PLAN 672
Final Project Proposal
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Energy Burden of N.C. Households by Electric Utility

Introduction

Energy burden is a statistic defined as the proportion of household income spent on energy bills. The procurement of electricity, natural gas, fuel oil, wood, coal, solar, and other fuel sources included in this metric are considered essential to the health and safety of prosperous societies. The lower the energy burden, the more discretionary income is available to the household for other necessary goods and services, for savings and investments that contribute to economic growth and community well-being. Inversely, high energy burdens constrict households' participation in society, and are a contributing factor in poverty boradly. While per-unit energy costs in the United States are lower than many other countries on average, many Americans still struggle to afford their energy bills. The universal and fundamental nature of this metric makes it one of public policy interest. The Federal Low Income Home Energy Assistance Program (LIHEAP) and the Weatherization Assistance Program (WAP) seek to address aspects of energy poverty through bill payment assistance and energy efficiency measures.

As part of these programs, energy burden has been assessed comprehensively by census tract, county, state, and nationally. Research based on this data and related methods have found that gender, age, housing age, tenure type, energy inefficiency, education, employment, geography, socioeconomic status, and race/ethnicity are associated with high energy burdens. However, energy burden has not been examined comprehensively at the scope of the energy provider service territory.

The energy service territory is more relevant than these other cadastral scopes because the service provider is the authority for determining the costs of energy for each of its customers: in vertically integrated energy markets the monopoly utility is the only option available to all consumers, and in organized energy markets the utility is designated as the provider of last resort for those unable or unwilling to participate in competitive procurement of energy. In some markets, specialized rates or programs are available for Low and Moderate Income consumers (LMI), who may have higher energy burdens. In fact, 51% of all funding directed to address high energy burdens in the U.S. is from utility ratepayer funded bill and energy efficiency assistance [source]. This relevance especially holds true for electricity because it is a commodity delivered via a stationary grid system. Even in organized markets where energy supply is competitive, local utilities retain ownership of the transmission and distribution of electricity to end consumers. Furthermore, the lack of storage infrastructure on the grid and behind each meter means that households are beholden to electricity providers for the time of use. It stands to reason that energy costs, and therefore energy burdens, might be related to the electric service territory in which a household is located.

This project will estimate the dynamics of energy burden across each electric service territory in North Carolina in order to understand **whether energy burdens vary by retail electricity service providers**.

Data

This analysis will rely on two primary sources of data: Low-Income Energy Affordability Data (LEAD) furnished by the U.S. Department of Energy and the Electric Retail Service Territories (ERST) provided by the U.S. Department of Homeland Security. It will also rely on three datasets from which the LEAD dataset was formed.

1. Low-Income Energy Affordability Data (LEAD)
    a. This dataset represents an estimate of the monthly energy bills and average incomes of households in the united states, segmented by the following characteristics:
        i. Geographic level
            1. National
            2. 50 States plus D.C. and Puerto Rico
            3. County
            4. City
            5. Census tract
        ii. Household income level
            1. Area Median Income (AMI): 0-30%, 30-60%, 60-80%, 80-100%, 100+%
            2. Federal Poverty Level (FPL): 0%- 100%, 100%-150%, 150%-200%, 200%-400%, 400% +
        iii. Housing unit type
            1. Tenure: home owners versus renters
            2. Building year of first construction
            3. Number of units in the building
            4. Housing unit primary heating fuel type
    b. Estimated residential energy consumption by cohort is calculated by applying an iterative proportional fitting (IPF) algorithm to cross-tabulations from the 2016 5-year American Community Survey (ACS5).
    c. The data are then scaled to match aggregate annual values from utility reported sales and revenues reported in Energy Information Administration Forms 861 and 176.
2. Electric Retail Service Territories (ERST)
    a. These shapefiles represent electric power retail service territories. These are areas serviced by electric power utilities responsible for the retail sale of electric power to local residential, industrial, or commercial customers.
    b. The LEAD dataset is created using a proprietary set of shapefiles to represent utility service territories, as opposed to this open dataset.
3. 2016 TIGER/Line Shapefiles (TIGER)
    a. Provides shapefiles of census tracts and block groups
4. 2016 5-Year American Community Survey (ACS5)
    a. Provides housing unit counts by type and block group for reallocating the LEAD dataset among service territories
5. 2016 Energy Information Agency Form 861 (EIA-861)

a. Provides customer counts for each utility for weighting housing unit counts to customer counts

As part of the calibration process in the creation of the LEAD dataset, utility service territories were mapped to census tracts using a simple intersection. The average of energy prices was used for tracts with more than one utility present. The consumption and expenditure estimates for each tract were rescaled and weighted based on these assumptions. This process means that the consumption and cost assumptions along census tracts shared by multiple utilities (i.e. along territory borders) may show a mean-reversion bias. These assumptions could be relaxed by recreating the LEAD dataset from scratch from the underlying data and methods while incorporating the spatial distribution of housing units in each tract by block group, but this is outside the scope of this project. Instead, I will assess the systemic bias of the dataset along service territory borders to determine whether this is an issue.

Lower income groups may have variable or seasonal income that might not show up in the annualized census data. These monthly peaks are more important to households when energy bills are higher (e.g. summer air conditioning or winter heating). Furthermore, the impacts of rate structures are not accounted for in the consumption estimates. This dataset does not control for weather, so the relative efficiency of households cannot be inferred.

Methods

1. Assign census block groups to electric retail service territories shapefiles using a simple intersect, creating a table of unique utility_block_groups.
2. Determine whether a utility_block_group is in a bordering tract or block group between two utilities using a simple intersect between the territories shapefiles and census tracts and block groups, then joining this table with the utility_block_group table.
3. Attribute housing units of each type in each tract to each utility_block_group based on the proportion of housing units of each type per census block group covered by each utility, and weight by the proportion of total housing units to residential customers of each utility.
4. Join the LEAD dataset with the electric service provider dataset using the utility_block_group table.
5. Regress energy burdens by utility_block_group against the LEAD data attributes, service territory attributes, and whether the block group or tract is on a utility boundary.
6. Perform a sensitivity analysis of the results by examining the significance of whether a utility-block is in a census tract or block group on the border between utilities.
7. This analysis controls for only some attributes known to be associated with high energy burdens. Further analysis depending on time available will consider more attributes such as:
    a. Gender
    b. Age
    c. Energy inefficiency
    d. Education
    e. Employment

f. Geography
g. Socioeconomic status
h. Race/ethnicity
i. Climate