden 2			
No, electricity bills don't cause me stress	978 (62%)	209	*1187*
Yes, electricity bills cause me stress	587	246 (54%)	*833*
Total	*1565*	*455*	

Note: 54% of objectively energy burdened are also experiencing subjective energy burden 2

Appendix C. Contingency Tables: Medicaid and Objective and Subjective Energy Burdens(s)

	Medicaid Use		
	No	Yes	*Total*
Objective Energy Burden			
<8%	1418 (90%)	341	*1759*
≥8%	147	114 (20.5%)	*261*
Total	*1565*	*455*	

Note: 20.5% of those enrolled in Medicaid are also experiencing objective energy burden

	Medicaid Use		
	No	Yes	*Total*
Subjective Energy Burden 1			
No difficulty paying for electricity bill	1186 (89%)	573	*1759*
Yes, difficulty paying for electricity bill	141	120 (17.3%)	*261*
Total	*1327*	*693*	

Note: 17.3% of those enrolled in Medicaid are also experiencing subjective energy burden 1

	Medicaid Use		
	No	Yes	*Total*
Subjective Energy Burden 2			
No, electricity bills don't cause me stress	1047	712	*1759*
Yes, electricity bills cause me stress	140	121 (14.5%)	*261*
Total	*1187*	*833*	

Note: 14.5% of those enrolled in Medicaid are also experiencing subjective energy burden 2

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