# PATTERNS OF POVERTY: A REGIONAL EXPLORATION OF POVERTY IN AMERICA

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## ABSTRACT

Existing research on American poverty largely focuses on the national average experience of poverty, offering sweeping conclusions. This article describes regional differences in poverty outcomes, challenging the notion that there is a nearly singular experience of poverty. For example, while some research argues poverty occurs most commonly in minority communities, this research provides evidence for, and descriptions of, poverty in mostly white areas on average. 725 counties were grouped into four distinct regions based on proximity, and Census definitions of US Regions. K-means clustering was leveraged across each of the regions, producing two clusters per region. One cluster presented a notably higher mean poverty rate than the other in all cases. Employment, health, and sociodemographic cluster means varied, revealing unique patterns of poverty-relevant outcomes. The relationship of cluster and poverty was validated against an external measure reflective of poverty using Analysis of Variance (ANOVA). The relationship was found to be significant in two of four regions. Tukey's post-hoc testing further detailed significant pairwise cluster differences. These results offer support for the utility of smaller-scale state or local anti-poverty policy, and support the hypothesis that poverty manifests differently across relatively small geographic regions.

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# INTRODUCTION

Anti-poverty policy in the United States is in a period of intense focus due to the SARS-CoV-2 (COVID-19) pandemic. Recent analyses at the national-level provide evidence that, during the COVID-19 crisis, America's impoverished – as in, a singular national community - have been worst off in terms of *health* outcomes (such as transmission and mortality rates);[1] *economic* outcomes (such as lack of paid sick leave for low-income workers, providing "essential" in-person goods or services); and *sociodemographic* (social) outcomes (such as increased rates of criminal violence within certain aged racial groups, possibly due to COVID-related school and business closures).[2] In a short period of time, and on a grand scale, the COVID-19 pandemic exposed the critically different conditions low-income Americans have faced decades over.

The federal response to economically aid Americans was robust. Suspending federal student loan payments, for example, reflected the sweeping, national-level approach the federal government often takes in aiding the poverty community. The consistent nationwide approach to poverty alleviation reflects the idea that poverty shows up "the same" from coast to coast, even in a massive geographic region like the US. Instead, this analysis explores the theory that the expression of poverty,[3] access to

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[1] Christine Little et al., "The Impact of Socioeconomic Status on the Clinical Outcomes of COVID-19; a Retrospective Cohort Study." *Journal of Community Health* 46, 4 (2021): 794–802, doi:10.1007/s10900-020-00944-3.

[2] Julia P. Schleimer et al., "Neighborhood Racial and Economic Segregation and Disparities in Violence During the COVID-19 Pandemic." *American Journal of Public Health* 112, 1 (2022): 144–53, doi:10.2105/ajph.2021.306540.

[3] Such as the average age, race, or employment makeup of the poverty group.

poverty-alleviation resources,[4] and the surrounding social structure of the area[5] is different on average across America. For instance, a high poverty rate county in a Northeastern state may experience a different set of poverty-relevant outcomes and resources than a county in a Southeastern state, despite receiving aid from the same federal programs.[6] While important, and often effective, federal anti-poverty policy may be so large-scale and sweeping in nature, that it obscures the underlying political and economic processes that actively marginalize, displace, or limit the opportunities of low-income Americans in varied geographic regions.

This article contains a k-means cluster analysis that seeks to answer the question of whether poverty-relevant outcome measurements are generally the same across the US, in all high poverty rate areas; or, if there are significant differences in poverty-relevant outcomes in impoverished areas across US regions.[7] The theoretical background that guided health, economic, and social variable selection for this analysis is described in the literature review; the variables are mapped to the concepts they represent in Appendix

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[4] Such as expanded eligibility criteria for Medicaid.

[5] Such as political leaning of the area.

[6] Of note here, perhaps the political party leanings of an area affect how federal anti-poverty programs are applied. The average political leaning (in the case of this analysis, a score of conservatism) of small-scale geographic areas (counties) will therefore be a discussion point of, and included variable in, this analysis. For more information regarding the interplay between poverty and party, see: David Brady, "The Politics of Poverty: Left Political Institutions, the Welfare State, and Poverty." *Social Forces* 82, no. 2 (2003): 557–88, http://www.jstor.org/stable/3598202.

[7] Refer to the Data and Methods section for information on how regions were determined for this analysis.

Table 1. Hypothesis testing provides evidence for variation in poverty, and whether cluster has a statistically significant relationship with poverty in each US region.

Results of this analysis provide descriptive evidence that poverty-relevant outcomes are inconsistent in high poverty clusters across the US. ANOVA and Tukey's testing provide evidence that two of the four high poverty clusters have a significant relationship with poverty. While the other two clusters also yielded strong results, there were some data issues that rendered ANOVA and Tukey results unreliable.[8] Despite this, regional cluster descriptions, and the evidence of cluster significance in two regions, provide compelling evidence that poverty manifests uniquely across the US, and cannot be summed as a one-size-fits-all experience.

The utility of this cluster analysis is that if poverty manifests differently across the US, it is reasonable to suggest that poverty could therefore be more wholly served with state or locally targeted poverty-alleviation programs and policies, supplemental to existing federal initiatives. Clusters will tell a useful story of poverty, anti-poverty policy, and successful policy outcomes to fuel state and local policymaking research.

# LITERATURE REVIEW

## SECTION 1.1. HEALTH AND WEALTH: THE INTERSECTION OF POVERTY AND WELLBEING

As early as the nineteenth century, scholars have identified that people living in poverty face a lack of access to resources to prevent and treat illnesses. As scholars Link

[8] To be discussed in the Results and Conclusion sections.

and Phelan identify in their 1995 review of 240 poverty-related, peer-reviewed, health research articles, this lack of access puts people in poverty at greater risk of chronic illness or early death.[9] Today, despite dramatic improvements in access to public resources compared to the nineteenth century, the poverty community still faces major health disparities compared to higher income groups (as described in Section 1.2).[10]

One way people living in poverty can experience greater health and income equality is through the receipt of public health care. For example, a data analysis published in the Journal of Economic Perspectives identified that, in 2014, $11,400 was spent on the average Medicare recipient.[11] Given that $11,400 was approximately one third of median family income that year, but that the elderly (those eligible to receive Medicare) tend to have lower incomes than families, researchers concluded that Medicare has the power to reduce income and health inequalities.[12]

Despite the evidence that public health insurance can be a powerful equalizer, recent national events have altered insurance rates in some states. Many low-income Americans have recently lost their health insurance depending on how their state responded to a changing federal anti-poverty policy, the Affordable Care Act. Subsequent

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[9] Bruce G. Link, and Jo Phelan, "Social Conditions As Fundamental Causes of Disease." *Journal of Health and Social Behavior*, (1995): 80–94, https://doi.org/10.2307/2626958.

[10] See the Price article cited therein for additional reading on income-relevant health disparities.

[11] Robert Kaestner, and Darren Lubotsky, "Health Insurance and Income Inequality." *The Journal of Economic Perspectives* 30, no. 2 (2016): 53–77, http://www.jstor.org/stable/43783707.

[12] Kaestner, and Lubotsky, "Health Insurance and Income Inequality," 53–77.

cluster analysis will provide insights into the potentially evolving relationship between insurance status, health outcomes, and poverty rate during 2018.

### SECTION 1.2. IF AVERAGE AMERICANS ARE BECOMING SICKER, ARE POOR AMERICANS BECOMING SICKEST?

In 2018, a large-scale trend analysis of US vital statistics among racial and ethnic groups was published in the BMJ (formerly the British Medical Journal). It covered mortality trends from 1999-2016. The analysis provided unique evidence that mortality rates "increased across a broad spectrum of diseases involving multiple body systems"[13] over time, and across all races and ethnicities.[14] This work lacked an exploration into the effects of income, but the findings point to the need to examine systemic causes of declining health in the US. The systemic conditions faced by the American poverty community specifically (such as limited access to quality health care in some areas) seem intuitively connected to worse health outcomes, and are therefore deserving of empirical exploration.

Complementing this exploratory work, is a 2016 large-scale data analysis published in the Journal of the American Medical Association. Using a sample of 1.4 billion deidentified tax records and death records, it features various correlation and regression analyses evaluating life expectancy in the US. The records were also used to create multiple adjusted life expectancy estimates (using mortality data and Gompertz

[13] Including the digestive, respiratory, nervous, circulatory, and endocrine systems.

[14] Steven H Woolf et al., "Changes in midlife death rates across racial and ethnic groups in the United States: systematic analysis of vital statistics." *BMJ* 362, k3096, (2018), doi:10.1136/bmj.k3096

log-linear modeling) per various geographic and demographic subsets, such as US location, race, ethnicity, or sex. Researchers also constructed life expectancy estimates per various income percentiles (such as quartiles and ventiles). Income-related life expectancy trends were then analyzed per the factors of interest (location, race, etc.) using linear regression.[15] Poignantly, researchers concluded that, on average, women in the top 1% of the income distribution were expected to live 10 years longer than women in the bottom 1% (95% CI, 9.9-10.3 years).[16] Men in the top 1% of the income distribution were expected to live 15 years longer than men in the bottom 1% (95% CI, 14.4-14.8 years).[17]

Researchers concluded there appeared to be a largely linear relationship between income and life expectancy, regardless of what variables were included, and that the relationship is becoming more severe with time.[18] Researchers also concluded that the effect of income on life expectancy was most pronounced for low-income individuals. In other words, this indicates income gains of a given dollar amount at high incomes were associated with smaller gains in life expectancy, compared to income gains of the same amount at lower incomes.[19]

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[15] Raj Chetty et al., "The Association Between Income and Life Expectancy in the United States, 2001-2014." *JAMA*, 315, 16 (2016):1750–1766. doi:10.1001/jama.2016.4226

[16] Women in the bottom 1% were expected to live 78.8 years.

[17] Men in the bottom 1% were expected to live 72.7 years.

[18] Researchers analyzed both *household* income and *individual* income distributions, and results were similar.

[19] Chetty et al., "The Association Between Income and Life Expectancy," 1750–1766.

The strong relationship at low-income levels points to the need for additional research on the relationship between low-income, and health and longevity. There is abundant literature on more objectively direct correlates of poorer health and shorter life expectancies in the poverty community (like cigarette consumption or obesity rates).[20,21] This research aims to, instead, provide insight on the social, political, or economic aspects of high poverty rate areas that potentially relate to poor health outcomes therein.

## SECTION 2.1. ECONOMIC TRENDS OF AMERICA'S IMPOVERISHED: INCOME INEQUALITY

A longitudinal trend analysis of American poverty spanning 1970-2000 provides evidence that the income inequality of an area, as measured by the Gini coefficient, is related to the poverty rate of that area. The study, published in the American Journal of Sociology, also provided support that income inequality had grown over time, and that it had grown most notably in nonwhite communities.[22] These findings suggest that communities with high poverty rates can also be expected to have more income inequality (a higher Gini coefficient), and the relationship is particularly evident in largely nonwhite low-income communities.

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[20] James H. Price, Jagdish Khubchandani, and Fern J. Webb, "Poverty and Health Disparities: What Can Public Health Professionals Do?" *Health Promotion Practice* 19, no. 2 (2018): 170–74. https://www.jstor.org/stable/26746916.

[21] Chetty et al., 1750–1766.

[22] Sean F. Reardon, and Kendra Bischoff, "Income Inequality and Income Segregation." *American Journal of Sociology* 116, no. 4 (2011): 1092–1153. https://doi.org/10.1086/657114.

However, there are several instances in scholarship indicating that income inequality is not greater in communities of color,[23] as well as indications that poverty rate itself is not higher in communities of color (as described in Section 3.1). Given the contradictory evidence in existing literature around the relationship between measures of poverty and the Gini coefficient of an area, this analysis seeks to provide further insight around income and income inequality trends in relation to poverty rate. Workforce variables (such as percent of population in the armed forces, or not in the labor force) will also be explored across clusters to enrich the exploration between income and poverty rate.

### SECTION 2.2. WEALTH OF A NATION VS. WEALTH OF ITS PEOPLE

Exploring how the economic concepts of poverty and GDP interplay in a wealthy nation is seemingly novel. This gap in the literature is perhaps related to the propensity of politicians and economists alike to assume that high GDP is a proxy measure for social wellbeing (a concept that includes lack of poverty), even across massive geographic regions like the United States. For example, a 2021 data analysis from economist Picciotto evaluated the GDPs and $CO_2$ emissions of the world's twenty largest economies. The analysis included a discussion of poverty and policymaking in those nations.

[23] Reardon and Bischoff, "Income Inequality and Income Segregation," 1092–1153.

Picciooto reported that the countries with notably higher GPDs were also the largest CO2 emitters. He posited that policymakers in those nations (including the United States) use GDP as a key performance indicator when measuring anti-poverty policy success; a potential conundrum considering the harm that can be caused to surrounding people and environments via major production. Thus, he concluded, governments continue to allow harmful, but revenue-generating, business activities to continue.[24]

Despite GDPs obvious link to the labor force (people), GDP research today exists largely apart from research around the causes or experiences of poverty. This represents a potential gap in the literature considering GDP is a measure of *all* production, even that which causes moral ills or ecological harm.[25] As such, it is worth exploring the idea that perhaps poverty-dense areas may also be highly productive (high GDP) areas.

## SECTION 3.1. POVERTY PERCEPTIONS VS. REALITY: THE GREAT RACE DEBATE

Since the 1970s, a pervasive trope has been that poverty is concentrated to racially segregated areas with dense concentrations of nonwhite minorities.[26] This view has been supported by some studies, and rejected by others. For example, in 1997, scholar

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[24] Robert Picciotto, "Beyond GDP: Tracking and Evaluating National Contributions to Social and Environmental Sustainability." *Journal of MultiDisciplinary Evaluation* 17, 41 (2021): 61–78. https://journals.sfu.ca/jmde/index.php/jmde1/article/view/717.

[25] Jens V. Hoff, Martin M. B. Rasmussen, and Peter Birch Sørensen, "Barriers and Opportunities in Developing and Implementing a Green GDP." *Ecological Economics* 181, (2021): 106905. doi: https://doi.org/10.1016/j.ecolecon.2020.106905.

[26] Lincoln Quillian, "Segregation and Poverty Concentration: The Role of Three Segregations." *American Sociological Review* 77, no. 3 (2012): 354–79. http://www.jstor.org/stable/41723037.

Jargowsky provided contradictory evidence to the assumption that race is a primary predictor of poverty rate with regression modeling. His findings suggested that there was "no tendency for concentrated poverty rates to be especially elevated" in largely nonwhite areas.[27]

In 2000, economic scholars Massey and Fischer revisited Jargowsky's work. They applied an interaction effect to Jargowsky's original model based on severity of neighborhood segregation (the assumption being that affluent minorities are less segregated from white people than are poor minorities). The Massey Fischer study provided evidence that race is a significant predictor of poverty when in a highly segregated neighborhood.[28]

A later review of their analysis in 2011, however, suggested that their results were weak: "a close reading of Massey and Fischer's tables actually provides much evidence that contradicts their claim of interaction of segregation and group income level […]. Indeed, Massey and Fischer seem to recognize (but do not emphasize) the mixed nature of their results[.]"[29] Because the relationship between race and poverty is still debated, this analysis seeks to provide further insight around a potential link between race and poverty across varied geographic clusters.

## SECTION 3.2. EVOLVING AGE-BASED POVERTY PATTERNS

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[27] Quillian, "Segregation and Poverty Concentration," 354–79.
[28] Quillian, 354–79.
[29] Quillian, 354–79.

Perhaps due to the success of Social Security in reducing elderly poverty, recent research on how elderly Americans experience poverty is relatively limited. A 2015 regression analysis by Levy, featuring a sample of 12,600 people aged 50 and over, even provided evidence that most elderly people in America who experience material hardship (such as food insecurity, or being unable to acquire medications) do not live in poverty, nor are they using transfer programs (such as the Supplemental Nutrition Assistant Program (SNAP)).[30]

This conclusion is a testament to elder poverty alleviation program success. However, the author identifies that elderly people in poverty still face an elevated risk for material hardship. For example, Levy identified that impoverished elderly people living with coresident children were more likely to experience hardship than those without live-in children. While the study did not specify the age range of coresident children, it is generally accepted that, like the elderly, young children constitute a high-risk poverty group. Also like the elderly, young children have been the focus of numerous poverty alleviation programs (such as Children's Health Insurance Program (CHIP) or Child Tax Credits).[31] The complex relationship between age and poverty is therefore deserving of

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[30] Helen Levy, "Income, Poverty, and Material Hardship Among Older Americans." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 1, no. 1 (2015): 55–77. https://doi.org/10.7758/rsf.2015.1.1.04.

[31] Lawrence M. Berger, Maria Cancian, and Katherine Magnuson, "Anti-Poverty Policy Innovations: New Proposals for Addressing Poverty in the United States." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 4, no. 3 (2018): 1–19. https://doi.org/10.7758/rsf.2018.4.3.01.

ongoing empirical exploration. Clusters will provide insights into high poverty areas, and if those areas also have high concentrations of children or elders.

## DATA AND METHODS

A sample of 725 US counties with populations over 62,600[32] was split based on proximity, and US region codes created by the census. The Census uses eight region codes to describe which states belong to geographically diverse regions such as New England, Middle Atlantic, South Atlantic, and so forth. For this analysis, regions were combined based on their proximity to form four US regions, comparable in total number of counties: The *Northeast* (New England and the Mid Atlantic), the *Southeast* (South Atlantic and East South Central), the *Northern Midwest* (East North Central and West North Central), and the *West & Southwest*[33] (West South Central, Mountain, and Pacific).

Data used for this analysis was obtained from the US Census Bureau's American Community Survey (ACS), the Bureau of Economic Analysis' Annual GDP per County Estimates, the Centers for Disease Control and Prevention's U.S. Small-Area Life Expectancy Estimates, the National Conference of State Legislatures' Annual State & Legislative Partisan Composition Table, and the Centers for Medicare and Medicaid Services' State and County Level Chronic Conditions Table. All data is specific to 2018.

[32] The Census generally only includes one-year estimates for counties with populations of over ~60,000 in its ACS survey, depending on the year. Cited from: "Geographic Areas Covered in the ACS." United States Census Bureau, 2020. https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs_geography_handbook_2020_ch01.pdf.

[33] The ampersand is used in "West & Southwest" to denote it represents one region. This does not indicate there is a West region *and* a Southwest region.

Repeating this cluster analysis in subsequent years is a valuable opportunity for future exploration that will be discussed in the Conclusion section.

Aside from the NCSL dataset, all datasets contained either a county name variable, or county level FIPS code variable. NCSL data was used to create a conservatism score variable that reflects the political leaning of the state, since state policy is intrinsically linked to county-level political outcomes.[34] The party variable was therefore merged with other data via state name, while all other variables were merged either on county name or county FIPS code. The final, merged dataset contained 725 observations of 17 variables[35] representing 3 poverty-relevant outcome themes. The primary variable of interest is the percent of population with annual income below the federal poverty level (FPL). See Table 1 in the Appendix for a full list of variables and their descriptions; Appendix Table 2 contains descriptive statistics for these variables, across all regions.[36]

Health, economic, and social variables for the k-means cluster analysis were chosen based on long researched relationships with the impoverished community, as described in the Literature Review. The "Avg. Spend per Chronically Ill Medicare Beneficiary" variable calls for further discussion.[37] The Medicare spend variable does not

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[34] See Appendix Table 1 for a description of how this variable was created.

[35] 18 total variables, when considering the ANOVA external validation variable of Worker Median Income.

[36] Note: Both Tables span multiple pages.

[37] This variable name was shortened to "Avg. Spend per Medicare Beneficiary" (sometimes with underscore separators) in some prose, tables, and visuals for aesthetic or legibility purposes. It still refers to chronically ill beneficiaries only in those cases.

perfectly reflect the poverty community, since eligibility is primarily based on age. However, over 12% of Medicare beneficiaries lived below the FPL, and nearly 34% lived at or below 200% of the FPL in 2018.[38] Even an income double the FPL could still be restrictive, considering the variable in this analysis reflects spend on chronically ill beneficiaries only; a group that likely faces elevated monthly expenditures due to their illness compared to healthful individuals. Still, average Medicare spend is relatively ambiguous in terms of the poverty community specifically. A high average Medicare spend could, but does not necessarily, indicate that low-income patients receive more effective or more regular medical care than low-income patients in low Medicare spend areas. Despite these potential shortcomings, the Medicare spend variable was included to enrich insights regarding other variables, like percent of population 65 or older, percent publicly insured, or life expectancy.[39]

Univariate outlier analysis was conducted by creating a histogram matrix depicting each variables distribution, per each region. Regional multivariate outlier analysis was completed by computing Mahalanobis Distance statistics. Additionally, scatter plots with labeled multivariate outliers were created using the uni.plot function in R. A small number of outlying counties were listwise deleted from each region, as

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[38] "Distribution of Medicare Beneficiaries by Federal Poverty Level." Kaiser Family Foundation, October 23, 2020. https://www.kff.org/medicare/state-indicator/medicare-beneficiaries-by-fpl/?currentTimeframe=1&sortModel=%7B%22colId%22:%22Location%22.

[39] See Appendix Table 1 for additional variable descriptions that may not have been extensively described in the literature review, but were included to complement the insights gained from other variables. The political party variable could inherently be relevant to several county-level outcomes in this analysis; and the male vs female median income variable could shed light on income measures, such as average Gini Coefficient.

deleting small numbers of outliers is widely recognized as inconsequential.[40] The eliminated counties were outliers across multiple variables. They included notably population dense areas, such as New York County, which contains Manhattan, or Los Angeles County.

To ensure the data was a fit for cluster analysis, a Hopkins statistic was generated per each regional data subset before clustering was completed. The elbow method was then used to determine the best fitting number of clusters per each region; the recommended number of clusters per the elbow method was then affirmed by computing the Gap Statistic. Agglomerative and divisive clustering methods were also tested, but k-means consistently yielded the strongest clusters. Quality of clustering was assessed by computing average silhouette widths per cluster. Altogether, this process resulted in 8 total clusters, described generally by Table 1.[41]

**Table 1. Regional Cluster Overview**

| | **Northeast Region** | | **Northern Midwest Region** | | **Southeast Region** | | **West & Southwest Region** | |
|---|---|---|---|---|---|---|---|---|
| | Hopkins Statistic: 0.73 | | Hopkins Statistic: 0.73 | | Hopkins Statistic: 0.72 | | Hopkins Statistic: 0.73 | |
| | Cluster 1: Low Poverty Cluster | Cluster 2: High Poverty Cluster | Cluster 1: High Poverty Cluster | Cluster 2: Low Poverty Cluster | Cluster 1: Low Poverty Cluster | Cluster 2: High Poverty Cluster | Cluster 1: High Poverty Cluster | Cluster 2: Low Poverty Cluster |
| | $n$ = 34 | $n$ = 109 | $n$ = 154 | $n$ = 24 | $n$ = 148 | $n$ = 81 | $n$ = 83 | $n$ = 92 |
| | Avg. Sil. Width = 0.26 | Avg. Sil. Width = 0.29 | Avg. Sil. Width = 0.22 | Avg. Sil. Width = 0.36 | Avg. Sil. Width = 0.10 | Avg. Sil. Width = 0.21 | Avg. Sil. Width = 0.17 | Avg. Sil. Width = 0.16 |
| **States (# Counties):** | | | Illinois (16) | Illinois (3) | Alabama (12) | Alabama (9) | Alaska (1) | Alaska (1) |
| | Connecticut (3) | Connecticut (5) | Indiana (22) | Indiana (1) | Arkansas (6) | Arkansas (5) | Arizona (6) | Arizona (1) |
| | | Delaware (2) | Iowa (9) | Iowa (1) | Florida (20) | Florida (11) | California (17) | California (18) |
| | | Maine (6) | Kansas (4) | Kansas (1) | Georgia (24) | Georgia (9) | Colorado (3) | Colorado (8) |
| | Maryland (9) | Maryland (5) | Michigan (26) | Michigan (2) | Kentucky (10) | Kentucky (1) | | Idaho (6) |
| | Massachusetts (3) | Massachusetts (8) | Minnesota (5) | Minnesota (7) | Louisiana (6) | Louisiana (8) | Montana (1) | Montana (5) |
| | New Hampshire (1) | New Hampshire (5) | Missouri (13) | Missouri (2) | Mississippi (5) | Mississippi (5) | | Nevada (2) |
| | New Jersey (9) | New Jersey (10) | Nebraska (3) | | North Carolina (23) | North Carolina (14) | New Mexico (7) | New Mexico (1) |
| | New York (5) | New York (30) | North Dakota (3) | | South Carolina (15) | South Carolina (7) | Oklahoma (6) | Oklahoma (4) |
| | Pennsylvania (3) | Pennsylvania (35) | Ohio (33) | Ohio (3) | Tennessee (14) | Tennessee (5) | Oregon (6) | Oregon (9) |
| | Rhode Island (1) | Rhode Island (2) | South Dakota (1) | | Virginia (11) | Virginia (2) | Texas (26) | Texas (22) |
| | | Vermont (1) | Wisconsin (19) | Wisconsin (4) | West Virginia (2) | West Virginia (5) | | Utah (7) |
| | | | | | | | Washington (9) | Washington (7) |
| | | | | | | | Wyoming (1) | Wyoming (1) |

*The table should be read as follows: Connecticut (3) indicates 3 counties from Connecticut were placed into the cluster. Blank cells indicate 0 counties from a state appeared in the respective cluster.*
*Note: Avg. Sil. Width indicates the average silhouette width of each cluster.*
*Sources: Census, BEA, CDC, CMS, NCSL*

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[40] Elizabeth K. Anthony, "Cluster Profiles of Youths Living in Urban Poverty: Factors Affecting Risk and Resilience." *Social Work Research* 32, no. 1 (2008): 6–17. https://doi.org/10.1093/swr/32.1.6.

[41] See reference list for full citations for table sources. Note: All three Hawaiian counties from the original merged dataset were removed as outliers for this analysis.

The clusters were validated with ANOVA against an external measure reflecting poverty: worker median income. A low median worker income could indicate a larger portion of workers receiving poverty wages compared to areas with a high median worker income. ANOVA revealed if there were significant differences among group means, therefore allowing for conclusions to be drawn around whether cluster has a true relationship with poverty. Then, Tukey's Honestly Significant Difference (Tukey's HSD) post-hoc testing provided an estimate for what the average difference between clusters would be, allowing for pairwise comparisons of clusters.

Both ANOVA and Tukey's testing require homogeneity of variance and normal distributions of the data to produce reliable results. Homogeneity of variance was confirmed with Levene's Testing. QQ-plots were produced to confirm the assumption that residuals are normally distributed. Not all regions satisfied the homogeneity and normality assumptions. Results cannot be considered reliable in those cases; however, they are provided for explanatory purposes, to highlight potential study design improvements, and to fuel future poverty-alleviation research.

# RESULTS

## SECTION 1. NORTHEAST HIGH POVERTY RATE CLUSTER DESCRIPTION

Counties in the Northeast Region (*n* = 143) belong to 11 states in the New England or Mid-Atlantic regions, listed in Table 1. Cluster 1 has a lower poverty rate on average (6.5%) compared to Cluster 2 (12.1%). Cluster 2 will therefore be referred to as the “high poverty [rate] cluster” or the “HP cluster”.[42] The Northeast high poverty cluster has the lowest poverty rate of any HP cluster in this analysis.

The Northeast high poverty cluster is distinguished in health outcomes. It has the longest life expectancy of any high poverty cluster, and it is the only high poverty cluster to report above the national average life expectancy of 78.7 years.[43] Compared to the other HP clusters, the Northeast cluster has the lowest rate of uninsured individuals on average. These metrics, along with a high average spend per chronically ill Medicare beneficiary, may suggest a strong political commitment to providing robust public health systems in these areas. For instance, at the time of this analysis, all Northeastern states have opted to expand Medicaid eligibility under the Affordable Care Act.[44] The positive health outcomes of the Northeast HP cluster are comparable to the Northern Midwest cluster, but quite unique when compared to the health outcomes of the Southern clusters. See Appendix Table 3 for a full breakdown of all cluster means (including for the low poverty clusters).[45]

The Northeast high poverty cluster also has relatively strong economic outcomes. The cluster average GDP ($17.9 Billion) is more than double that of the lowest

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[42] Subsequent cluster descriptions will follow this naming convention.

[43] Elizabeth Arias, and Jiaquan Xu, “United States Life Tables, 2018.” Centers for Disease Control and Prevention. Centers for Disease Control, November 17, 2020. https://www.cdc.gov/nchs/data/nvsr/nvsr69/nvsr69-12-508.pdf.

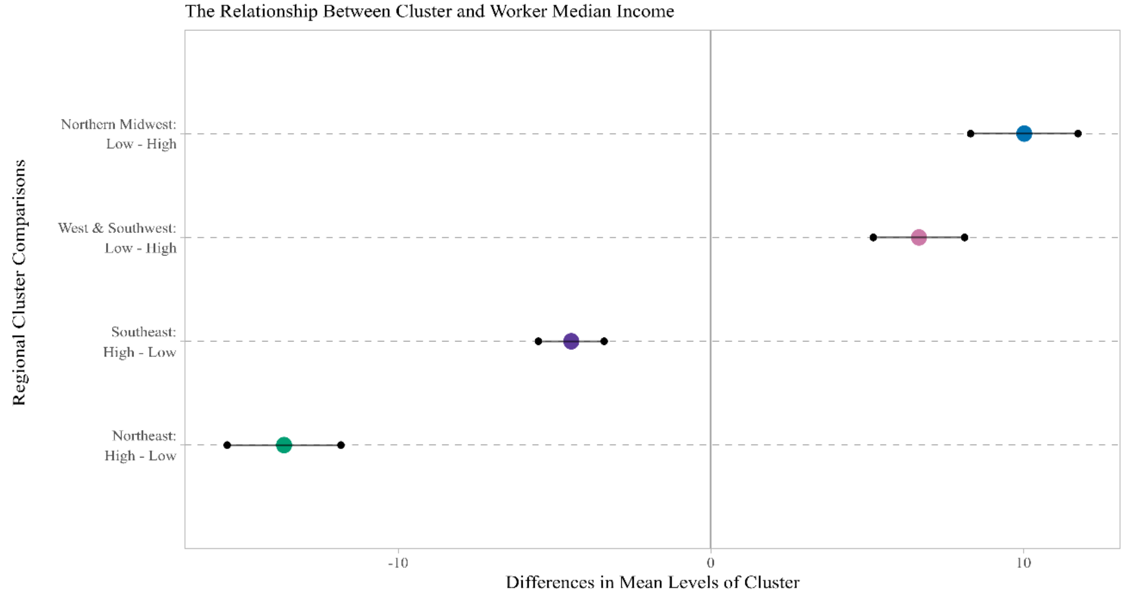
[44] “Status of State Medicaid Expansion Decisions: Interactive Map.” Kaiser Family Foundation, April 26, 2022. https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/?msclkid=9a32cf93ce6a11ecb91c8ded9110dfda.

[45] Also see Figures 2-4 in Section 3 of Findings, and Appendix Figures 1-3 for more on cluster means.

GDP cluster (the Southeast HP cluster, $7.0 Billion). It also has relatively low gender-based pay inequity, and the highest median income. While median income, for example, does not directly benefit someone living in poverty, it does potentially indicate such counties belong in areas with robust state or local poverty-alleviation policies, such as a minimum wage above the federal minimum. Indeed, another distinguishing characteristic of the Northeast HP cluster is that it the most liberal on average by a considerable margin.

***ANOVA and Tukey's Test Results.*** The ANOVA results indicate that the relationship between Northeast cluster and poverty is unlikely to be due to chance at the 95% confidence level (F-statistic = 226.1, p-value = 0.00). The Tukey's test results in Figure 1 suggest that a median wage worker living in a county from the high poverty rate

**Figure 1. Within Cluster Pairwise Comparison at 95% Family-Wise Confidence Level**
The Relationship Between Cluster and Worker Median Income




*Note: Cluster numbers "2" or "1" have been replaced with "Low"(poverty) and "High"(poverty) for ease of interpretation.*

cluster could expect to make approximately $13,652 less per year than a median wage worker in the low poverty cluster in 2018.[46]

## SECTION 2. NORTHERN MIDWEST HIGH POVERTY RATE CLUSTER DESCRIPTION

Counties in the Northern Midwest Region ($n$ = 179) belong to 12 states in the East North Central or West North Central regions (Table 1). Cluster 2 has a lower poverty rate on average (5.7%) compared to Cluster 1 (13.3%). The Northern Midwest (NMW) HP cluster appears distinct from the two Southern high poverty clusters in terms of having a relatively low rate of publicly insured residents, paired with a high rate of privately insured residents. This is perhaps correlated to the cluster having the largest percent of residents in the workforce on average of any HP cluster, and a relatively high median income.

The Northern Midwest high poverty cluster is the most conservative HP cluster in this analysis, and counties have the largest white populations on average. This high poverty cluster has the most severe differences in median pay between men and women.[47] Of course, it is important to note that there could be more women taking on unpaid family care roles in this cluster (on average) compared to other clusters, rather than some form of outright gender-based discrimination. Regardless, despite the gender-based income inequality, the Gini coefficient of this cluster is the lowest overall, indicating the lowest degree of income inequality of any HP cluster in this analysis. While low poverty

[46] Subsequent region-specific cluster descriptions will also refer to Figure 1.

[47] A median earning man is expected to make nearly $12,000 per year more than a median earning woman in this cluster.

rate clusters are not the focus of this analysis, it is interesting to note here that low poverty rate clusters produced more severe gender-based pay differences on average than high poverty rate clusters in all regions.[48]

***ANOVA and Tukey's Test Results.*** ANOVA results indicate that the relationship between cluster and poverty is unlikely to be due to chance (F-statistic = 132.8, p-value = 0.00, $\alpha = 0.05$). The Tukey's test results (Figure 1) suggest that a typical median wage worker living in a county from the low poverty rate cluster could expect to make approximately $10,032 more per year than a median wage worker in the high poverty cluster in 2018.

## SECTION 3. SOUTHEASTERN HIGH POVERTY RATE CLUSTER DESCRIPTION

Counties in the Southeastern Region (*n* = 229) belong to 12 states in the South Atlantic and East South Central regions (Table 1). Cluster 1 has a lower poverty rate on average (12.7%) compared to Cluster 2 (18.2%). The Southeastern high poverty rate cluster has the highest poverty rate of any cluster in this analysis. It also has the lowest median income of any cluster ($45,422), lowest GDP ($7.0 Billion), and highest percentage of residents out of the labor force (43%) on average. Counties of this cluster have the largest nonwhite populations of any high poverty cluster in this analysis (30.1%) on average.

[48] This could also be due to women taking on more unpaid family care roles. It could be fruitful to explore if this appears primarily related to a position of comfort, such as an adequate or high spousal income (considering the low incidence of poverty in those clusters), or if there are stronger correlates with this phenomenon.

The high percentage of people out of the labor force is striking, but this cluster has a large average elder population (18.3%) which may account for some of the lack of participation in the labor force. Perhaps related to the labor force or elder population means (or both), this cluster also has the highest rate of publicly insured residents on average (42.9%). Of note, the Southeast HP cluster has a relatively low average spend per chronically ill Medicare beneficiary, and the lowest average life expectancy of any high poverty cluster in this analysis by a notable margin (75.3 years on average, 2.1 years shorter than the next lowest life expectancy estimate). Together, these health metrics may indicate that the low-income elderly population in this cluster is a vulnerable population. Improvements in the quality and provision of elder care could be an effective poverty alleviation initiative for areas in this cluster.

The Southeast cluster was a standout in terms of objectively negative outcomes across many of the economic variables (such as having the highest poverty rate). However, across the health variables (and a couple of economic variables), this cluster closely reflects the trends of West & Southwest cluster. This is especially notable when comparing the two Southern clusters to the two Northern clusters. See examples such as percent of population with income below poverty in Figure 2;

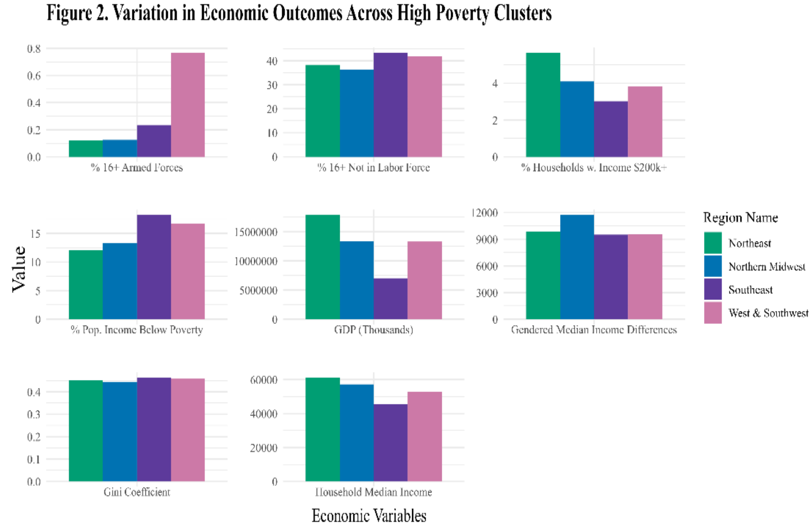



Figure 2. Variation in Economic Outcomes Across High Poverty Clusters

or percent of population publicly insured, privately insured, or uninsured Figure 3. In these examples, the two Northern clusters and two Southern clusters appear to have similar trends respectively. Still, there are major differences across the two Southern clusters. Compare, for example, the percent of population in the armed forces in Figure 2, or political lean in Figure 4 (among others). These differences will be discussed further in Section 4.

**Figure 3. Similar Health Outcomes Across North vs. South High Poverty Clusters**

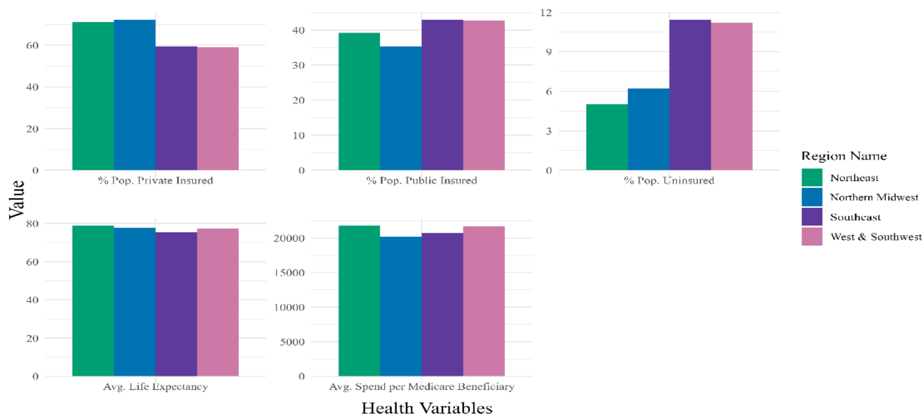
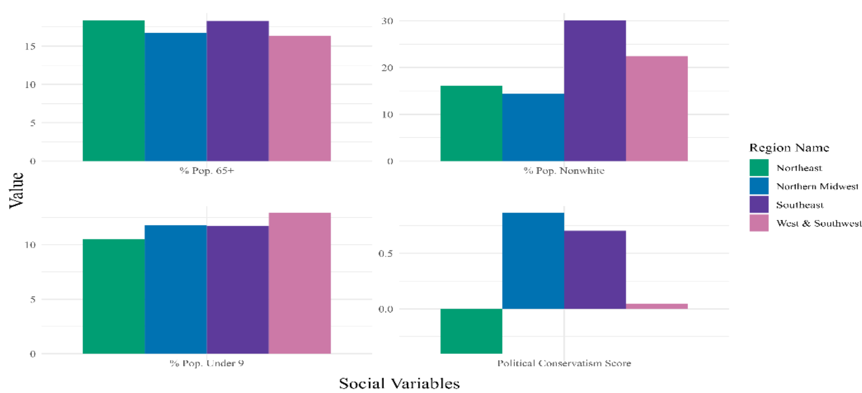



**Figure 4. Variation in Sociodemographic Makeup Across High Poverty Clusters**




***ANOVA and Tukey's Test Results.*** The ANOVA results appear to suggest that the relationship between Southeast cluster and poverty is significant (F-statistic = 69.81, p-value = 0.00, $\alpha = 0.05$). The Tukey's test (Figure 1) indicates that a median wage worker living in a county from the high poverty cluster could expect to make approximately $4,462 less per year than a median wage worker in the low poverty cluster in 2018.

However, a closer inspection of the data reveals that these results are not reliable. Assumptions for ANOVA analysis and Tukey’s testing are normal distribution of the data, and homogeneity of variance. A QQ-plot of model residuals suggests more kurtosis in the data than one would expect to find in a normal distribution. Levene’s suggests heterogeneity of variance (F-statistic = 11.12, p-value = 0.00).[49] So, while the results of the Southeast cluster are compelling, the relationship of cluster and poverty cannot be accepted under any traditional levels of significance given the violation of these prerequisite assumptions.[50] While the results are not reliable, they have been described and included in visuals for ease of comparison across regions, and to inspire future scholarship, as identified in the Conclusion section.

## SECTION 4. WEST & SOUTHWEST HIGH POVERTY RATE CLUSTER DESCRIPTION

Counties in the West & Southwest Region (*n* = 175) belong to 14 states in the West South Central, Mountain, and Pacific regions (Table 1). Cluster 1 has a higher poverty rate on average (16.7%) compared to Cluster 2 (10.4%). The West & Southwest (WSW) high poverty rate cluster has the largest percentage of working aged adults

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[49] The p-value is less than the significance level of 0.05. This means that the alternate hypothesis of unequal variances is accepted, and there is insufficient evidence for homogeneity of variances in the different treatment groups.

[50] Note: QQ-plotting and Levene’s testing were not discussed in the previous two sections, given those regional datasets satisfied the assumptions of homogeneity and normality.

employed by the armed forces of any HP cluster (nearly 1%). A high rate of participation in the armed forces (relative to the Northern clusters), paired with a high poverty rate, is a pattern consistent across both the Southern and WSW HP clusters.

Counties of the Southeastern and WSW clusters also have lower median wages, slightly higher (more unequal) Gini coefficients, and larger nonwhite populations on average compared to the two Northern HP clusters. Further, the two Southern HP clusters have high mean rates of publicly insured and uninsured individuals compared to the Northern HP clusters.

Despite these similarities, the WSW high poverty cluster has a lower poverty rate than the Southeastern HP cluster. Perhaps the difference in poverty rate is related to two notable differences between the two clusters: political conservatism, and percentage of children; a demographic group often treated sympathetically (compared to working aged adults) when it comes to poverty,[51] and targeted with specific poverty alleviation programs, as identified in the Literature Review. The WSW high poverty cluster is notably less conservative than the Southeast HP cluster, and has the largest population of children of all the HP clusters on average. Further unlike the Southeastern HP cluster, the WSW high poverty cluster has a relatively long-life expectancy, and a comparatively high average spend per chronically ill Medicare beneficiary. Of note, these two outcomes are more consistent with the Northeastern HP cluster.

[51] Bas W. van Doorn, “Pre- and Post-Welfare Reform Media Portrayals of Poverty in the United States: The Continuing Importance of Race and Ethnicity.” *Politics and Policy*, 43 (2015): 142-162. https://doi.org/10.1111/polp.12107

***ANOVA and Tukey's Test Results.*** The ANOVA results appear to confirm that the relationship between cluster and poverty is significant (F-statistic = 80.97, p-value = 0.00, $\alpha = 0.05$). The Tukey's test results suggest that a median wage worker living in a county from the low poverty rate cluster could expect to make approximately $6,662 more per year than a median wage worker in the high poverty cluster in 2018.

However, like the Southeastern region, the WSW region data does not satisfy the assumptions of normality and homogeneity of variance. Upward deviation from the slope = 1 line on the rightward-end of the QQ-plot suggests the data is positively skewed, rather than normally distributed. Levene's testing (F-statistic = 17.61, p-value = 0.00) provides evidence that the data fails the homogeneity of variance assumption. The results regarding the potential relationship between West & Southwest cluster and poverty therefore cannot be accepted under any traditional levels of significance given the violation of these prerequisite assumptions.

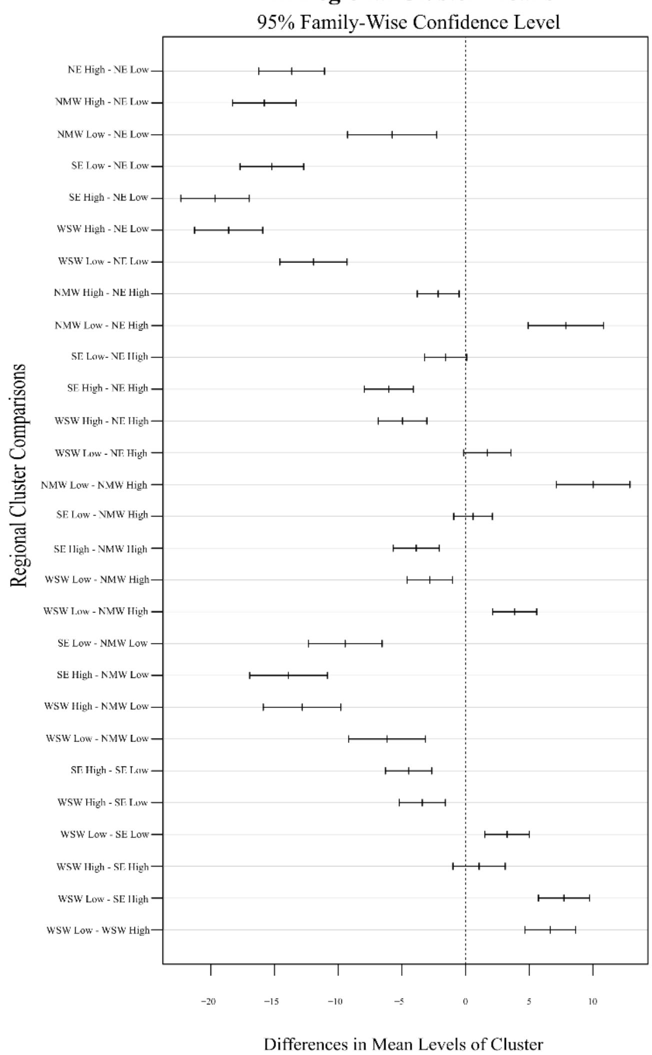
## SECTION 5. ALL REGION CLUSTER ANOVA AND TUKEY'S TESTING

Prior sections have established that trends across economic, health, and sociodemographic outcomes are not consistent across all high poverty regions. Appendix Figures 1-3 show how standardized, centered cluster means varied across each regional cluster in 2018. If poverty manifested as a singular experience across the US, one would expect cluster means to generally follow the same pattern across selected variables. Instead, it appears that regional outcomes are largely unique. There are instances, as mentioned, where some regional outcomes are quite similar, but the trend does not persist across all variables and concepts. See, for example, in Appendix Figures 1-3 or Findings

Figures 2-4, that the Southern regions appear quite similar in terms of health outcomes, but appear quite different across several economic and social outcome means.

All regional cluster data was combined for final ANOVA and Tukey's test. The ANOVA results appear to confirm the relationship between cluster and poverty (F-statistic = 103.7, p-value = 0.00, α = 0.05). The Tukey's test results in Figure 5[52] appear to suggest that the pairwise differences between clusters were significant in nearly all cases. Significant pairwise differences occur anywhere that zero is not included in the 95% confidence interval.[53]

**Figure 5. Multiple Pairwise Comparisons of All Regional Cluster Means**




*Note: Cluster numbers "2" or "1" have been replaced with "Low"(povery) or "High" (poverty) respectively.*

However, these results cannot be accepted as reliable. An analysis of the QQ-plot of

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[52] Region names have been shortened for legibility. NE = Northeast, SE = Southeast, NMW = Northern Midwest, WSW = West & Southwest.

[53] A confidence interval that does not include 0 indicates that the p-value for these pairwise differences is < 0.05.

residuals reveals that the points of the graph curve away from the extremities of the slope = 1 line. This behavior tends to indicate that the data have more extreme values than one might expect from a truly normal distribution. Levene's testing results (F-statistic = 6.51, p-value = 0.00) does not provide sufficient evidence for homogeneity of variance. So, while the results of the Tukey's test results appear quite strong, results cannot be accepted under traditional levels of significance. Next steps for refining the study design, or exploring potential relationships identified herein are identified in the Conclusion section.

# CONCLUSION

This analysis explored whether the experience of poverty in the US is best described as a national phenomenon, with a standard set of expected outcomes. Existing research tends towards describing American poverty with sweeping strokes (e.g., that poverty occurs in mostly nonwhite communities). This analysis provides nuance to the existing body of work; initial results herein provide compelling evidence that poverty manifests differently across the United States.

The relationships between regional cluster and poverty were affirmed with ANOVA and post-hoc Tukey's testing in the Northeast and Northern Midwest regions. Data issues (to be discussed) prevented the Southeast and West & Southwest cluster relationships from being confirmed as statistically significant. If poverty were a singular national experience, best described by a set of average national outcomes, one would expect to find no significant cluster relationships, and nearly the same mean outcomes for poverty-relevant health, economic, and sociodemographic variables across all regions.

Instead, as seen in Appendix Figures 1-3, there are hardly any consistent patterns across all, or multiple, high poverty regional clusters.

For example, one of the more pronounced patterns in Appendix Figure 1 are the health outcomes of the Southern and WSW clusters. However, although the means for the three insurance variables (private, public, uninsured) are nearly identical, the clusters vary when it comes to life expectancy, and average spend per chronically ill Medicare beneficiary. This indicates that although the provision of insurance is similar across the two clusters, related outcomes (like life expectancy) are not necessarily similar. Poverty-relevant differences like this, where major structural conditions are similar (e.g., insurance status rates), but the outcomes are notably different (e.g., life expectancy), are worthy of additional exploration.

This research question and process of clustering and post-hoc testing is flexible, furthering its political utility and potential policy implications. It can be extrapolated to other communities or specific demographics, and adapted to add or remove variables as needed. Further, analyses can be repeated year after year to determine if programs and policies have been effective at lifting residents out of poverty; ultimately sorting the community of analysis out of the high poverty cluster. There were several instances throughout this analysis where opportunities to explore specific regions or demographic subsets presented themselves.

First, this analysis could be repeated using rural and small population geographic area data only. One potential limitation of this study was the population minimum cutoff of approximately 62,600 residents. This means that states with more rural populations were represented by few counties in this analysis. In the Northern Midwest region, for example, Nebraska, North Dakota, and South Dakota were represented by a total of seven counties given the population minimum; in contrast, other singular states in that region are represented by a double-digit number, or even dozens, of counties. Since much of the utility of this analysis is informing poverty alleviation policymaking, the minimum population cutoff of the sample could present a potential limitation of the study if results are overgeneralized, and applied to low population counties, or extrapolated out to describe certain states at large. Such counties are, instead, deserving of novel analysis.

The Southeast region is also worthy of additional exploration. The high poverty cluster bore some of the most striking results of the analysis, several of which seemed to support some claims identified in the Literature Review: the cluster had the largest population of nonwhite individuals, the lowest annual GDP, and the shortest life expectancy on average. Here, another potential limitation of the study becomes apparent: the nonwhite variable is ambiguous. A more nuanced race breakdown could improve insights gained from future iterations of this analysis. Cluster analyses exploring regional poverty outcomes using race-specific datasets could also yield compelling new insights.

Another potential limitation of the study is that the Pacific, Mountain, and Southwest states were combined to create the West & Southwest region, so it would have a sample size more comparable to the other regions. However, this may have caused some anomalies in the data, perhaps lending itself to the failed significance tests identified in Findings Sections 3-5. Consider, for example, the different political conditions of California and Texas. Repeating this analysis to be region specific (e.g., analyzing the Southwest, Mountain, and Pacific regions separately), and allowing for a different population cutoff, may produce more robust samples that could satisfy the assumptions of ANOVA. Further, ANOVA is sensitive to unequal sample sizes, which were present in some regions of this analysis. Taking a new approach to population cutoffs may produce more equal sample sizes, and benefit ANOVA results. Alternatively, the existing study design be repeated as is. Significance results could improve by employing a different post-hoc test across all regions. The Kruskal-Wallis test, for example, is an alternative option that does not carry the same assumptions as ANOVA.

This analysis provided evidence that poverty is not a one-size fits all condition, and it could be better alleviated with state and local initiatives supplemental to existing federal programs. Policymakers can replicate this method of cluster analysis as a comparative analysis tool on any geographic scale of interest. For example, a local political analyst or data scientist working for a city with a high poverty rate could run this analysis with “City” as their unit of analysis. If their city is in a high poverty cluster, the analyst could find a city with similar characteristics (such as population size and demographic makeup) that was sorted into a low poverty cluster. After comparing outcome means of interest, and researching the policies and programs that may have had an impact on positive outcomes in the other town, the analyst can present findings to local policymakers. The hypothetical local government could thereby be influenced to adapt existing programs, or create new ones, to replicate the improved outcomes observed in the other city. By supplementing federal anti-poverty programs, local, as well as state governments, may be able to better facilitate more equitable outcomes across all income levels.

## REFERENCES


Anthony, Elizabeth K. "Cluster Profiles of Youths Living in Urban Poverty: Factors Affecting Risk and Resilience." *Social Work Research* 32, no. 1 (2008): 6–17. https://doi.org/10.1093/swr/32.1.6.

Arias, Elizabeth and Jiaquan Xu. "United States Life Tables, 2018." Centers for Disease Control and Prevention. November 17, 2020. https://www.cdc.gov/nchs/data/nvsr/nvsr69/nvsr69-12-508.pdf.

Berger, Lawrence M., Maria Cancian, and Katherine Magnuson. "Anti-Poverty Policy Innovations: New Proposals for Addressing Poverty in the United States." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 4, no. 3 (2018): 1–19. https://doi.org/10.7758/rsf.2018.4.3.01.

Brady, David. "The Politics of Poverty: Left Political Institutions, the Welfare State, and Poverty." *Social Forces* 82, no. 2 (2003): 557–88, http://www.jstor.org/stable/3598202.

Bureau of Economic Analysis. "Archive: GDP by County." Accessed March 20, 2022. https://www.bea.gov/news/archive?field_related_product_target_id=971&created_1=All&title=.

Centers for Medicare & Medicaid Services. "Chronic Conditions." CMS.gov. December 1, 2021. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Chronic-Conditions/Downloads/CC_Spend_County.zip.

Centers for Disease Control and Prevention. "U.S. Small-Area Life Expectancy Estimates Project - USALEEP." June 9, 2020. https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NVSS/USALEEP/CSV/US_A.CSV.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. "The Association Between Income and Life Expectancy in the United States, 2001-2014." *JAMA*, 315, 16 (2016):1750–1766. doi:10.1001/jama.2016.4226

Hoff, Jens V., Martin M. B. Rasmussen, and Peter Birch Sørensen. "Barriers and Opportunities in Developing and Implementing a Green GDP." *Ecological Economics* 181, (2021): 106905. doi: https://doi.org/10.1016/j.ecolecon.2020.106905.

Kaestner, Robert, and Darren Lubotsky. "Health Insurance and Income Inequality." *The Journal of Economic Perspectives* 30, no. 2 (2016): 53–77, http://www.jstor.org/stable/43783707.

Kaiser Family Foundation. "Distribution of Medicare Beneficiaries by Federal Poverty Level." October 23, 2020. https://www.kff.org/medicare/state-indicator/medicare-beneficiaries-by-fpl/?currentTimeframe=1&sortModel=%7B%22colId%22:%22Location%22.

Kaiser Family Foundation. "Status of State Medicaid Expansion Decisions: Interactive Map." April 26, 2022. https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/?msclkid=9a32cf93ce6a11ecb91c8ded9110dfda.

Levy, Helen. "Income, Poverty, and Material Hardship Among Older Americans." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 1, no. 1 (2015): 55–77. https://doi.org/10.7758/rsf.2015.1.1.04.

Link, Bruce G., and Jo Phelan. "Social Conditions as Fundamental Causes of Disease." *Journal of Health and Social Behavior* (1995): 80–94, https://doi.org/10.2307/2626958.

Little, Christine, Mathilda Alsen, Joshua Barlow, Leonard Naymagon, Douglas Tremblay, Eric Genden, Samuel Trosman, Laura Iavicoli and Maaike van Gerwen. "The Impact of Socioeconomic Status on the Clinical Outcomes of COVID-19; a Retrospective Cohort Study." *Journal of Community Health* 46, 4 (2021): 794–802, doi:10.1007/s10900-020-00944-3.

National Conference of State Legislatures. "2018 State & Legislative Partisan Composition." November 7, 2018. https://www.ncsl.org/Portals/1/Documents/Elections/Legis_Control_110718_2_26973.pdf.

Picciotto, Robert. "Beyond GDP: Tracking and Evaluating National Contributions to Social and Environmental Sustainability." *Journal of MultiDisciplinary Evaluation* 17, 41 (2021): 61–78. https://journals.sfu.ca/jmde/index.php/jmde1/article/view/717.

Price, James H., Jagdish Khubchandani, and Fern J. Webb. "Poverty and Health Disparities: What Can Public Health Professionals Do?" *Health Promotion Practice* 19, no. 2 (2018): 170–74. https://www.jstor.org/stable/26746916.

Quillian, Lincoln. "Segregation and Poverty Concentration: The Role of Three Segregations." *American Sociological Review* 77, no. 3 (2012): 354–79. http://www.jstor.org/stable/41723037.

Reardon Sean F., and Kendra Bischoff. "Income Inequality and Income Segregation." *American Journal of Sociology* 116, no. 4 (2011): 1092–1153. https://doi.org/10.1086/657114.

Schleimer, Julia P., Shani A. Buggs, Christopher D. McCort, Veronica A. Pear, Alaina De Biasi, Elizabeth Tomsich, Aaron B. Shev, Hannah S. Laqueur, and Garen J. Wintemute. "Neighborhood Racial and Economic Segregation and Disparities in Violence During the COVID-19 Pandemic." *American Journal of Public Health* 112, 1 (2022): 144–53, doi:10.2105/ajph.2021.306540.

United States Census Bureau. "Census ACS Data Products." Accessed March 20, 2022. https://data.census.gov/cedsci/table.

United States Census Bureau. “Geographic Areas Covered in the ACS.” 2020. https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs_geography_handbook_2020_ch01.pdf.

United States Census Bureau. “Income and Poverty in the United States: 2018.” September 10, 2019. https://www.census.gov/library/publications/2019/demo/p60-266.html.

van Doorn, Bas W. “Pre- and Post-Welfare Reform Media Portrayals of Poverty in the United States: The Continuing Importance of Race and Ethnicity.” *Politics and Policy*, 43 (2015): 142-162. https://doi.org/10.1111/polp.12107

Woolf, Steven H., Derek A. Chapman, Jeanine M. Buchanich, Kendra J. Bobby, Emily B. Zimmerman, and Sarah M. Blackburn. “Changes in midlife death rates across racial and ethnic groups in the United States: systematic analysis of vital statistics.” *BMJ* 362, k3096 (2018), doi:10.1136/bmj.k3096

## APPENDIX

**Table 1. Variable Names, Descriptions, and Concepts**

| | Varaiable Name | Coded Name | Description | Source |
|---|---|---|---|---|
| **Primary Variable of Interest** | *% Pop. Income Below Poverty* | *percent_total_pop_income_below_poverty* | *Percent of all people (single, or in a household) in a given geographic area who received an annual income below the Federal Poverty Level in a calendar year. Based on income reported as an annual figure.* | *Census, ACS Survey* |
| **ANOVA Validation** | *Worker Median Income* | *worker_income_median* | *Median income of workers in a given geographic area. "Workers" include people who are self-employed, working in the private sector, or in government (including active duty military).* | *Census, ACS Survey* |
| **HEALTH** | % Pop. Uninsured | percent_total_pop_uninsured | Percent of all people in a given geographic area who do not have any form of health insurance. | Census, ACS Survey |
| | % Pop. Public Insured | percent_total_pop_insured_public | Percent of all people in a given geographic area who receive public health insurance. | Census, ACS Survey |
| | % Pop. Private Insured | percent_total_pop_insured_private | Percent of all people in a given geographic area who receive private health insurance. | Census, ACS Survey |
| | Avg. Spend per Chronically Ill Medicare Beneficiary* | avg_spend_chronic_illness_per_beneficiary | Average annual spend per chronically ill Medicare beneficiary in a given geographic area. Chronic illnesses represented by this variable include 21 conditions listed exhaustively here: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Chronic-Conditions/CC_Main | CMS, State/County Level Chronic Conditions Table |
| | Avg. Life Expectancy | avg_life_expty | Average live expectancy as calculated from birth in a given geographic area. | CDC, U.S. Small-Area Life |

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[54] This table continues for two more pages. The size is for legibility purposes.

| | | | | |
|---|---|---|---|---|
| ECONOMIC | Household Median Income | household_ income_median | Median annual income of household units of a given geographic area. | Census, ACS Survey |
| | % Households w. Income $200k+ | percent_ households_w_ income_ 200kplus | Percentage of households with annual income over $200k. This variable is intended to reflect percentage of high income earners in a given geographic area, and enrich the insights that can be gained around median income, poverty rate, gini coefficient, etc. | Census, ACS Survey |
| | Gendered Median Income Differences | male_median_ income_minus_ female_median | Female median income subtracted from male median income of a given geographic area. This variable is intended to reflect gender based income inequality in a given geographic area, and enrich the insights that can be gained around median income, gini coefficient, etc. | Census, ACS Survey |
| | Gini Coefficient | gini_index | A numeric variable ranging from 0-1 reflecting income inequality of a geographic area. 0 reflects perfect income equality (i.e. everyone has the same income), and 1 indicates perfect income inequality (i.e. one person has all the income, while everyone else has zero income) | Census, ACS Survey |
| | GDP (Thousands) | gdp_2018_ thousands | Annual GDP, measured in thousands of USD, of a given geographic area. Includes all industry annual GDPs combined. | BEA, GDP by County |
| | % 16+ Armed Forces | percent_16plus_i n_armed_ forces | Percent of working-aged people (aged 16+) in a given geographic area that are in active duty with the US armed forces. | Census, ACS Survey |
| | % 16+ Not in Labor Force | percent_16plus_n ot_in_labor_forc e | Percent of working-aged people (aged 16+) in a given geographic area who are not in the labor force. Importantly, this means both unemployed *and* not looking for work. | Census, ACS Survey |

| | | | | |
|---|---|---|---|---|
| SOCIAL | % Pop. Nonwhite | percent_total_pop_nonwhite | Percent of all people in a given geographic area that are not white race alone. | Census, ACS Survey |
| | % Pop. 65+ | percent_total_pop_over_65 | Percent of all people in a given geographic area that are aged 65 and over. | Census, ACS Survey |
| | % Pop. Under 9 | percent_total_pop_under_9 | Percent of all people in a given geographic area that are aged 9 or under. | Census, ACS Survey |
| | Political Conservatism Score | numeric_Partyvar | A numeric variable where 1 = Conservative (Republican), 0 = Moderate, and -1 = Liberal (Democratic). This variable is intended to reflect the overall political lean of clusters. It was created using a count of state legislators per party, and the party of the governor. States where a majority of legislators were conservatie and the governor was conservative were coded with a 1 (majority liberal legislators and liberal governor = -1). States where the majority party of the legislators did not match the party of the governor were coded with a 0. Despite being a unicameral legislature, Nebraska was coded as a 1 given the party affiliation of its legislators and governor in 2018. This variable was included to enrich each cluster description, since state policy is inherently linked to county-level outcomes. | NCSL, State & Legislative Partisan Composition |

*Note: Data from all sources are specific to 2018.*

** This variable name was shortened to "Avg. Spend per Medicare Beneficiary" in some tables and visuals for asthetic purposes*

**Table 2. All Region Descriptive Statistics**

**Northeast Summary Statistics**

| Statistic | Mean | Std. Dev. | Min | Percentile (25) | Percentile (75) | Max |
|---|---|---|---|---|---|---|
| percent_total_pop_under_9 | 10.7 | 1.4 | 6.5 | 9.7 | 11.6 | 15.6 |
| percent_total_pop_over_65 | 17.9 | 2.9 | 11.8 | 16 | 19.7 | 30.7 |
| gdp_2018_thousands | 29,586,148 | 64,830,180 | 2,346,205 | 5,506,897 | 33,614,679 | 737,332,573 |
| gini_index | 0.5 | 0.03 | 0.4 | 0.4 | 0.5 | 0.6 |
| percent_total_pop_ nonwhite | 19.7 | 15.9 | 2.3 | 7.9 | 26.5 | 84.4 |
| avg_life_expty | 79.3 | 1.7 | 73 | 78.1 | 80.4 | 83 |
| percent_16plus_in_armed_forces | 0.3 | 1 | 0 | 0 | 0.2 | 11 |
| percent_16plus_not_in_labor_force | 36.8 | 4.5 | 28.3 | 33.7 | 39.7 | 46.7 |
| percent_households_w_income_200kplus | 8.3 | 5.7 | 0.9 | 3.5 | 11.4 | 24.7 |
| household_income_ median | 69,632.80 | 18,230.90 | 38,233 | 55,045 | 82,166 | 121,378 |
| male_median_income_minus_female_median | 11,128.70 | 4,797.80 | -2,985 | 8,392 | 14,066 | 24,973 |
| percent_total_pop_insured_private | 72.6 | 7.2 | 44.3 | 68.7 | 78.1 | 85.8 |
| percent_total_pop_insured_public | 37.1 | 6.9 | 22.9 | 31.8 | 42.4 | 57.5 |
| percent_total_pop_ uninsured | 5 | 2.2 | 1.9 | 3.5 | 5.9 | 12.9 |
| percent_total_pop_income_below_poverty | 11.1 | 4 | 4.1 | 7.6 | 13.8 | 27.4 |
| Numeric_ Partyvar | -0.4 | 0.6 | -1 | -1 | 0 | 1 |
| avg_spend_chronic_illness_per_beneficiary | 23,047.60 | 5,195.10 | 16,462.00 | 19,812.10 | 25,141.60 | 68,541.80 |

[55]

[55] This table continues for Three more pages. The size is for legibility purposes.

| Northern Midwest Summary Statistics | | | | | | |
|---|---|---|---|---|---|---|
| Statistic | Mean | Std. Dev. | Min | Percentile (25) | Percentile (75) | Max |
| percent_total_pop_under_9 | 12 | 1.4 | 6.7 | 11.1 | 12.8 | 16.2 |
| percent_total_pop_over_65 | 16.2 | 2.5 | 9.5 | 14.4 | 18 | 22 |
| gdp_2018_thousands | 16,868,726 | 35,623,175 | 1,708,966 | 4,341,707 | 14,135,977 | 412,854,451 |
| gini_index | 0.4 | 0.03 | 0.3 | 0.4 | 0.5 | 0.5 |
| percent_total_pop_ nonwhite | 14.8 | 9.1 | 2.9 | 8 | 18.1 | 52.9 |
| avg_life_expty | 78.1 | 2 | 73.4 | 76.5 | 79.6 | 82.4 |
| percent_16plus_in_armed_forces | 0.2 | 0.9 | 0 | 0 | 0.1 | 9 |
| percent_16plus_not_in_labor_force | 35.2 | 5.1 | 24.6 | 31.5 | 38.4 | 51.4 |
| percent_households_w_income_200kplus | 5.1 | 3.3 | 0.6 | 3 | 5.9 | 18.3 |
| household_income_ median | 61,397.20 | 13,203.90 | 36,944 | 51,647.50 | 66,702.50 | 100,963 |
| male_median_income_minus_female_median | 12,318.40 | 4,490.30 | -6,118 | 9,596 | 14,825.80 | 28,654 |
| percent_total_pop_insured_private | 73.5 | 7.5 | 51.8 | 68 | 79.1 | 89.2 |
| percent_total_pop_insured_public | 33.8 | 7.4 | 19.3 | 27.9 | 39.1 | 53.7 |
| percent_total_pop_ uninsured | 6.1 | 2.5 | 2.1 | 4.4 | 7.3 | 18 |
| percent_total_pop_income_below_poverty | 12.3 | 5 | 3 | 8.4 | 15.6 | 32 |
| Numeric_ Partyvar | 0.8 | 0.4 | 0 | 1 | 1 | 1 |
| avg_spend_chronic_illness_per_beneficiary | 20,503.10 | 2,568.00 | 14,448.80 | 18,688.00 | 21,974.50 | 28,337.00 |

| Southern Summary Statistics | | | | | | |
|---|---|---|---|---|---|---|
| Statistic | Mean | Std. Dev. | Min | Percentile (25) | Percentile (75) | Max |
| percent_total_pop_under_9 | 11.8 | 1.8 | 3.3 | 10.7 | 13 | 17.6 |
| percent_total_pop_over_65 | 17.2 | 5.6 | 9 | 13.9 | 18.8 | 56.8 |
| gdp_2018_thousands | 13,658,489 | 22,335,978 | 1,379,204 | 3,702,077 | 13,273,882 | 173,906,209 |
| gini_index | 0.5 | 0.04 | 0.4 | 0.4 | 0.5 | 0.6 |
| percent_total_pop_ nonwhite | 27.7 | 16.3 | 2.1 | 13.9 | 36.9 | 84.7 |
| avg_life_expty | 76.7 | 1.9 | 71.4 | 75.3 | 77.7 | 82.1 |
| percent_16plus_in_armed_forces | 0.8 | 2.3 | 0 | 0 | 0.3 | 24 |
| percent_16plus_not_in_labor_force | 39.5 | 6.6 | 20 | 35.3 | 43 | 75 |
| percent_households_w_income_200kplus | 5.2 | 3.9 | 0.7 | 2.9 | 6.5 | 30.9 |
| household_income_ median | 56,246.80 | 14,978.80 | 32,867 | 46,743.50 | 61,793.50 | 139,915 |
| male_median_income_minus_female_median | 10,461.70 | 5,837.70 | -2,835 | 6,546.50 | 13,333.50 | 36,799 |
| percent_total_pop_insured_private | 66.6 | 7.6 | 47.2 | 61.4 | 71.3 | 89.2 |
| percent_total_pop_insured_public | 36.7 | 8 | 13.4 | 31.2 | 42.2 | 68.8 |
| percent_total_pop_ uninsured | 10.2 | 3.1 | 2.4 | 8.1 | 12.3 | 18.8 |
| percent_total_pop_income_below_poverty | 14.5 | 5.3 | 3 | 10.8 | 17.5 | 36 |
| Numeric_ Partyvar | 0.7 | 0.5 | 0 | 0 | 1 | 1 |
| avg_spend_chronic_illness_per_beneficiary | 20,467.40 | 2,217.30 | 15,644.00 | 19,014.80 | 21,515.30 | 30,951.00 |

| West & Southwest Summary Statistics | | | | | | |
|---|---|---|---|---|---|---|
| **Statistic** | **Mean** | **Std. Dev.** | **Min** | **Percentile (25)** | **Percentile (75)** | **Max** |
| percent_total_ pop_under_9 | 12.8 | 2 | 7.8 | 11.5 | 14.1 | 18.4 |
| percent_total_ pop_over_65 | 15.5 | 4.1 | 7.7 | 12.7 | 17.7 | 31.7 |
| gdp_2018_ thousands | 32,983,934 | 77,050,445 | 1,312,882 | 4,328,720 | 27,129,686 | 752,017,612 |
| gini_index | 0.4 | 0.03 | 0.3 | 0.4 | 0.5 | 0.5 |
| percent_total_ pop_ nonwhite | 23 | 14.6 | 3.6 | 12.5 | 28 | 88.2 |
| avg_life_expty | 78.5 | 1.9 | 73.5 | 77.2 | 79.9 | 84.5 |
| percent_16plus_ in_armed_forces | 0.7 | 1.7 | 0 | 0 | 0.4 | 12 |
| percent_16plus_ not_in_labor_force | 38.5 | 6.7 | 26 | 34 | 41.9 | 64 |
| percent_ households_w_ income_200kplus | 6.5 | 5.1 | 0.6 | 3.3 | 8 | 29.6 |
| household_ income_ median | 63,731.20 | 17,075.50 | 30,207 | 51,208 | 72,906 | 126,606 |
| male_median_ income_minus_ female_median | 11,100.60 | 5,620.80 | 1,415 | 7,314 | 13,596 | 34,164 |
| percent_total_ pop_ insured_private | 65 | 10.5 | 24 | 58.9 | 72.3 | 87 |
| percent_total_ pop_ insured_public | 36.8 | 10.3 | 16.5 | 29.8 | 44.1 | 63.9 |
| percent_total_ pop_ uninsured | 10.5 | 5.2 | 2.7 | 6.7 | 12.5 | 30.6 |
| percent_total_ pop_ income_below_ poverty | 13.7 | 5.6 | 2.4 | 9.4 | 16.6 | 38.3 |
| Numeric_ Partyvar | 0 | 0.9 | -1 | -1 | 1 | 1 |
| avg_spend_ chronic_ illness_per_ beneficiary | 21,887.70 | 3,468.00 | 15,093.10 | 19,175.00 | 24,231.60 | 34,094.10 |

**Table 3. Regional Cluster Means**

| | Regions: | Northeast | | | Northern Midwest | | |
|---|---|---|---|---|---|---|---|
| | **Poverty & Relevant Outcomes** | **High Poverty Rate Cluster** | **Low Poverty Rate Cluster** | **Northeast Average** | **High Poverty Rate Cluster** | **Low Poverty Rate Cluster** | **Northern Midwest Average** |
| **HEALTH** | *% Pop. Income Below Poverty* | *12.1* | *6.5* | ***9.3*** | *13.3* | *5.7* | ***9.5*** |
| | % Pop. Uninsured | 5.0 | 4.2 | **4.6** | 6.2 | 4.2 | **5.2** |
| | % Pop. Public Insured | 39.2 | 28.7 | **33.9** | 35.4 | 25.9 | **30.6** |
| | % Pop. Private Insured | 71.2 | 80.7 | **75.9** | 72.3 | 82.5 | **77.4** |
| | Avg. Spend per Medicare Beneficiary | $21,779.01 | $24,349.16 | **$23,064.08** | $20,172.08 | $21,092.93 | **$20,632.51** |
| | Avg. Life Expectancy | 78.8 | 80.8 | **79.8** | 77.7 | 80.3 | **79.0** |
| **ECONOMIC** | Household Median Income | $61,324.94 | $96,680.56 | **$79,002.75** | $57,229.29 | $83,100.38 | **$70,164.83** |
| | % Households w. Income $200k+ | 5.7 | 15.9 | **10.8** | 4.1 | 9.2 | **6.7** |
| | Gendered Median Income Differences | $9,831.72 | $16,435.12 | **$13,133.42** | $11,717.34 | $16,099.96 | **$13,908.65** |
| | Gini Coefficient | 0.45 | 0.44 | **0.45** | 0.44 | 0.42 | **0.43** |
| | GDP (Thousands) | $17,873,951.28 | $41,546,508.03 | **$29,710,229.66** | $13,388,693.28 | $14,105,778.67 | **$13,747,235.98** |
| | % 16+ Armed Forces | 0.1 | 0.5 | **0.3** | 0.1 | 0.1 | **0.1** |
| | % 16+ Not in Labor Force | 38.3 | 32.5 | **35.4** | 36.2 | 30.0 | **33.1** |
| **SOCIAL** | % Pop. Nonwhite | 16.1 | 22.7 | **19.4** | 14.4 | 11.6 | **13.0** |
| | % Pop. 65+ | 18.4 | 16.7 | **17.5** | 16.7 | 15.0 | **15.8** |
| | % Pop. Under 9 | 10.5 | 10.8 | **10.7** | 11.8 | 12.5 | **12.1** |
| | Political Conservatism Score | -0.40 | -0.50 | **-0.45** | 0.86 | 0.58 | **0.72** |
| | **Regions:** | **Southeast** | | | **West & Southwest** | | |
| | **Poverty & Relevant Outcomes** | **High Poverty Rate Cluster** | **Low Poverty Rate Cluster** | **Southeast Average** | **High Poverty Rate Cluster** | **Low Poverty Rate Cluster** | **West & Southwest Average** |
| **HEALTH** | *% Pop. Income Below Poverty* | *18.2* | *12.7* | ***15.5*** | *16.7* | *10.4* | ***13.5*** |
| | % Pop. Uninsured | 11.4 | 9.7 | **10.5** | 11.2 | 9.5 | **10.4** |
| | % Pop. Public Insured | 42.9 | 33.7 | **38.3** | 42.8 | 31.2 | **37.0** |
| | % Pop. Private Insured | 59.4 | 70.0 | **64.7** | 59.1 | 70.8 | **65.0** |
| | Avg. Spend per Medicare Beneficiary | $20,717.73 | $20,057.71 | **$20,387.72** | $21,687.55 | $21,889.49 | **$21,788.52** |
| | Avg. Life Expectancy | 75.3 | 77.1 | **76.2** | 77.4 | 79.1 | **78.3** |
| **ECONOMIC** | Household Median Income | $45,442.22 | $59,737.37 | **$52,589.80** | $52,848.48 | $71,952.49 | **$62,400.49** |
| | % Households w. Income $200k+ | 3.0 | 5.6 | **4.3** | 3.8 | 8.0 | **5.9** |
| | Gendered Median Income Differences | $9,510.02 | $10,581.43 | **$10,045.73** | $9,523.86 | $11,934.21 | **$10,729.03** |
| | Gini Coefficient | 0.46 | 0.45 | **0.46** | 0.46 | 0.43 | **0.45** |
| | GDP (Thousands) | $7,035,890.04 | $11,939,215.52 | **$9,487,552.78** | $13,302,723.51 | $34,881,838.99 | **$24,092,281.25** |
| | % 16+ Armed Forces | 0.2 | 0.7 | **0.5** | 0.8 | 0.3 | **0.5** |
| | % 16+ Not in Labor Force | 43.3 | 37.6 | **40.5** | 41.9 | 34.8 | **38.4** |
| **SOCIAL** | % Pop. Nonwhite | 30.1 | 25.4 | **27.8** | 22.5 | 20.2 | **21.3** |
| | % Pop. 65+ | 18.3 | 16.4 | **17.3** | 16.3 | 14.5 | **15.4** |
| | % Pop. Under 9 | 11.7 | 11.9 | **11.8** | 12.9 | 12.8 | **12.9** |
| | Political Conservatism Score | 0.70 | 0.73 | **0.7** | 0.05 | -0.01 | **0.02** |

*Note: "Gendered Median Income Differences" indicates how much more a median earning man is expected to earn compared to a median earning woman.*

**Figure 1. Similar Health Trends Across Northern and Southern High Poverty Clusters Respectively**
Standardized, Centered Regional Cluster Means

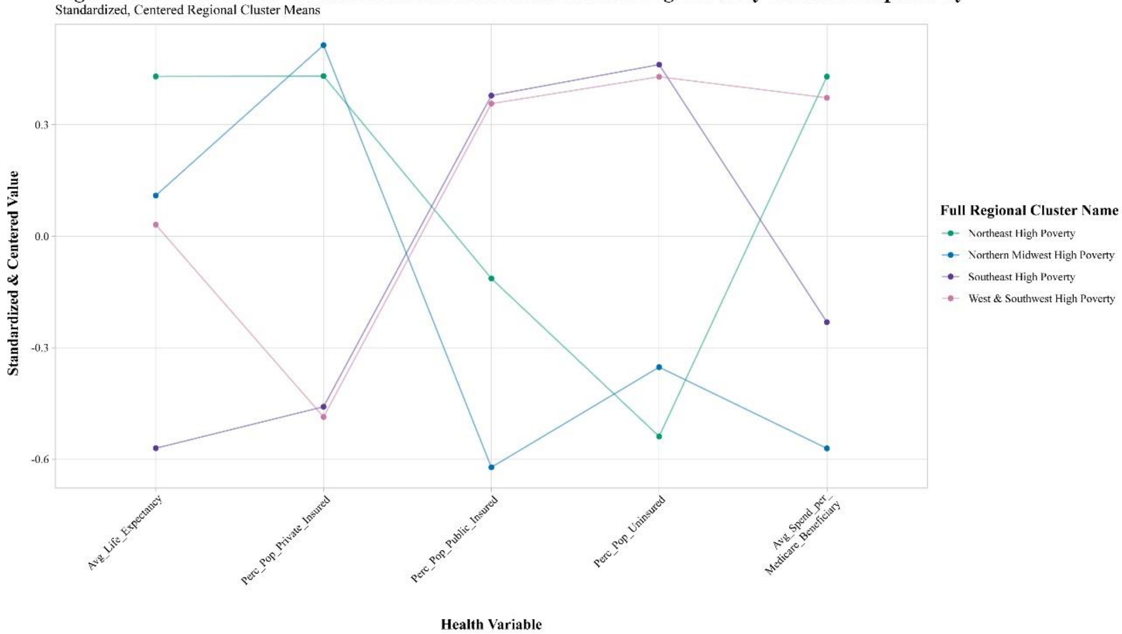



**Figure 2. Differing Economic Trends Across High Poverty Clusters**
Standardized, Centered Regional Cluster Means

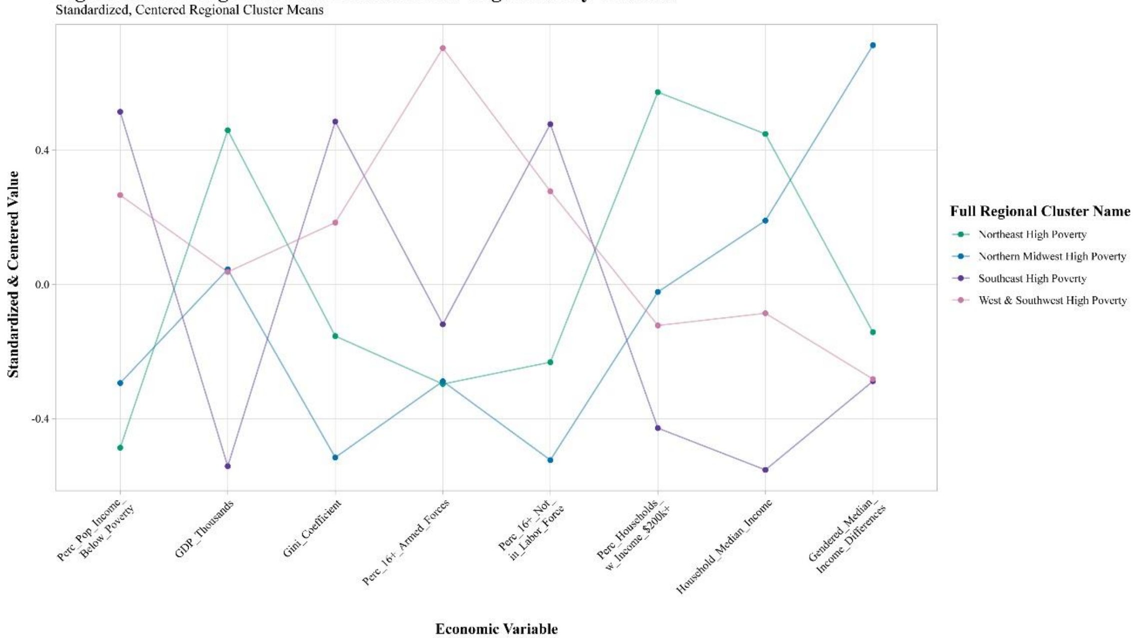
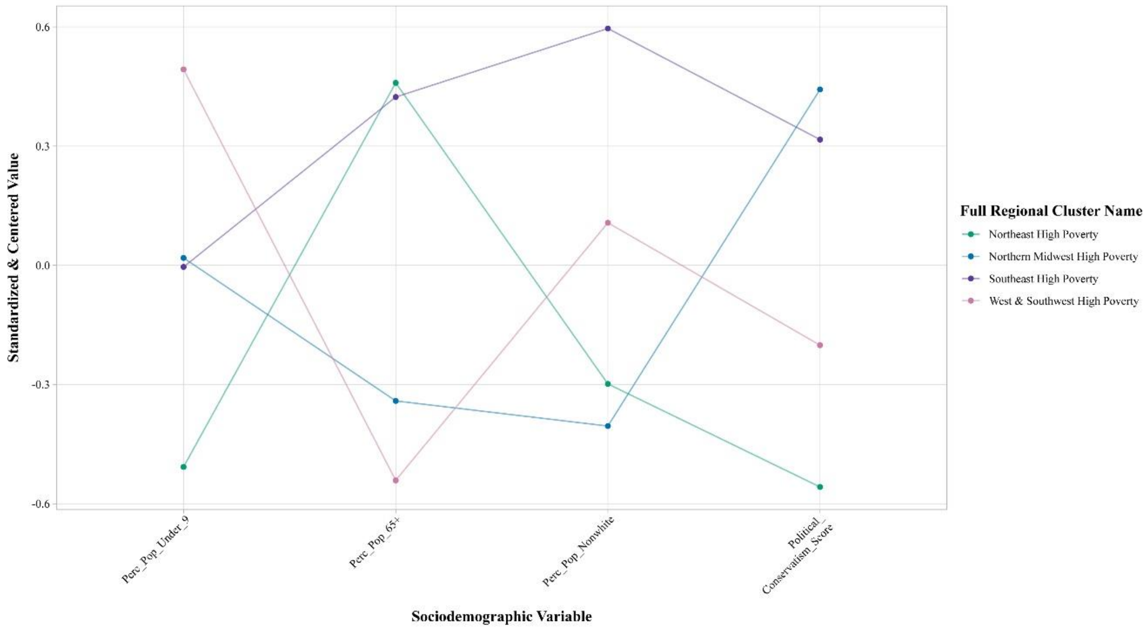


**Figure 3. Inconsistent Sociodemographic Makeup in High Poverty Clusters**
Standardized, Centered Regional Cluster Means



# CURRICULUM VITA

## Jackie M. Clark

Data Analytics & Policy Graduate Student at Johns Hopkins University
Data Analyst & Paid Media Strategist at Relay Resources

### Profile

Passion for data analysis, and visualizing the human experience through numbers. Advocate for a more equitable world through data-driven systems. Adept in identifying inefficiencies and synthesizing complex information for colleagues, clients, and senior management for monthly and quarterly audits, and/or performance reporting. Skills Include: R & Python Programming, SQL, Data analysis, Data visualization, Data reporting, Digital advertising, Google Analytics, Tag Manager, Data Studio, Social analytics, Research, Microsoft Excel, & Tableau.

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### Education

Johns Hopkins University, Baltimore, MD

*M.S. Data Analytics & Policy*

*August 2020-May 2022 Proposed Graduation Date, Currently Maintaining 4.0 GPA*
*Concentrations: Statistical Analysis; Political Behavior and Policy Analysis*

- A unique program bridging the divide between political science theories, and actual data-driven policymaking in practice. Pursuing a dual concentration in Statistical Analysis; and Political Behavior and Policy Analysis
- Studying how governments can use data to create better political outcomes for constituents. Coursework includes R & Python Programming, Local and State Political Analysis, Probability & Statistics, & participated in a semester long Local Government Simulation as a City Budget Director
- Upcoming coursework: SQL, Data Science for Public Policy, Economic Decision-Making in Public Policy

University of Michigan, Ann Arbor, MI

*B.A. Research Psychology, B.A. Communication Studies*

*September 2011-May 2015, Graduated with Honors*

- Self-tailored education around the study of marginalized groups. Focused on mass mediated perceptions therein, how biased behavior translates from media to the external world, and actual neuropsychological responses to diversity

### Research

Sari Van Anders Social Neuroendocrinology Lab
Study: Sexual Modulation of HIV-Relevant Immunity
*Data Entry Specialist & Research Assistant, 2014-2015*

- Studied the behaviors of antimicrobial peptides and pathogen defense within mucous membranes
- Study sought to better understand HIV-relevant mucosal immunities in women, to foster a better understanding of both HIV transmission and suppression
- Data entry in SPSS, translating qualitative interview data into numeric values
- Manipulation and storage of human fluid samples in preparation for lab processing
- Recruitment initiatives for study participants including local advertising, and conducting interviews
- Maintained contact with, and behavior oversight of, participants throughout the study