A Discussion of Energy Poverty and Energy Injustice in The Case of Texas, U.S.

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Abstract. Insufficient access to modern energy resources is a crucial issue in the development of a country. Plenty of resources were devoted to measuring energy poverty, but the equality of energy access within regions is largely ignored, especially on the county-by-county level with spill-over effect analysis. This paper begins with data related to Texas household demographics and spatial distribution to construct a quantitative measurement of energy burden and energy injustice, in the case of Texas. Moran’s Index and local indicators of spatial correlation (LISA) were utilized to analyze the relationships between energy-burdened counties and their locations. Then, the spatial error model (SEM) was introduced to evaluate the spatial dependence in the error term. A statistically significant result regarding energy injustice and demographic characteristics within Texas was confirmed. The result has crucial implications regarding assessing Texas energy injustice on a county level and recognizing the factors contributing to the energy burden. The methodology and concept can be expanded into similar topics of interest.

Keywords: Energy Burden, Energy Injustice, Energy Poverty, Local Indicators of Spatial Autocorrelation, Spatial Analysis.

1. Introduction

Energy poverty is the lack of access to sustainable modern energy services and products as defined by the World Economic Forum. Globally, in developing countries, inaccessibility and unaffordability both weigh on individuals' and households' energy consumption burden. In OECD countries, energy poverty is significantly less than non-OECD countries that lack modern energy infrastructures [1].

In comparison to developing countries that suffer from the inaccessibility of modern energy, energy is available to most populations in the U.S. According to the U.S. Energy Information Administration's latest data [2], in 2021, there has been 4,116 billion kilowatt hours (kWh) of electricity generated in the U.S. at utility-scale electricity generation facilities domestically. Nevertheless, energy affordability remains a significant issue in the U.S.

The situation where a household must pay a disproportionate amount for energy use is defined as energy poverty. The price of energy to end-users in the United States is determined largely by several factors, such as the cost of transmission, deployment, investment, the scale of production and technology development, etc. Energy Injustice occurs when the factors mentioned above are not equally distributed [3].

Although there are many states to be considered when it comes to measuring energy poverty and energy injustice, Texas stands out among them. Unlike the rest of the other states, which were divided into western and eastern interconnection power grids, the state itself has a unique power grid system - ERCOT - separating most of the Texas territory from the rest of the country as illustrated by Figure 1. According to Texas Energy Poverty Research Institute's official website, 840,000 Americans are being driven below the poverty line for every 10% increase in home energy expenses, and Texas residents are the most vulnerable among all states to this issue [4]. The adoption of Senator Bill 7 brought about the deregulation of the electricity grid [5]. Because of the competitive electricity market, private utility companies that generate their own electricity gain the power to bill end-users directly. With the intention of granting customers the freedom to switch providers, the government realized later on that the deregulation ended up causing higher bills on consumers' end - on average, 21%

higher than what they could have paid [6]. The situation has not been alleviated with the introduction of wind energy.

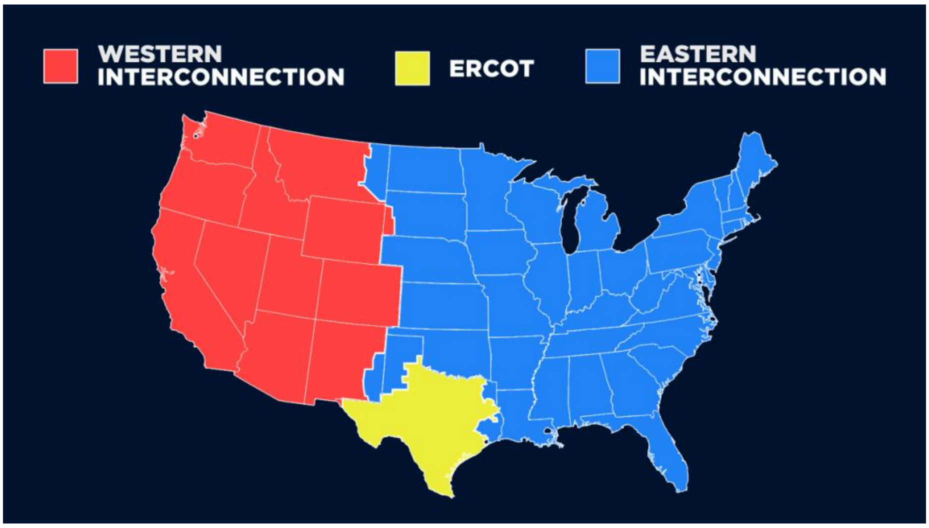

Figure 1. U.S. Power Grid.

Source: https://www.ksat.com/news/local/2021/04/06/ksat-explains-the-total-breakdown-of-the-texas-power-grid/

Texas, consisting of 254 counties, poses a difficult task for researchers to measure Energy Poverty and Energy Injustice holistically. Individual regions have varying energy poverty due to fluctuations in energy prices, and Texas itself actually contains three power grid systems as shown in Figure 2 with ERCOT being the main grid, rendering it difficult to retrieve electricity pricing information for researchers.

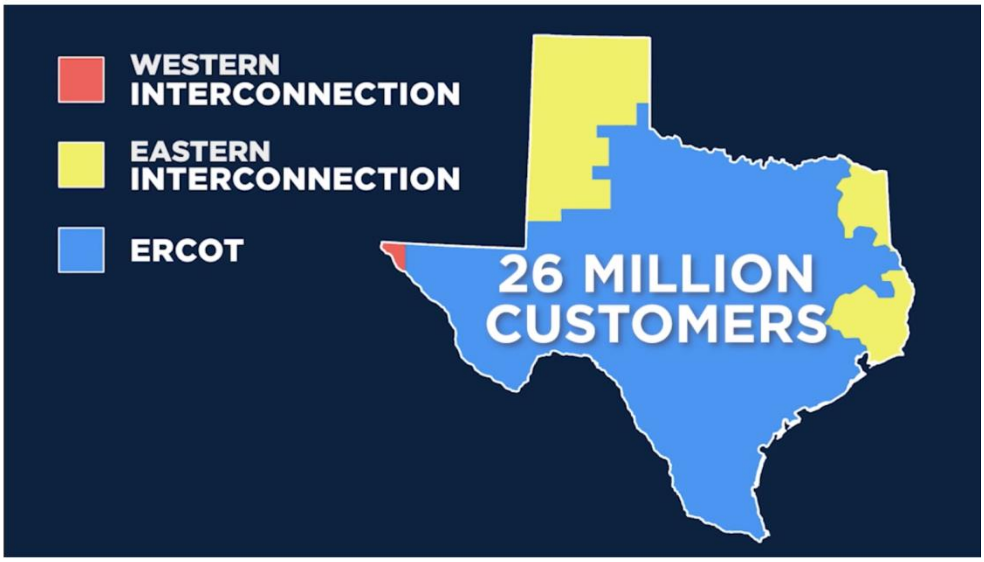

Figure 2. Texas Power Grid Map.

Source: https://www.ksat.com/news/local/2021/04/06/ksat-explains-the-total-breakdown-of-the-texas-power-grid/

Regarding the challenges associated with measuring electricity consumption, research has previously been done on the associations between Texas's energy poverty and several demographic factors [7-9]. However, existing research did not focus on quantifying spatial analysis nor did the studies cover the spillover effect on Energy Burden from a demographic perspective. The goal of this paper is to offer more clarity on the spatial implication of energy burden in Texas state and to fill in the blanks to identify relationships between Texas state-focused Energy Poverty and Energy Injustice from a spatial analysis perspective with respect to residents' demographics. The paper will explore the scale of demographics' spill-over effect on Energy Burden by implementing tools in GeoDa and

STATA with data obtained from EIA and Center of Geospatial Technology. The Energy Poverty indicators are not consistent across literature internationally. In this study, any home that spends more than 8% of its income on energy consumption is considered to be in energy poverty. The reason that the paper does not take the traditionally recognized threshold from 8%-10% was because the data would otherwise exclude most of the family, leaving a small sample to analyze [10-12]. However, when the paper adopted 8-10% as energy burden threshold for analysis, the sample size was insufficient. This led to the adoption of the 6% threshold set up by Texas Energy Poverty Research Institute. According to the website, there are approximately 22% of households being classified as “energy burdened” that spend more than 6% of the household income on energy use, providing the paper a reliable reference for analysis [4]. With a higher threshold, the sample would be smaller than ideal for statistical analysis. In addition, the U.S. Environmental Protection Agency specifies that multiple dimensions other than income contribute to energy burdens such as the age of household members, education, average household size, unemployment rate, and racial profile [13]. The paper will take the factors above into the regression model to investigate the correlation between energy burden and the socioeconomic profiles of Texan households and individuals. This research places strong emphasis on demographics and geographic areas that experience the highest levels of energy poverty for the stakeholders to better allocate their resources. Since large energy poverty differences occur regionally, the result of the research will help the government identify groups vulnerable to energy price increases.

2. Texas Research and Policy

The Texas government has been aware of the rising Energy Poverty, and they seek changes through various channels and programs. However, legislative support and aid are not adequate. The LITE-UP Texas program was designed to provide helpful assistance to low-income families state-wide. With the program expiring in 2016, coinciding with the depletion of the System Benefit Fund (SBF), which sustained the program, Texas communities have not received the same assistance [7]. Around 12% of the nation's total net power generation was produced in Texas in 2021, but Texas residents have not been paying a low price for energy that reflects this privilege on the supply side. According to Texas Energy Poverty Research Institute, low-income households in Texas use an average of 10% of their income on energy costs, while only 3% of income was spent on energy for households that are not low-income [4]. Even though Texas as a whole was not ranked among the lowest five states for energy poverty by the U.S. Department of Energy in the year 2019, in some regions in Texas, the situation varies. For example, southwest Texas families spend the most on energy bills, exposing them to extreme energy poverty; in more developed and populated locations such as Dallas and Austin, there are differences in the percentage of energy spending in household income [7-8]. Therefore, correctly identifying demographics in need of affordable energy is crucial to reducing energy injustice and energy poverty in Texas.

3. Methodology

The paper was composed after analyzing information from an eclectic selection of literature regarding energy poverty and energy justice, especially since 2018. Figure 3 offers a visual representation of the literature related to energy.

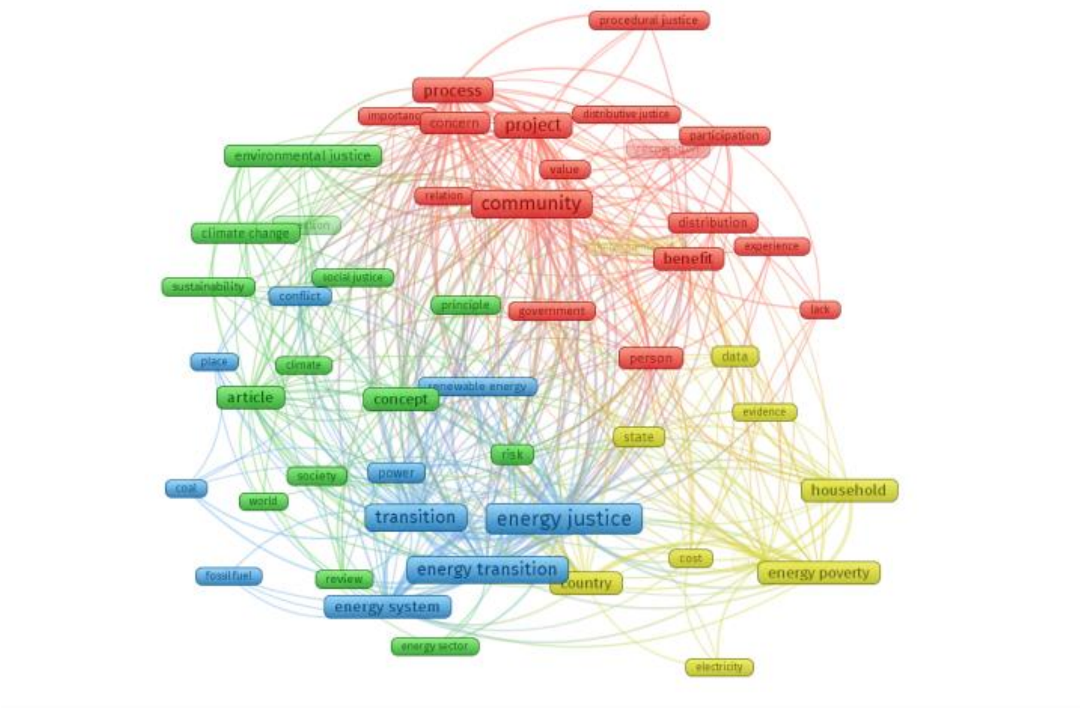

Figure 3. The literature relationships created by Vosview

The emphasis on overlapping topics in literature can be summed up into four key categories, as seen in the graph above:

The in-depth study of energy poverty in specific regions and countries

The relationship between climate change and energy poverty

Analysis of how energy transition (e.g., as the following action to achieve carbon neutrality) affects the extent of energy poverty

Analysis regarding the observed or suspected energy injustice in certain regions or countries

Researchers have extensively investigated the relationship between energy poverty and demographic factors and have made multiple appearances [9]. Nevertheless, the element of spatial analysis does not show a frequent presence in the literature review. In the case of Texas, previous research has covered the topic of the non-parametrically regional effect associated with energy burden [8]. However, a parametric method has never been applied to explore the extent of spatial clustering in counties suffering from energy injustice. The paper will fill in the gaps of the topics mentioned earlier and investigate the spatial effect of energy poverty with energy injustice using parametric methods. In terms of quantifying methods, two methods have been selected in order to achieve the research goal.

First, this paper applies Moran's Index to examine the correlation between energy-burdened counties and their locations. It is a measure of spatial autocorrelation developed by Patrick Alfred Pierce Moran in the 1950s, which then became increasingly popular and can be seen in many GIS research studies. Later on, it was also utilized to test whether spatial effects played a part in the correlation between demographic factors and energy burden in Texas's counties, and the test result turned out to be positive (p-value < 0.05), which rejects the OLS estimation in the following regression session and proceed with a spatial autoregressive model. The result of Moran's Index test can be seen in Appendix 1.

The Spatial Error Model (SEM), the second primary method in this paper, measures the relationship between energy burden and each demographic factor (1), incorporating spatial dependence in the error term (2).

$$\mathrm{EB_i} = \beta_1 \mathrm{X_i} + \epsilon_\mathrm{i} \tag{1}$$

$$\epsilon_\mathrm{i} = \lambda \mathrm{W} \epsilon_\mathrm{j} + \zeta_\mathrm{i} \quad (\mathrm{j} \neq \mathrm{i}) \tag{2}$$

Using spatial regression models is not uncommon among spatial analyses regarding energy poverty [13-15]. The paper selects the spatial error model specifically but not the Spatial Lagged model because of the result of the LM test - both the LM and robust LM tests have been done to test which term between spatial lag and spatial error turned out to be more statistically significant. According to the test result in Appendix 2, the spatial error is comparatively more significant for all factors, thus making SEM the final choice. Accordingly, the estimated parameter would be calculated via maximum likelihood estimation. For parameters derived from actual data sources, more details are placed in Appendix.1 for viewing. These models then together will be used to inspect the problem initially proposed.

4. Results

The data calculated from GeoDA shows a significant Moran's Index for Energy Burden at a value of 0.379, which confirms the existence of a certain extent of spatial clustering of energy burdened counties. In terms of local Moran's, I, a Local Indicators of Spatial Automation (LISA) map has also been crafted to show the county-level detail and hotspot relationship visually.

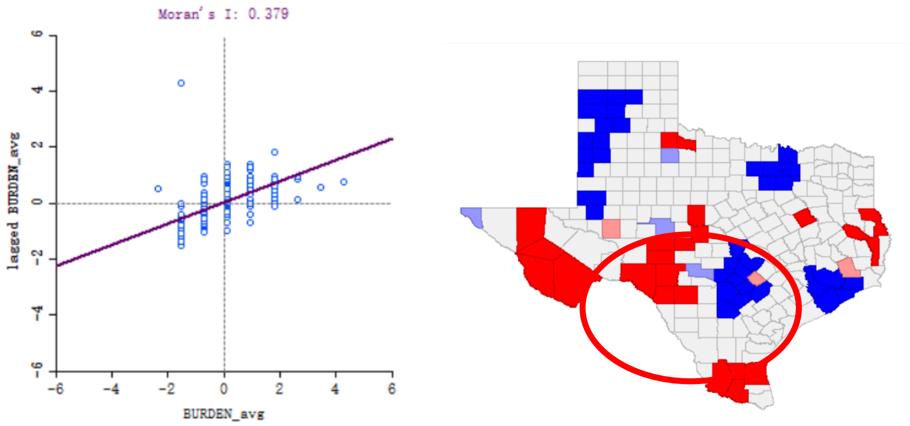

Figure 4. Display of Moran's Index and LISA graph of Energy Burden (% of Income) by Counties using GeoDa.

Two observations are worth noting from Figure 4:

(1) High-High clusters tended to locate in Southern or Western Areas.

(2) Low-Low clusters tended to locate in Northern or Central Areas.

First, while High-High and Low-Low clusters usually have a relatively long distance between them due to their unique local characteristics, a High-High cluster was geographically close to another LL cluster in this graph. Second, a small High-High cluster appeared over the Eastern borders of Texas, contrasting with the general location of other High-High clusters.

It should be mentioned that both observations share the same trait of locating the borderline between electricity grid zones, demonstrated by the first graph below.

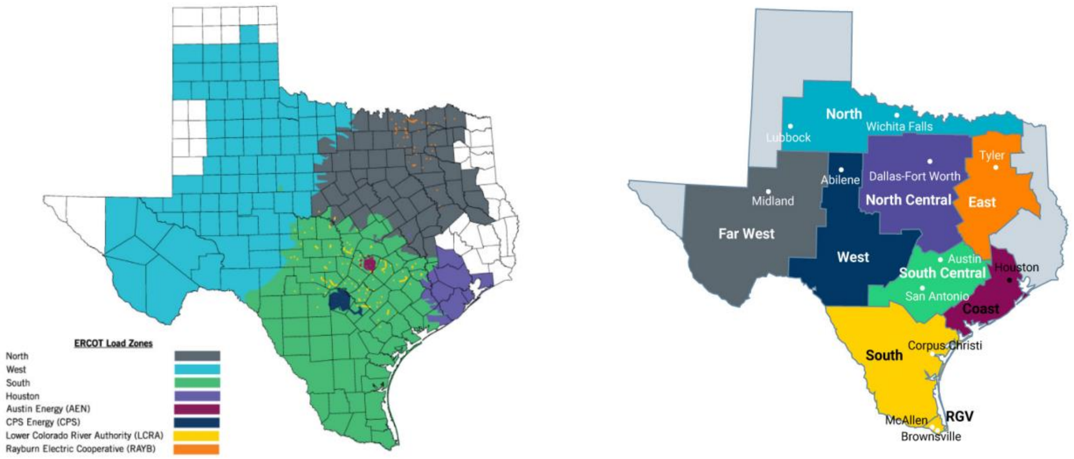

Figure 5. Visualization of ERCOT load zone (left) and Weather zone map (right). Source: https://www.ercot.com/news/mediakit/maps

This fact may offer a possible explanation. As previously stated in the introduction part, while most US counties' electricity grid is provided by one single organization, Texas has three - Figure 5 visualizes the separation of the grid zone. It contributed to the local electricity market's complexity, increasing household transaction costs. Although considering this did not happen with every zone border, it is also possible that this proximity of the High-High cluster to the Low-Low cluster has stemmed from the weather-level heterogeneity of the energy market between them, as shown by figure n.

Lastly, the paper used SEM to measure the relationship between energy burden with demographic variables, along with spatial dependence. Among six demographic dimensions, age, financial, education, and household number factors have a statistically significant correlation with energy burden, with a Household number (-0.903) & Average Medium Wage (-0.793) being the most significant factor. The result is shown by Figure 6 below.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	eb	eb	eb	eb	eb	eb	eb	eb	eb	eb
eb										
lnI	-0.793*** (-9.23)									
lnage85		0.270*** (5.25)								
lnpvt			0.326*** (5.51)							
lnpvt18				0.350*** (6.66)						
lnedu					-0.412** (-2.89)					
lnage65						0.421*** (6.72)				
lnblack							-0.0447** (-2.83)			
lnhisp								-0.0358 (-1.16)		
lnjob									0.0936 (1.67)	
lnHHN										-0.903*** (-4.19)
_cons	9.972*** (10.62)	1.109*** (21.20)	0.444** (2.76)	0.257 (1.60)	3.110*** (4.97)	0.0998 (0.54)	1.349*** (30.28)	1.426*** (12.77)	1.147*** (10.93)	2.180*** (10.26)

Figure 6. SEM result

On a more general level, it also matches with the fact that energy burden clusters on maps usually have a relatively disadvantageous financial background and smaller household sizes as clearly shown in Figure 7.

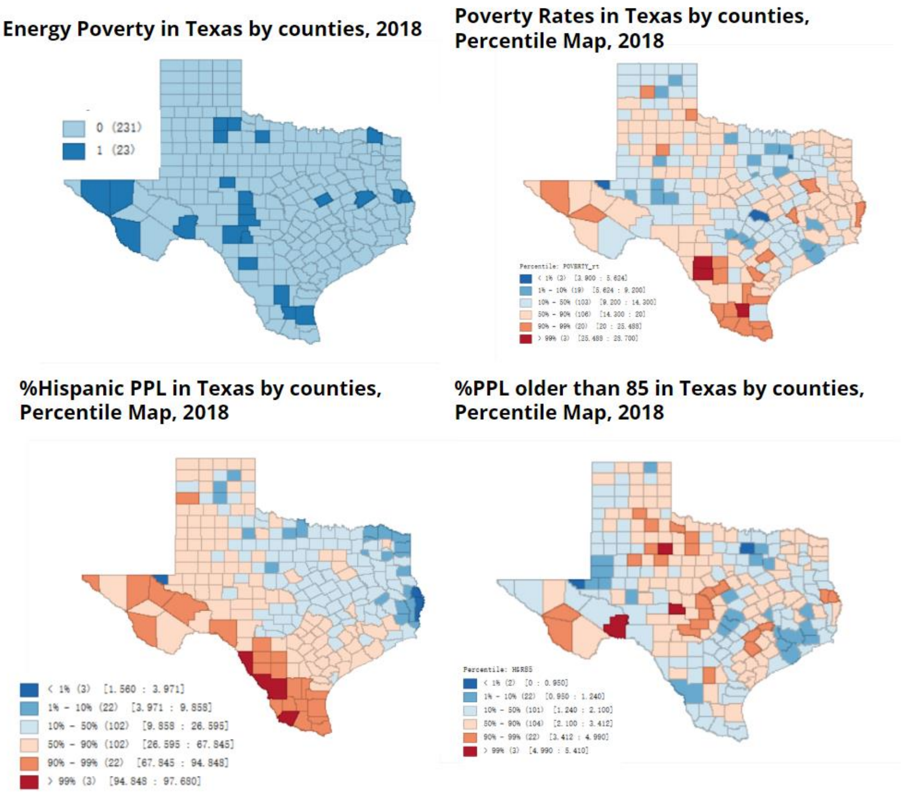

Figure 7. Geo-representation of energy poverty, poverty rate, Hispanic demographics, and senior (>85) demographics

Although individuals who live in the relatively poorer state tend to spend a higher proportion of their income on basic demands, it can be mitigated by the transfer of payment, which has yet to be done properly in Texas.

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5. Conclusions

The transition of energy justice is still in the early embryonic stage. The research provided insights into discovering groups of people vulnerable to Energy Burden. Data analysis indicates the spatial implications of the impact of regional energy poverty. According to Moran's Index derived from energy burden data, energy burdened counties tend to cluster in the Southern and Western parts and the borderline between grid zones in Texas. These are also the places where people tend to have lower average income and smaller household sizes, which confirms that the clustered energy-burden counties were also counties suffering from energy injustice.

The research contains strong policy implications based on findings from the literature review on Texas policy and research as well as those from the quantitative study. In terms of government actions, it is recommended that the government offer a similar program as the LITE-UP program to resume the financial support for energy poverty groups. It would be beneficial for the government to distribute mandatory surveys to households on a national level to capture energy poverty on a micro-level so that analysts can quantify the energy burdens regionally. In addition, since the deregulation of electricity might be one of the reasons utility costs are high, the paper suggests the government implement price regulation of electricity prices, especially during peak hours and in counties that are further away from the generators.

On the consumer-facing side, the Texas government can consider refundable sales tax credits resulting in a net payment to low-income individuals on electricity consumption when they are identified as energy-poor. Since the Texas residents are less responsive to prices, the Texas government should re-examine if that market structure is in consumers' best interests in light of the inflated economy at this moment. The legislature must consider the expedient approach to increasing the reliability of the Texas grid - this area has not been supported due to a lack of investment.

In addition, to reduce market abuse, the consumers have the power to balance the market if sufficient competition is introduced into the playing field. A good approach to diversify Texan consumers' electricity bills is to introduce more accessible renewable energy such as wind energy and solar energy to boost their energy consumption efficiency, flexibility, and affordability. The general public should also receive adequate education on efficient ways of energy conservation as well as self-identification of energy poverty and energy inefficiency. By doing so, consumers are more likely to independently identify their energy poverty status, make cost-effective decisions, get financial support, and eventually improve their living standards.

Although Texas has a unique position in the energy market, it still provides sufficient insights for other states into domestic energy poverty and the people's vulnerability to energy injustice. In the U.S. the affordability of energy for consumers remains a crucial topic and should not be ignored in policy discussions. The results of this research aim to demonstrate the value of adding spatial analysis into energy injustice measurement to accurately capture energy poverty on a multi-dimensional basis. The methodology could be informative and helpful to policy makers in terms of similar objectives.

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Appendix 1: Parameters

Parameters	Description	Ideal Data Source
EBi	The indicator of energy burden in county i	Empirically measured median percentage of income spent on energy bills.
Xi	A vector of explanatory independent variables including six types of demographic factors including: ● Age, ● Financial background, ● Education, Unemployment, ● Race, ● Household size.	Empirically collected demographic data regarding each aspects.
W	The spatial weights that associated with the error term εi	
β1, λ	A vector of estimated parameters regarding the relationship between independent variable and dependent variable	\
εi (i≠j)	A vector of error terms resulted from the regression between Energy Burden and demographic factors	\
ζi	A vector of error terms resulted from the spatial regression between *εi & εj*	\

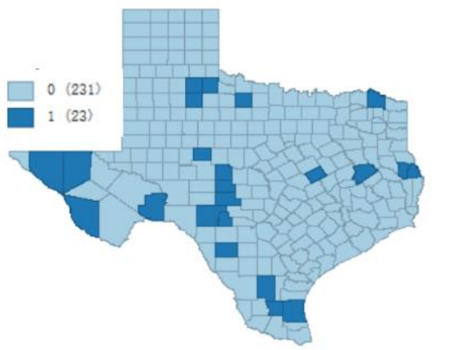
Parameters	Ideal Data Source	Actual Data Source
EBi	Empirically measured median percentage of income spent on energy bills.	The average percentage of income spent on energy bills, secondary data. (***)
Xi	Empirically collected demographic data regarding each aspects.	For each aspects: ● Age %ppl older than 65

		%ppl older than 85 ● Financial Average Median income, poverty rate %ppl under 18 in poverty ● Education %High School Graduate or higher ● Unemployment ● Unemployment Rate ● Race %ppl White %ppl Black %ppl Hispanic (Texas association of counties, 2018) ● Household size Average Household size (Center for Geospatial Technology, 2022)
W	The spatial weights that associated with the error term εi	The continuity spatial matrix built in Geoda, then transferred into Stata.

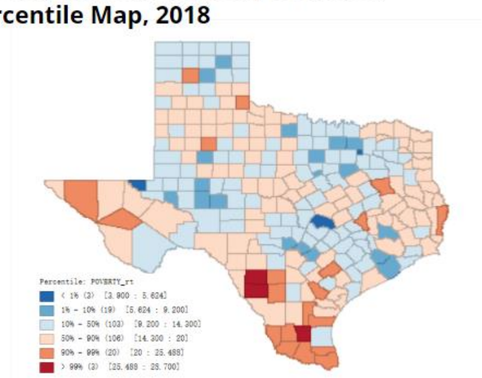
Appendix 2: Stata log file
https://drive.google.com/file/d/1aIwbeE-xZ2LrDFTI--qCK_O_xqT7ST_o/view?usp=sharing

Appendix 3: Maps

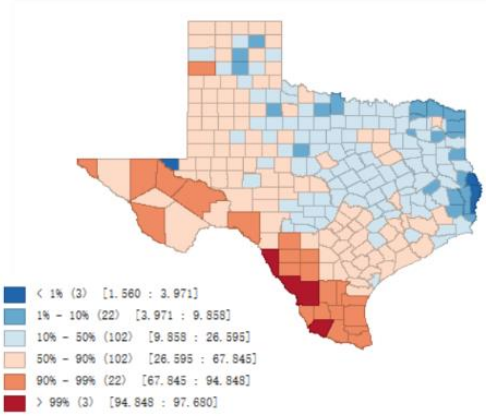
Energy Poverty in Texas by counties, 2018



Poverty Rates in Texas by counties, Percentile Map, 2018



%Hispanic PPL in Texas by counties, Percentile Map, 2018



%PPL older than 85 in Texas by counties, Percentile Map, 2018