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Evaluating Geographic Differences in Electricity Burdens: An Analysis of Socioeconomic and Housing Characteristics in Erie County, New York

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Abstract The increasing cost, and demand for, household energy has increased attention to the phenomena of energy burdens. Despite this increased attention, a lack of consensus remains in pinpointing the strongest predictors, and geographic differences, that exist within the energy ecosystem. This study addresses this gap by utilizing a series of dummy variable regressions across cities, suburbs, and rural areas within Erie County, New York—a county noted to have particularly high energy burdens. Specifically, three types of predictor sets were incorporated into the methodology: a set of socioeconomic variables, physical variables, and a combination of both variable sets. The results of this study suggest that cities tend to have the highest electricity burdens. Despite the aging infrastructure in Erie County, high energy burdens were driven primarily by socioeconomic factors such as housing cost burden and poverty status. Lastly, this study explores various planning and policy implications Erie County can utilize to reduce energy burdens. In turn, this study highlights the importance of focusing policy efforts on existing social service programs to provide support to the region's neediest households.

Keywords Energy Burden, Geographic Differences, Dummy Variable Regression, Socioeconomic Characteristics, Housing.

I. Introduction

Recently, the price and demand for residential electricity has increased across the United States and globally; this trend has been exacerbated by the Covid-19 Pandemic's stay at home orders (Agbim, Araya, Faust, & Harmon, 2020; Chen, Feng, Luke, Kuo, & Fu, 2022; Graff & Carley, 2020; Kawka & Cetin, 2021; Krarti, & Aldubyan, 2021). Specifically, it is estimated that residential household electricity consumption increased between 4-5% during the Covid-

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19 lockdowns (Lou, Qiu, Ku, Nock, & Xing, 2021). Simultaneously, this likely increased the amount households spend on electricity and the number of energy burdened households. Specifically, energy burden refers to the percentage of income one spends on their electricity-related costs (Brown, Soni, Lapsa, Southworth, & Cox, 2020; Moore & Webb, 2022). Thus, there are two major components in the calculation of energy burdens: income and energy-related costs. While various thresholds exist for defining energy burden, a 6% threshold is a mutually agreed upon standard (Brown et al., 2020).

This threshold is typically represented through annual energy expenditures. However, energy costs typically follow seasonal patterns; many households utilize more electricity and heating (or air conditioning) during the winter (or summer) months (Brown et al., 2020). Thus, some households may be considered energy burdened in the mid-summer or winter—but not in other seasons. In addition, this 6% objective measure may not adequately capture those who are frugal and aim to minimize energy usage. At the same time, our society is becoming increasingly dependent on electricity for work, transportation, recreation, and basic needs. Overall, many households do not meet this objective criterion, but feel they spend a lot on energy-related expenses (Agbim et al. 2020). In essence, as our society's dependence on electricity increases, many households are seeing this reflected in their energy-related expenses.

While the research on energy burdens is relatively new, it will become a more pressing issue because of its impacts on health, household economics, and quality of life. For many households, energy costs are a preeminent household expense as it is tied to essential household activities, such as heating and cooking (Bohr, & McCreery, 2020). When households are on a tight budget, they reduce their expenditures on other items (such as food and health care) to pay for their electric or gas bills (Brown et al. 2020; Hernández, 2015). At the same time, delaying access to health services often accumulates into greater adverse consequences over time (Hernández, 2015). Several diseases and illnesses, such as respiratory diseases, thermal discomfort, and mental health problems, have been noted to be exemplified by the economic trade-offs associated with electrical shut-offs (Brown et al., 2020; Reames, Daley, & Pierce, 2021). In short, while electricity expenditures appear to be a small portion of households' budget—it is not an expense that people want to be paying or should skimp out on.

However, energy burdens remain insufficiently understood. As our reliance on energy, and the cost of it, increases—it is imperative for municipalities to gain an in-depth understanding of the causes and effects of high energy burdens. In turn, this knowledge will be advantageous in local climate change mitigation and adaptation planning strategies—especially for municipalities committed to equitable transitions to clean energy. Subsequently, the primary purpose of this study is to investigate the causes and regional differences in energy burdens across Erie County, New York—a county committed to an equitable transition to clean energy (Poloncarz, 2018). Furthermore, particular attention is given to how regional government entities (such as counties), that lack many legislative and powers, can support local municipalities' transition to clean energy.

II. Causes of Energy Burden

Brown et al. (2020) established five correlates of energy burdens: location and geography, housing characteristics, socioeconomic factors, behavioral factors, and energy prices and policies. Taken together, the built environment, socioeconomic, and political factors all, to some degree, have an effect on energy burden rates. Simultaneously, they may interact and result in disproportionate impacts on certain communities. Most importantly, Brown et al., (2020) suggest that these five factors disproportionately impact low-income populations.

2.1 Location and Geography

Several lines of research have demonstrated that geography is one of the most imperative factors in energy burdens. Across the United States, energy burdens tend to be highest in the warm southern states (e.g., Florida) and in cold northern states (e.g., Michigan and Maine). In particular, these regions have higher energy burdens due to their climate (Brown et al., 2020). Furthermore, many Northeastern states, such as Massachusetts, have high energy costs due to high demands for energy during the cold winters (Borenstein & Bushnell, 2022). Thus, the typical climate patterns in a region may cause households to increase their energy spending.

At the local level, research suggests that rural areas and cities have the highest energy burdens. In rural areas, this is often attributed to low population densities, long transmission distances required to deliver services, and financial constraints for infrastructure development (Brown et al., 2020; MacDonald, Winner, Smith, Juillerat, & Belknap, 2020; Michalski, 2019; Ross, Drehobl, & Stickles, 2018). On the other hand, many scholars suggest the high energy burdens of cities to be related to low-incomes, old and low-quality housing, and high proportions of multi-family housing (Brown et al., 2020; Kontokosta, Reina, & Bonczak, 2020).

2.2 Housing Characteristics

Housing primarily impacts energy burdens through its degree of energy efficiency (Brown et al., 2020). Specifically, this refers to the implementation of measures that use less energy to produce the same result. Primarily, this reduces energy bills by reducing the amount of electricity used (Brown et al., 2020). This can come in numerous forms such as new energy-efficient appliances, weatherization, improving insulation, or heating and cooling systems. However, many of these upgrades are quite expensive and unaffordable—especially for low-income households.

Older homes contribute to higher energy burdens as they are less energy efficient than newer construction; this is the consequence of outdated building codes, construction methods, and building materials degrading in quality and effectiveness (Brown et al., 2020; Moore & Webb, 2022). It is generally agreed upon that larger homes require more energy—especially for heating purposes (Huebner, Hamilton, Chalabi, Shipworth, & Oreszczyn, 2015; Kontokosta et al., 2020). However, there is an inconsistency in the literature regarding energy burdens and the type of housing. Some suggest that multifamily housing tends to be highly correlated with energy burdens (Brown et al., 2020; Moore & Webb, 2022; Ross et al., 2018) whereas others found single-family homes to be more prominent drivers of energy burdens (Elnakat, Gomez, & Booth, 2016). In contrast, Berry, Hronis, & Woodward (2018) found that mobile homes and smaller multifamily units (2-4 units) have the highest energy burden rates.

Not to mention, multi-family housing and mobile (manufactured) homes have largely been left out of energy efficiency incentives and policy-making decisions (Brown et al., 2020; Webb & Moore, 2020). Renters lack direct control in the decision making for their housing units; in turn, this creates a split-incentive where landlords may not pursue energy efficiency upgrades as they will not be the primary beneficiary of them (Brown et al., 2020; Webb & Moore, 2020). Furthermore, there is a high degree of heterogeneity within the multi-family umbrella. Multifamily units can range from relatively small structures (three units) to large structures (500+ units). In conjunction, a lack of uniform construction type, methods, or utility paying structures complicates wide-spread and uniform policy implementation (Webb & Moore, 2020).

2.3 Socioeconomic Factors

Socioeconomic variables are imperative to consider as they are correlated with income and subsequently, ability to afford electricity and energy efficiency home improvements (Brown et al., 2020; Chen et al., 2022). In part, these disparate energy burdens may share linkages with racist and discriminatory policies, such as redlining, that created spatial inequalities along racial and economic lines. This, in turn, subsequently led to disinvestment in low-income and minority neighborhoods, social services, and public education systems: all of which are imperative in wealth generation and obtaining access to high-paying jobs.

Several studies have documented that members of minority groups (particularly Blacks and Hispanics) have higher energy burdens than white households (Chen et al., 2022; Graff Carley, Konisky, & Memmott, 2021; Hutchins, 2021; Maxim & Grubert, 2022; Reames, 2016; Ross et al., 2018; Wang, Kwan, Fan, Lin, 2021). However, these studies have been inconclusive in pinpointing a causal relationship. Some studies (e.g., Moore & Webb, 2022 & Chen et al., 2022) found race to be a significant predictor of energy burdens. In contrast, Graff et al. (2021) suggests that other variables, such as income and housing conditions, act as mediating variables in this relationship. Regardless, minority populations pay more towards their energy bills than white individuals do. However, this issue is not limited to racial minorities. Other research suggests that women (Chen et al., 2022; Elnakat, Gomez, & Booth, 2016), elderly individuals (Graff et al., 2021; Moore & Webb, 2022; Ross et al., 2018), those receiving public assistance (Chen et al., 2022; Graff et al., 2021), low education levels (Elnakat et al., 2016; Moore & Webb, 2022; Reames, 2016; Wang et al., 2021), and those who live in rental units (Graff et al., 2021; Moore & Webb, 2022; Ross et al., 2018; Wang et al., 2021) are more likely to experience energy burdens.

2.4 Energy Prices and Policies

The cost of energy is one of the highest correlates of energy burden (Wang et al., 2021). If the cost of energy infrastructure and fixed-costs are high, these translate into higher costs for customers (Brown et al., 2020). These fixed costs are often reflected in static charges placed onto each customer's electric bill. Consequently, no matter how much energy one uses, they will at least be charged this static delivery charge. In conjunction, a region's electric rates are regulated by a state or city Public Service Commission (PSC). This is done to ensure that fair and affordable service is provided to customers (Gabel, Swartz, & Zeitlin,1974). However, if a region has low energy service rates (e.g., in the Southern United States), it becomes difficult for households to want to pursue energy efficiency improvements—primarily because there are little returns-on-investment (Brown et al., 2020). Put simply, if customers have low electric bills, it may take several years, or decades, for them to break-even with the initial cost of the energy improvement.

The availability of energy affordability programs and policies are imperative to help address energy burdens. These programs are offered by government agencies (local, state, and federal), utility companies, and other community-based organizations. The largest program is the Federal Government's Low-Income Home Energy Assistance Program (LIHEAP). However, the program only provides slight financial assistance on energy bills. Whereas LIHEAP typically addresses the income portion of energy burdens, the Weatherization Assistance Program (WAP) aims to directly improve energy efficiency. This often takes the form of home upgrades such as air sealing, window repairs, and heating upgrades (Brown et al. 2020). It is estimated that $0.08 in electricity expenditures is saved for every $1 spent on weatherization; over time, this translates into a savings-to-investment ratio of around 1.4 (Brown et al., 2020; Zivin & Novan, 2016). However, this type of program is most beneficial for single-family homes as multi-family structures are challenging to weatherize and result in less energy savings (Tonn, Rose, & Hawkins, 2018; Webb & Moore, 2020). Furthermore, low-income households are less likely to partake in weatherization programs as they often require upfront costs or are incentivized with tax credits—which provide little benefit to low-income households (Brown et al., 2020). While these are two of the largest low-income energy programs, their funding and eligibility is limited and typically does not meet society's full demand (Brown et al., 2020).

2.5 Behavioral Factors

Behavioral factors refer to the various behaviors people engage in pertaining to energy usage. These behaviors may be influenced by or are closely related to one's knowledge, intentions, cultural lifestyles, and actions taken to reduce energy expenditures (Brown et al., 2020; Huebner et al., 2015). Similarly, there may be some value and behavior incongruence pertaining to energy usage. For example, many individuals may claim that they want to reduce their energy expenditures; however, they may not be enrolled in local energy assistance programs, may leave lights turned on when not needed, etc. (Brown et al., 2020). In addition, many renters who may want to participate in energy assistance programs or home upgrades may not be able to due to not having complete control over the structure; this may be most evident for renters whose utilities are included in their rent or live in rural areas (Brown et al., 2020; MacDonald et al., 2020).

III. Energy Burdens and the Climate Crisis

Climate change is expected to pose additional challenges to the United States' currently inadequate housing and energy systems (Maxim & Grubert, 2022). In tandem, addressing equity issues that already exist within energy burdens will be imperative to address. Currently, low-income, minority households, renters, and households living in multifamily housing consume low amounts of electricity, but generally have higher energy bills compared to other similar households (Brown et al., 2020; Reames, 2016).

Maxim & Grubert (2022) suggest that climate migration and increased energy burdens will be two major impacts of climate change. Through climate migration, many regions in the Midwest and the Northeast are expected to see increases in their population (Maxim & Grupert, 2022). This is imperative to consider as it significantly impacts the needed infrastructure within a region; in particular, the increasing need for housing and additional energy infrastructure. Subsequently, this will have direct and indirect impacts on each region's energy burdens. Directly, this is likely to occur through the increased usage of cooling (e.g., air conditioning) to mitigate the effects of extreme heat caused by climate change (Maxim & Grubert, 2022). Indirectly, this may occur through household electrification (the replacement of gasoline power sources with electric energy supplies). As the burning of fossil fuels, such as gasoline, has been one of the most significant contributors to climate change, various electrification strategies have been some of the most commonly proposed climate change mitigation methods (Maxim & Grubert, 2022). At the same time, the rapid electrification of heating could potentially overload the current energy infrastructure (Vaishnav & Fatimah, 2020). Thus, significant clean energy investment will be required to enable widespread electrification to occur. Yet one of the main challenges to these types of infrastructure are the high development costs which typically get displaced onto local ratepayers (Alagappan, Orans, & Woo, 2011). This is imperative to address as electricity is more expensive than the current gas infrastructure (Maxim & Grubert, 2022). In sum, climate change, without proper mitigation techniques, will result in significantly higher energy expenditures for residents.

IV. Justification for Erie County as a Study Area

An assessment of energy burdens within Erie County is warranted for several reasons. The City of Buffalo, and other surrounding municipalities, are expected to see a large influx of residents due to climate migration (City of Buffalo, 2019). As Maxim and Grubert (2022) suggest, this influx of residents will drive up the demand and costs of the region's electricity. Erie County currently has a unique built environment and sociodemographic characteristics. Within Erie County, the City of Buffalo contains the country's oldest housing stock (CZB LLC, 2017; Schilling, 2008). While the county's suburbs have been progressively developed after the City of Buffalo, they are now experiencing many of the same old-age housing issues (Schilling, 2008). Put simply, an aging housing infrastructure is a detrimental barrier in achieving energy efficiency and climate justice.

Alongside an aging infrastructure, Erie County contains a high proportion of low-income and minority residents—both strong correlates of energy burdens. Historically, discriminatory policies, such as redlining, have resulted in Buffalo becoming the 8th most segregated city in the United States (Blatto, 2018). Consequently, the City of Buffalo's East Side has become home to majority of the city's Black residents; in tandem, years of historical disinvestment in infrastructure, housing, and social institutions has resulted in high levels of poverty in these neighborhoods (Blatto, 2018). These factors are likely to contribute to higher energy burden rates for these residents. However, many older-central cities are seeing more individuals taking up interest in revitalization and are returning to the city; simultaneously, gentrification and displacement of low-income households is on the rise (Brown et al., 2020). Consequently, an increase in diversity and inequality is occurring in the County's first-ring suburbs (Gee & Dewey, 2021). These demographic shifts have increased suburban poverty and energy affordability that have yet to be sufficiently studied.

Most importantly, the costs of electricity are increasing. National Grid, one of the two utility companies in the county, forecasted a 6% increase (approximately $27) in electricity costs in the winter of 2022; almost 60% of this is attributed to an increase in the supply charge—the portion of the bill based on a household's actual electrical consumption (National Grid, Personal Communication, Sept. 22, 2022). In turn, around 40% of this price increase will likely be due to factors outside of the individual's control. Due to Erie County's location in the Northern United States and along Lake Erie, it typically experiences cold winters. This is of particular concern in terms of electrification of heating sources as it may significantly drive up one's electricity costs (Maxim & Grubert, 2022). This becomes especially problematic for the County's low-income and vulnerable populations (i.e. elderly individuals) who may be more vulnerable to extreme heat.

Understanding the core components of the region's energy burdens is of paramount interest to the County in their commitment to the Paris 2050 Climate Agreement and the New York State Climate Leadership and Community Protection Act (CLCPA) goals of 100% clean energy by 2040 (Poloncarz, 2018; New York State Climate Action Council, 2022). Moving to a zero-emission clean energy economy will require the electrification of the majority of vehicles and household utilities (i.e., heating and gas). This is imperative as it can increase electricity usage and costs. Thus, this research aims to address two overarching questions. First, what are the predictors of electricity burden in Erie County; furthermore, if households in different geographic locations in Erie County have different electricity burden rates.

V. Methodology

5.1 Data Collection

All data used in this study was obtained from IPUMS USA's 2019 ACS (5-year samples) for Erie County. Specifically, the 2019 data was utilized as 2020 was an atypical economic and social year with the Covid-19 pandemic; thus, 2020 values may not be not be representative of the typical energy consumption patterns (Ruggles, Flood, Goeken, Schouweiler, & Sobek, 2022). As IPUMS preserves the linkages between an individual's data values, this data set is better suited to observe how social and built environment characteristics directly relate to energy burdens.

This analysis included two groupings of predictor variables: socioeconomic variables and physical (built environment) variables. The variables included in the socioeconomic predictors were: housing tenure, age, years of education (since elementary school), poverty level (income earned as percentage of the poverty line: higher values indicate higher incomes), food stamp recipients, minority status, number of individuals in the household, housing cost burden (income spent on housing) and social security income. These variables were included as they touch on the different dimensions of energy burdens (e.g., food stamps and the "Heat or Eat" tendency) and demographics associated with higher energy burdens (e.g., minority groups and age). In contrast, the physical predictor variables included: building age, number of rooms in one's housing unit, number of bedrooms, housing type, and electric heating systems. Overall, these sets of variables were selected as they pertain to Brown et al.'s (2020) 5 dimensions of energy burdens, categories (physical and socioeconomic) utilized in prior studies such as Moore & Webb (2022), and were available through IPUMS.

In this study, households served as the primary unit of analysis since utility data is typically collected at the household level. The majority of variables utilized were collected at the household level except for five variables: race, education level, age, Social Security income, and poverty status. For these variables, the head of household's information was utilized. Lastly, geographic location was operationalized through the IPUMS metropolitan status classification. Within Erie County, there are three classifications of PUMA's: central cities, intermediate areas (mixed central/peripheral city), and areas not in central or peripheral cities. These categories equate to the City of Buffalo being the central city, first-ring suburbs representing intermediate (mixed) areas, and rural areas representing "not located in central or peripheral cities."

5.2 Methods

This analysis utilized an OLS regression approach to predict electricity burdens through sets of physical and socioeconomic variables. Households that had electricity costs included in their rent or had questionably low incomes (e.g., $1) were excluded from the analysis. After these exclusions, 17,060 households were included in the analyses. A majority of which (9,252) were located in rural areas. In contrast, 4,335 were located within central cities and 3,473 in suburban areas.

Energy burden was calculated by dividing each household's annual electricity expenditures by their annual income; subsequently, this number was multiplied by 100 to achieve a percentage. Specifically, this study was strictly interested in electricity; thus, energy burden calculations were limited to energy costs related to electricity. Secondly, the proportion of income spent on housing was computed by annualizing the "selected monthly homeownership costs" (for homeowners) or "monthly gross rent" (for renters) and dividing that number by each household's annual income.

To test for geographic differences, two dummy variables were created for the three geographic locations. Central city households were utilized as the reference group; subsequently, dummy 1 (D_1) referred to rural areas whereas dummy 2 (D_2) represented suburban areas. Furthermore, the "units in structure" variable was re-coded into two dummy variables. In this dummy variable set, single-family structures served as the reference group. The small multi-family structures variable (2-19 units) was computed to be a single dummy variable (D_3) and housing structures larger than 20 units represented large multi-family units (D_4). Two other categorical variables (race and home heating fuel) were re-coded to be race (0 = white & 1 = minority) and electric heating (0 = other heating source, 1 = electric heating). Lastly, four variables (household income, social security income, poverty levels, and percentage of income spent on housing expenses) were standardized into Z scores to achieve a similar scale among the other variables. Before proceeding with the regressions, Pearson's Correlation coefficient r was computed among all the predictor variables; results of this analysis were used to pre-detect multicollinearity and remove highly correlated variables.

Six OLS linear regressions were conducted as part of the analysis. To start, two regressions were performed: each with only one set of the predictor variables. Subsequently, an additional regression included all predictor variables for both sets of predictors (physical and socioeconomic). Specifically, these regressions took the form of the following equation: $Y_i = \beta_0+D_1+D_2+D_3+D_4+\beta_1X_{i1} + \cdots + \beta_nX_{in} + \varepsilon_i$. Here Y_i represents energy burden, X_{in} represents n number of independent variables for observation i, β_0 is the intercept, D_1 represents rural areas, D_2 represents suburban areas, D_3 are small multi-family units, D_4 being large multi-family units, and β_n represents n number of regression variables.

Using the variables from the best performing model from the prior regressions (combination, socioeconomic, and physical), an additional regression will be performed for each geographic region in the county. Primarily, this aims to uncover if there are any differences in which significant predictors within each region. This equation will largely mimic the ones from the prior models, however, dummy variables one and two will be excluded as they will not be necessary. The primary difference is that each model will only contain the households within that geography. Lastly, two software packages were utilized in this research. SPSS were utilized for the data analysis: computation of variables, correlation analysis, and regression analyses. In addition, the electricity burden map was created using ArcMap 10.8.2 and shapefiles from the U.S. Census Bureau.

VI. Results

Erie County contains three cities, 13 villages, and 25 townships amassing a total population of 919,385 in 389,585 households; the City of Buffalo hosts the majority of this population with around 256,480 residents in 110,427 households (U.S. Census Bureau, 2019). Many of the suburban and rural areas have much smaller populations. Overall, Erie County's electricity burden is around 2.89% (SD=4.37%). For those with electric heating, the average electrical burden was 4.61% (SD=6.32%). Among the three geography types, central cities had the highest rates at around 4.09% (SD=5.74%). In contrast, suburban (M=2.62%, SD =3.51%) and rural areas (M=2.42%, SD=3.77%) had lower electricity burdens. Thus, electricity burdens do not appear to be distributed equally throughout Erie County (Figure 1).

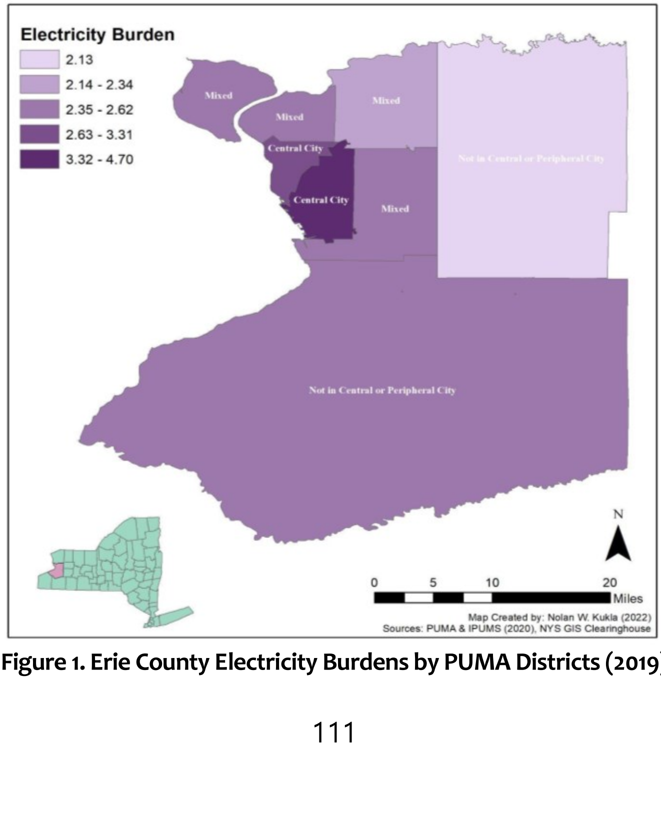

Figure 1. Erie County Electricity Burdens by PUMA Districts (2019)

Across the three geographies, many of the demographics were similar. However, there were differences regarding income and housing related variables. Central cities had the lowest incomes (M=$64,294, SD=$77,304), highest poverty levels, highest housing-cost burdens (M=33.48%, SD=50.70%), and the highest percentage of residents receiving food stamps (26.60% of residents). Rural and suburban areas primarily consisted of homeowners whereas central cities had a balance of renters and homeowners. Furthermore, a majority of the County's minority residents are located in central cities. Additionally, the majority of the County's housing stock was built in the 1950's (SD=2.41 decades) with the oldest housing stock being located in central cities (1940's). Simultaneously, the majority of this housing in the County is single-family housing (73.79%). For more detailed descriptive statistics, please refer to Appendix A.

Pearson's Correlation Coefficient indicated that most of the predictor variables were only slightly correlated (r coefficients ranging from .1-.3); in turn, this suggests little overlap among the variables. However, two pairs of variables had high correlations. As expected, the number of rooms and number of bedrooms were highly correlated ($r=.74$, $p<.01$). To prevent multicollinearity, the number of rooms was removed from subsequent regression analyses. Similarly, housing tenure and housing type (units in structure) had a correlation of ($r=.63$, $p<.01$). However, this may be expected as most homeowners live in single-family units; thus, both variables were included. To see the full correlation matrix, please refer to Appendix B.

Across the three regression models, the physical predictor set explained the least amount of variance (adjusted $R^2=.044$, $F(7,17279)=113.43$, $p<.001$). The dummy variables indicated that central cities had higher electricity burdens than other county geographies. Specifically, this translates into about 13.84% ($p<.001$) lower electrical burdens in rural areas and about 12.36% ($p<.001$) lower in suburban areas. Only two predictors had negative regression coefficients. Of these two, the number of bedrooms was the stronger predictor at -.309 ($p<.001$). Notably, electric heating was the strongest predictor in the model with a coefficient of 1.365 ($p<.001$); thus, having electrical heating increases household electrical expenses by 1.365% of their income. To see the full predictor coefficient values for this model, please refer to Table 1.

Table 1. Physical Predictors Regression

Intercept	5.156		<.001
Rural	-1.384	-0.158	<.001
Suburban	-1.236	-0.114	<.001
Building Age	-0.062	-0.034	<.001
Electric Heating	1.365	0.073	<.001
Small Multi-Family	0.274	0.027	0.002
Large Multi-Family	0.698	0.029	<.001
Num. of Bedrooms	-0.309	-0.069	<.001

The socioeconomic model explained more variance than the physical predictor set (adjusted R^2 =.617, $F(11,17060)=2498.95$, $p<.001$). The total household income variable was removed as it was not a significant predictor ($p>.05$). Nevertheless, all other predictors in this model were significant at the $p<.001$. Similar to the physical predictor set, central city households had the highest electrical burdens. However, the values of the coefficients were much smaller: rural areas had lower electrical burdens by .337% and suburban areas by .533% (in comparison to central cities). The predictors directly related to income were the strongest predictors of electrical burdens. Notably, the proportion of household income spent on housing was the strongest predictor (b=2.651). This was followed by food stamp recipients as the second strongest predictor (b=1.242). Similarly, poverty status (b=-1.024) and Social Security Income (b=-.204). Both suggest that as income increases, electricity burdens decrease.

Homeowner status was the strongest demographic predictor of electrical burdens; compared to homeowners, renters had .807% lower electrical burdens. Similarly, compared to whites, minority households had .616% higher electrical burden rates. Interestingly, family size was negatively associated with electrical burdens. Two predictors (age and educational levels) were found to only have small impacts on electrical burdens. To see the full set of predictor coefficient values for this model, please refer to Table 2.

Table 2. Socioeconomic Predictors Regression

Variable	Coefficient	Standardized	Significance
Intercept	2.802		<.001
Rural	-0.337	-0.039	<.001
Suburban	-0.533	-0.049	<.001
Income on Housing	2.651	0.603	<.001
Poverty Status	-1.024	-0.235	<.001
Minority Status	0.616	0.066	<.001
Education	-0.05	-0.026	<.001
Food Stamps	1.242	0.093	<.001
Renter	-0.807	-0.08	<.001
Age	0.018	0.70	<.001
Family Size	-0.113	-0.03	<.001
Social Security Income	-0.204	-0.047	<.001

The combination of the socioeconomic and physical predictors slightly increased the model's performance. Surprisingly, household income was not a significant predictor (p>.05) and was removed from subsequent analyses. This combined model explained the highest proportion of the variance (adjusted R^2 =.621, F(16,17060)=1,751.15, p<.001). Similar to prior models, central cities had higher electricity burden rates than rural areas (by .376%) and suburban areas (by .588%). When comparing the socioeconomic model and combined models, the majority of predictors retained similar coefficient values. In essence, there were no major differences in terms of strength of the predictors.

In contrast, the physical predictors showed greater changes. The most notable changes are among the housing types; in comparison to single-family structures, multi-family structures were less likely to experience electricity burdens. In particular, households in large multi-family housing units spent .868% less of their income on electrical expenses than those in single-family structures. The building age and electric heating predictors dropped slightly in their magnitude. Essentially, newer homes and those with electric heating are still predicted to spend higher proportions of their income on electricity; specifically, for each decade old the housing structure is, it will increase electricity burden by .042%. In contrast, those with electric heating will spend an additional 1% on their income on electricity costs. For the full set of predictor coefficient values for the combined model, please refer to Table 3.

Table 3. Combined Predictors Regression

Intercept	2.741		<.001
Rural	-0.376	0.061	<.001
Suburban	-0.538	-0.05	<.001
Income on Housing	2.662	0.605	<.001
Poverty Status	-1.01	-0.232	<.001
Minority Status	0.606	0.049	<.001
Education	-0.048	-0.025	<.001
Food Stamps	1.221	0.073	<.001
Renter	-0.45	-0.045	<.001
Age	0.018	0.073	<.001
Social Security Income	-0.208	-0.048	<.001
Family Size	-0.14	-0.042	<.001
Building Age	-0.042	-0.023	<.001
Electric Heating	1.003	0.054	<.001
Number of Bedrooms	0.066	0.015	0.011
Small Multi-Family	-0.561	-0.055	<.001
Large Multi-Family	-0.868	0.135	<.001

As a follow-up, three additional regressions were performed utilizing the combination model set as it explained the most variance in the prior regressions. These regressions aimed to gauge a deeper understanding of how each predictor performed within each geographical region. Of these three regressions, the suburban (R^2 =.640) and rural regions (R^2 =.637) had slightly more of the variance explained than central cities (R^2 =.600). For households in central cities, all predictors were significant except three of the physical predictors: large multi-family buildings, number of bedrooms, and building age. Similar to the prior models, many socioeconomic variables were the strongest predictors. Many of the predictors contained similar coefficient values to the central city regression and the prior regression models.

The suburban model had the most surprising results as about half of the predictors were not significant. In particular, minority status, building age, electric heating, and housing tenure were variables that were strong predictors among the other geographies, but were not in the suburban areas. Essentially, the predictors pertaining to dimensions of income were the primary drivers of electricity burdens in the suburbs. Shockingly, electric heating was not a significant predictor in the suburban model (p=.757). Across all three geographies, housing burdens had the largest coefficient. Specifically, for each unit increase (standardized Z-score) in housing burdens, electricity burdens, on average, increase between 2-3%. To see the full set of predictor variables and their coefficients, please refer to Table 4.

Table 4. Combined Predictors by Geography Type

Adjusted R^2	0.600***	0.640***	0.637***
Variable	Coefficient	Coefficient	Coefficient
Intercept	2.078***	2.114***	2.461***
Income on Housing	3.088***	2.368***	2.508***
Poverty Status	-1.185***	-0.971***	-0.984***
Minority Status	.645***	0.169	.624*
Years of Education	-0.70**	-0.016	-0.029*
Food Stamps	1.222***	.587***	1.176***
Renter	-0.595***	-0.04	-0.580***
Age	.031***	.012***	.017***
Social Security Income	-0.371***	-0.125**	-0.170***
Family Size	-0.226***	-0.084**	-0.118***
Building Age	-0.025	-0.036	-0.046***
Electric Heating	1.388***	0.060	1.040***
Number of Bedrooms	0.100	0.095	0.024
Small Multi-Family	-0.458***	-0.526***	-0.508***
Large Multi-Family	-0.383	-1.588***	-1.030***

$P < .05$*, $P < .01$**, & $P < .001$***

VII. Discussion

Overall, households in central cities experienced the highest electricity burdens. This was most profound in the physical predictor model. Interestingly, there was no consistency among which of the two other geographies, suburban and rural, had lower electricity burdens. In the socioeconomic and combined models, suburban areas had lower electricity burdens than rural areas. In contrast, rural areas had lower electricity burdens in the physical predictor model. This may be due to differences in physical infrastructure or demographics of each region. However, as the physical regression models explain little variance—the majority of physical and structural may have minimal impacts on energy burdens.

The central city region likely had the highest electricity burdens for several reasons. Within the County, there are two electrical utility providers: National Grid and New York State Energy and Gas (NYSEG). National Grid primarily serves the western portion of Erie County whereas NYSEG territory is primarily on the County's eastern (rural) side. Notably, the central city is located entirely within National Grid service territory. This is important to acknowledge as geographic differences in service quality or prices exist. In particular, National Grid's monthly electricity rates were about $11 higher than NYSEG rates (Robinson, 2019). That is, central city residents tend to pay more for the same amount of electricity. In tandem, the central city region had lower incomes and higher concentrations of poverty. Taken together, these lower-incomes and higher service rates would greatly contribute to higher energy burdens.

However, it is imperative to recognize that the central cities contain a plethora of higher income residents. For these residents housing can represent a significant investment and cost. Particularly, the City of Buffalo (the central city) is known for having an abundance of historic homes (Schilling, 2008). Notably, these homes are typically expensive, less energy-efficient, and challenging to weatherize or perform energy efficient upgrades (Brown, 2020; Webb, 2017). In turn, this housing can be more expensive to own (or rent) and maintain. Electric heating with lower housing quality would result in higher prices

Furthermore, the regional differences observed are unlikely entirely due to behavioral and socioeconomic factors. Regional disparities typically arise from the combination of two overarching concepts: the region's natural conditions and municipal economic plans and policies (Zali, Ahmadi, & Faroughi, 2013). In other words, external forces constitute a meaningful role in contributing to high electricity burdens. Since the 1950's, Erie County has seen rapid suburbanization and the movement of wealthy residents to the suburbs (Blatto, 2018). As such, infrastructure investments have largely remained within the City of Buffalo and its surrounding suburbs. This development pattern is imperative as it leaves rural municipalities with far less investments compared to its counterparts. As such, many energy assistance resources are concentrated within the City and suburbs. For instance, the County's HEAP office is located in the City and 5 of the 6 WAP vendors are located within the City (Erie County, 2023). Consequently, many rural residents are located far away from any sort of available assistance.

In addition, many of the County's suburban communities may be more adept in pursuing clean energy and addressing energy burdens. This is evident in the County's municipalities participation in NYSERDA's (New York Energy Research and Development Authority) Clean Energy Communities Program. This program aims to reward municipalities for pursuing sustainable and clean energy related projects such as solar development, energy code enforcement, and upgrading facilities to clean energy (University at Buffalo Regional Institute, 2022). Notably, in 2020 a total of 7 of 9 of the County's suburban communities (defined within PUMA districts) have earned a clean energy community designation; that is, they have completed at least 4 high impact action items

(University at Buffalo Regional Institute, 2020). In turn, the impacts and cost savings of these actions could be passed onto residents. In contrast, only 2 rural communities (defined within PUMA districts) were designated as a clean energy community; the majority of rural municipalities and the City of Buffalo have completed 1 or 0 high impact actions. In essence, suburban municipalities may be the best equipped to handle electricity burdens due to their demographics, proximity to resources, and the local governments' interest in sustainable energy.

Overall, these results largely mimic Moore & Webb's (2022) as the combination of physical and socioeconomic variables explained the most variance in the county's energy burdens. This relationship was primarily driven by socioeconomic factors; specifically, the majority these variables which were the only ones to remain constant across all geographies in the follow-up regressions. Similar to Moore & Webb (2022), the introduction of physical predictors only slightly improved the overall model's performance; however, the physical predictor set only explained a small amount of variance in electrical burdens.

Based on prior research, the majority of the predictors utilized (both physical and socioeconomic) had similar effects on electricity burdens. However, there were a few unexpected results. Household income was not a significant predictor of energy burdens. This implies that electricity burdens are not a uniquely low-income experience. At the same time, other income-related variables, such as poverty status and receiving food stamps, were significant predictors. These variables may contain additional attributes that hone in on factors that represent extreme financial-need. Perhaps the most unexpected result is that the proportion of income spent on housing was the strongest predictor of electricity burdens. This is especially important as planning programs for affordable housing often exclude energy expenditures and energy efficiency upgrades (Brown et al., 2020; Kontokosta et al., 2020; Webb & Moore, 2020). This has a special unique local implication as Buffalo's housing affordability issues are primarily driven by low-incomes (CZB LLC, 2017). Consequently, it is likely that low-incomes are drivers of both housing and electricity burdens. Nonetheless, housing affordability will be imperative to address as low-incomes can become preventative to making necessary housing repairs and energy-efficient upgrades; consequently, potentially resulting in the gradual degradation of housing structures.

These results found mixed results for the role of single-family housing. In the combination model, single-family structures had higher electricity burden rates than small and large multi-family units. In contrast, the physical predictor model found that single-family units to have lower electricity burdens. In conjunction, renters were less likely to experience electricity burdens than homeowners were. This is in contrast to much of the literature on this topic (e.g., Graff et al., 2021;

Moore & Webb, 2022; Ross et al., 2018; Wang et al., 2021) This may be due to several reasons. First, there may be different socioeconomic associations or differences within who can afford to own and live in single-family structures. For instance, while minority status was a significant predictor of electrical burdens, it could potentially be a mediating factor for income and housing variables—especially given the City of Buffalo's disinvestment and segregation of communities of color.

Due to Erie County's reputation for old housing, it was expected that housing age would be one of the strongest predictors of electricity burdens. While housing age was a significant predictor, it had the lowest predictive value of the physical predictors. However, a majority of the region's housing is maintained fairly well due to historic preservation efforts. In particular, the majority of housing in North and West Buffalo is considered "good" or "above average" (CBZ LLC, 2017). This is not to say that dilapidated housing does not exist within the region; a majority of this dilapidated housing is concentrated on the East Side of Buffalo (CBZ LLC, 2017). Thus, this spatial concentration of poor housing conditions and poverty may result in higher energy burdens in the East Side; however, additional analyses would need to be performed to confirm or deny this claim.

At first glance, these percentages appear to be relatively small. However, when put into context of other factors, these figures can accumulate to large amounts. For instance, 1% of a $50,000 annual income is around $500. Thus, for some predictor variables, such as electric heating, that surpassed 1%, household energy costs would exceed this amount. Over the long term, that $500, in conjunction with other additional costs, could accumulate and subsequently push households into poverty. For this reason, it is imperative to act against the rising costs of energy.

VIII. Policy and Planning Implications

Agbim et al., (2020) identified the need for localized accounts of energy burdens; in turn, better accounting for variability within larger geographies. These results exemplify the benefit of these individualized approaches. Erie County's suburbs had slightly different predictors of electricity burden than other parts of the county; a targeted approach addressing the significant predictors of each geographic classification is the best way to direct resources and policy efforts. Across all three geographies, income-related variables were large predictors of electrical burdens; thus, regional governments and organizations (e.g., Erie County & New York State) should focus on addressing the common predictors across the county (e.g., incomes and energy prices). In turn, individual municipalities could focus their efforts and resources on the significant predictors within their specific geography. For instance, geographies with old housing and electric heating as significant predictors should work to address those specific issues. To be most effective, these efforts must be paired with regional efforts to address income-related issues and overall energy prices. In addition, regional governments and organizations could utilize their existing programs and grants, such as Community Development Block Grants (CDBG) to assist municipalities in addressing issues like household electrification and aging infrastructure.

As socioeconomic variables were the strongest predictors of electricity burdens, policies and planning initiatives must address the cost of electricity or raise resident's incomes. From this sample, it is estimated that only a small percentage of Erie County residents currently have electric heating (about 6%). As the CLCPA and Paris Climate Agreement require a shift away from fossil fuels, electric heating will become the new standard. This study found electric heating to be one of the most significant physical predictors of energy burdens. Consequently, it is necessary to couple this transition with subsidized electricity to directly reduce the cost of electricity.

A clean-energy transition without an equity focus will exacerbate existing inequalities within the county. This is imperative to address as energy burdens can be triggering events that can push households into poverty (Bohr, & McCreery, 2020). As it stands, low-income populations have been excluded from the transition to clean energy. Precisely, this has been, in part, due to the low ROIs and upfront costs associated with these developments. The Inflation Reduction Act of 2022 aims to improve equity in clean energy development and reduce energy costs; these initiatives include, but are not limited to, energy efficiency rebate programs, electrification assistance, tax-credits, and community development block grants. When Erie County, or individual municipalities within the county, receive funding from the Inflation Reduction Act, it will be imperative that communities whose socioeconomic composition were indicated to be significant predictors of electrical burdens be at the forefront of these investments.

Several possibilities exist for addressing energy burdens at the income level. The first is increasing the amount for energy subsidy programs such as LIHEAP or Utility energy affordability programs (EAP). This additional funding could be used to expand the number of individuals served or increase the funding given to each program recipient. However, because of income-restrictions these programs can only be accessed by low-income individuals. One effective tactic could be to utilize the 6% energy burden as an eligibility criterion for LIHEAP or EAP enrollment; in addition, eligibility criteria could be expanded to those demographics with high electricity or housing burdens. Specifically, these expanded criteria would help those who have high electricity costs, but may not meet state or federal low-income guidelines.

At the local level, community solar initiatives are another example of an income-related program to address electricity burdens (Brown et al., 2020). These are offsite solar-facilities where individuals can elect to receive their electricity from. Thus, these are accessible to both homeowners and renters. As part of their enrollment, customers receive bill credits on their electrical bill (typically 10%). Most importantly, as income-related variables are strong predictors of electricity burdens, this 10% will not sufficiently address this issue. This may be especially concerning as reliance and cost of electricity increases. While community solar programs are on the rise, the lack of zoning ordinances and building codes have prevented widespread developments (Nolon, 2015). Consequently, planning efforts within individual municipalities should be directed at reducing these barriers, and in turn, facilitating the development of solar farms on vacant lands and suitable buildings.

These results present interesting implications for developing countries. As these countries urbanize and grow, they will require advanced, affordable, and reliable energy systems. Within Erie County, and the majority of the United States, the energy system is primarily controlled by government and quasi-government (such as utility companies) organizations. Historically, there has been few entry points for the private sector to enter into the market. As such, there have been no competitive forces to encourage new, innovative, and more effective energy services to residents. This has recently changed with the emergence of community solar (and other renewable energy) programs: many of which are being utilized to bring energy independence and cost-savings to residents. However, these types of developments are expensive and financing is hard to come across. Thus, governments could provide incentives to private markets to help facilitate renewable energy development.

In particular, a priority should be to ensure affordability for residents; if electricity is unaffordable, it will likely hinder further economic development. As such, it will be imperative to ensure that this infrastructure, such as energy systems and housing, is equitably distributed among rural and urban areas; this distribution can help prevent certain areas from experiencing higher electricity or energy burdens than other areas. In turn, preventing high energy burdens from further concentrating poverty and negative health outcomes in a particular area.

In particular, regional disparities are often the result of the concentration of resources within a small localized area (Zali et al., 2013). As seen with Erie County, the concentration of infrastructure and energy resources has likely contributed to higher electricity burdens in the region's rural communities. In particular, a common feature of developing countries is their high concentrations of the population and resources within small portions of a region (Zali et al., 2013). Notably, the sharp distinction between urban and rural may be more profound in developing countries. As such, it will be imperative for developing countries, as they pursue global sustainable development goals, to ensure that electricity resources and infrastructure are equitably distributed throughout their respective regions. In turn, this equitable distribution will help reduce geographic inequities in electricity burden rates.

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IX. Limitations

While this research demonstrated geographic differences in electricity burdens, there are several limitations to the study. In this study, energy burden was restricted to only electricity costs. Therefore, this does not include gas, water, any utilities included in rent, and any other utility costs. If gas costs or other types of heating fuel were included, energy burden rates would likely have been higher—especially in Erie County's rural areas that rely on expensive propane fuels (U.S. Census Bureau, 2019). While those utility costs are important drivers of energy burdens, this study was aimed specifically at gauging a better understanding of the electricity-related portions of energy burdens.

This study was able to directly incorporate three of Brown et al.'s (2020) five correlates of energy burdens: geography, housing, and socioeconomic characteristics. The other two correlates (energy prices or policies and behavioral factors) were not included as predictors in the analyses. In particular, behavioral factors are hard to accurately quantify and measure; consequently, there were no available datasets able to be incorporated. Furthermore, energy prices may be assumed from how much was paid in annual electricity costs, but it is not a perfect indication.

Furthermore, the PUMA classifications may not be the best classification for municipalities in Erie County. Many municipalities commonly referred to as second-ring suburbs, such as Hamburg and Orchard Park, are grouped with rural municipalities; thus, grouping may have prevented a true rural classification. Lastly, a majority of the households in this sample were homeowners (73.79%). This is slightly higher than the U.S. Census Bureau's (2019) estimates of 64.58%. In this study, renters with electricity costs included in their rent were from the analysis due to a lack of data: subsequently, the sample size of renters was smaller. This exclusion is imperative as many of the county's lowest-income residents are located within subsidized housing structures such as Public Housing and Section 8 HCV programs which include utilities in their rent.

Lastly, the housing-related variables may not have been robust enough to accurately demonstrate housing quality's role in the electricity burdens.

Granular housing data, such as an assessment of conditions, is hard to assess and quantify. Therefore, the inclusion of building age and approximate size likely only captured general housing quality information. In addition, this dataset is unable to provide insight on which homes have energy efficiency upgrades such as weatherization and solar panels. However, those upgrades may be reflected in the lower costs that households pay for electricity. In conjunction, this study was unable to include IPUMS' "house value" variable as that information was not available for renters. This information, coupled with the number of bedrooms, could provide a better proxy for housing conditions; for example, by comparing each home's value to the median value of a similar-sized and aged home. These findings are not to say that housing is unrelated to electricity burdens, but rather new assessment methods need to be developed to clarify this relationship.

X. Conclusion

By utilizing public-use microdata, this study expanded upon the existing energy burden literature and knowledge within Erie County. The methods utilized in this study are unique in a few ways. To begin, few studies have explicitly investigated the electricity component of energy burdens—an increasingly important aspect of the energy ecosystem. At the surface level, Erie County's electrical burden rate (2.89%) was comparable to the New York State and Overall United States energy burden rates of 3% (U.S. Department of Energy, 2021). However, as noted before, energy burden statistics typically include the cost of gas (primarily for heating) and heating in which this study did not. This is important as Erie County residents are paying a similar proportion of their income (on just electrical costs) as other regions are for both gas and electricity. Nonetheless, much of the existing literature on energy burdens focus on individual cities and only a few investigate energy burdens across larger geographic regions. Subsequently, this study surpassed those limitations by investigating geographic differences in energy burdens across a large geographical scope.

Notably, this study demonstrated that within Erie County, households in central cities have higher electricity burdens than those in other geographies. Primarily, these high energy burdens were driven by socioeconomic factors that relate to income. This has important implications for the County's climate change planning techniques. That is, to achieve an equitable reduction in energy burdens the focus of energy-related policy must pertain to individuals and sociodemographic characteristics—particularly those in poverty or enrolled in social service programs. In addition, housing cost burden was the most significant predictor of energy burdens; in turn, this reflects the need and interconnectivity of the two issues. Subsequently, it is imperative to address electricity burdens within the lens of housing affordability.

Most importantly, it is imperative to recognize that many residents likely feel the impacts of many of these variables. For example, if a household is in poverty, it is likely that they are burdened by their housing costs, receiving food assistance, etc. That is, these variables culminate into larger energy burdens. This effect may be most evident within the County's central city (the City of Buffalo) as the City's East and West Sides have numerous areas of concentrated poverty (Blatto, 2018); in turn, this likely contributes to the Central City's highest energy burdens. As such, a holistic approach to addressing energy burdens is imperative. In essence, those most susceptible to the impacts of energy burdens are the county's most socially and economically vulnerable residents.

Due to the limitations in this study, further research should be performed to further clarify how these factors are related to electricity burdens. Primarily, future studies should clarify the role of specific housing conditions and how those interact with socioeconomic predictors. Notably, granular housing quality data is hard to achieve and access across the entire County. As such, data could be gathered from New York State's Weatherization Assistance Program (WAP), electrical usage and bill data from utility companies, or from municipal property tax assessments to gain a more robust analysis.

Lastly, this study cannot provide a causal identifier as to why regional disparities exists; subsequently, these results are limited to identifying that disparities exists across Erie County. As such, further research should clarify the differences in infrastructure and service quality that could result in differences in electricity costs across the region. Within Erie County, many suburban communities, such as West Seneca and Cheektowaga, contain have the highest mix of national grid and NYSEG households (National Grid, 2023). As such, case studies could be performed between households (of similar socioeconomic status or living situations) from each utility provider. In turn, these studies could help eliminate the confounding variable that multiple utility providers introduce. Similarly, further research should investigate why certain characteristics, such as renter status, minority status, and electric heating, in suburban households appear to be more resilient to energy burdens than those in other geographies. As these variables were large and significant predictors in the other two geographies—understanding the difference here is imperative.

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Appendix A: Descriptive Statistics

Table 5. Physical and Socioeconomic Characteristics

	Central City		Suburban		Rural		Overall	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Total Household Income	$64,294	$77,304	$70,628	$57,614	$94,990	$90,281	$82,194	$82,525
Income Spent on Housing	33.48%	50.70%	26.84%	43.53%	25.65%	43.86%	27.88%	45.75%
Social Security Income	$4,234	$7,638	$5,739	$8,847	$5,938	$9,334	$5,462	$8,860
Income as Percent of Poverty Line	272.50%	163.49%	325.48%	147.17%	364.83%	145.04%	333.23%	155.28%
Annual Electricity Costs	$1,157	$797	$1,083	$675	$1,212	$762	$1,172	$756
Age of Head of Household	52.13	17.53	55.84	17.36	56.26	16.74	55.12	17.16
Years of Education (Since Elem. School)	7.49	2.47	7.46	2.04	8.2	2.183	7.87	2.261
Family Size	1.93	1.355	2.10	1.258	2.08	1.247	2.04	1.282
Building Age (decades since 1930)	2.11 (1940s)	1.92	3.64 (1950s)	1.89	4.23 (1960s)	2.5	3.57 (1950s)	2.41
Number of Rooms	6.32	2.49	6.05	1.87	6.6	2.2	6.42	2.28
Number of Bedrooms	3.82	1.12	3.88	0.87	3.98	0.95	3.92	0.98

Source: IPUMS USA 2019 5-Year ACS

Table 6. Frequency Distributions for Physical & Socioeconomic Characteristics

	Central City		Suburban		Rural		Overall	
	Count	*Percent*	*Count*	*Percent*	*Count*	*Percent*	*Count*	*Percent*
Minority Households	1,793	40.60%	264	7.50%	502	5.40%	2,559	14.81%
Homeowners	2,419	54.70%	2,717	77.40%	7,617	81.40%	12,753	73.79%
Renters	2,000	45.30%	795	22.60%	1,736	18.60%	4,531	26.21%
Electric Heating	275	6.20%	136	3.90%	602	6.40%	1,013	5.86%
Food Stamp Recipients	1,176	26.60%	371	10.60%	571	6.10%	2,118	12%

Source: IPUMS USA 2019 5-Year ACS

Table 7. Housing Typologies Across Geographic Classification

	Central City		Suburban		Rural		Overall	
	Count	*Percent*	*Count*	*Percent*	*Count*	*Percent*	*Count*	*Percent*
Single-Family	2,169	49.08%	2,620	74.60%	7,704	82.37%	12,493	72.28%
Small Multi-Family	1,974	44.67%	832	23.69%	1,378	14.73%	4,184	24.21%
Large Multi-Family	276	6.25%	60	1.71%	271	2.90%	607	3.51%
Total	4,419		3,512		9,353		17,284	

Source: IPUMS USA 2019 5-Year ACS

Appendix B: Predictor Variable Correlation Matrix

Table 8. Combined Predictors by Geography Type

Variable	1	2	3	4	5	6	7	8	9	10
1. Housing Tenure	1									
2. Food Stamps	.33**	1								
3. Units in Structure	.63**	.22**	1							
4. Family Size	-0.14**	.06**	-0.22**	1						
5. Poverty Status	-0.39**	-0.45**	-0.25**	.07**	1					
6. Electric Heating	0.24**	.11**	.34**	-0.08**	-0.12**	1				
7. Education Level	-0.13**	-0.23**	-0.06**	.06**	.38**	-0.02**	1			
8. Minority Status	.24**	.26**	.17**	.05**	-0.23**	.06**	-0.12**	1		
9. Building Age	-0.02**	-0.10**	.06**	.02**	.14**	.10**	.10**	-0.11**	1	
12. Housing Burden	.22**	.21**	.16**	-0.10**	-0.46**	-0.12**	.06**	.11**	-0.07**	1

$P<.05$* & $P<.01$**