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Relationship Between Socioeconomic Inequality and Traffic Crashes on Virginia Roads at the County and Census-Tract Levels

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Final Report VTRC 24-R12

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16. Abstract:

Socioeconomic inequality is a critical challenge our society faces, as its mitigation enhances group cohesion, social mobility, and long-term economic growth. Traffic crashes may be viewed as a domain that is marginally affected by socioeconomic inequality. Prior studies, however, have reported more fatalities and injuries in poorer neighborhoods. This leads to research questions about socioeconomic disparities, particularly on Virginia roads. To address the research question, this study analyzed large-scale panel data in two phases. The panel data for Phase 1 focused on county level analysis. The data consisted of 1,064 observations between 2013 and 2020 and used four heterogeneous big data sources: Virginia crash data, Virginia traffic vehicle miles traveled data, the American Community Survey, and County Health Rankings and Roadmaps. The panel data for Phase 2 focused on census tract level analysis. It was comprised of 8,068 observations between 2015 and 2021 across 1,485 census tracts in Virginia, derived from Virginia crash data and the American Community Survey. The analysis of this project's empirical results indicates:

1. There are socioeconomic inequality correlations with the safety of Virginia roads. Education and income emerge as significant contributing factors in decreasing traffic crash measures. Disadvantaged communities experience higher traffic crash rates than advantaged communities. Census tracts with a high proportion of households with no vehicle access generally exhibit higher rates of traffic crashes.

2. Higher traffic crash rates are correlated with race on Virginia roads. Neighborhoods with a higher Black population show higher rates of serious injury crashes and people injuries. The combination of secondary roads, disadvantaged communities, and Black neighborhoods has the highest rates of people injured in crashes.

3. Virginia has experienced an increase in the road fatality rate. Specifically, the fatal crash rate has increased on all non-interstate roads, secondary roads, and urban roads. Additionally, the pedestrian fatality rate has also increased on all non-interstate roads. Furthermore, the total crash rate on rural roads has been found to increase during the same time period.

4. Results show that pedestrian fatality rates are higher in both very affluent and poor neighborhoods. Census tracts with higher levels of education exhibit higher pedestrian injury rates as do census tracts with higher levels of poverty.

Supplemental files can be found at: https://library.virginiadot.org/vtrc/supplements

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FINAL REPORT

RELATIONSHIP BETWEEN SOCIOECONOMIC INEQUALITY AND TRAFFIC CRASHES ON VIRGINIA ROADS AT THE COUNTY AND CENSUS-TRACT LEVELS

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ABSTRACT

Socioeconomic inequality is a critical challenge our society faces, as its mitigation enhances group cohesion, social mobility, and long-term economic growth. Traffic crashes may be viewed as a domain that is marginally affected by socioeconomic inequality. Prior studies, however, have reported more fatalities and injuries in poorer neighborhoods. This leads to research questions about socioeconomic disparities, particularly with regard to Virginia roads. To address the research question, this study analyzed large-scale panel data in two phases. The panel data for Phase 1 focused on county-level analysis. The data consisted of 1,064 observations between 2013 and 2020 and used four heterogeneous big data sources: (1) Virginia crash data, (2) Virginia traffic vehicle miles traveled data, (3) the American Community Survey, and (4) County Health Rankings & Roadmaps. The panel data for Phase 2 focused on the analysis of data at the census-tract level. It was composed of 8,068 observations between 2015 and 2021 across 1,485 census tracts in Virginia, derived from Virginia crash data and the American Community Survey. The county-level analysis provides a broader understanding of socioeconomic inequality related to traffic crashes, while the census-tract analysis allows for a more nuanced examination of this important research topic for Virginia roads. Cluster analysis, an unsupervised machine learning algorithm, enabled this study to identify disadvantaged communities based on criteria such as education, median household income, supplemental nutrition assistance program participation rate, poverty rate, and the Gini index. This study also conducted a longitudinal analysis along with econometric models, adjusting rate variables per 1,000 people in a locality, to investigate the causal inference of socioeconomic status with different road types, following the categorization of Virginia crash data. The analysis of this study's empirical results indicated the following:

1. There are socioeconomic inequality correlations with the safety of Virginia roads. Education and income emerge as significant contributing factors in decreasing traffic crash measures. Disadvantaged communities experience higher traffic crash rates than advantaged communities. Census tracts with a high proportion of households with no vehicle access generally exhibit higher rates of traffic crashes.

2. Higher traffic crash rates on Virginia roads are correlated with race. Neighborhoods with a higher Black population show higher rates of serious injury crashes and people injuries. The combination of secondary roads, disadvantaged communities, and Black neighborhoods has the highest rates of people injured in crashes.

3. Virginia has experienced an increase in the road fatality rate. Specifically, the fatal crash rate has increased on all non-interstate roads, secondary roads, and urban roads. Additionally, the pedestrian fatality rate has also increased on all non-interstate roads. Furthermore, the total crash rate on rural roads has been found to increase during the same time period.

4. Results show that pedestrian fatality rates are higher in both very affluent and poor neighborhoods. Census tracts with higher levels of education exhibit higher pedestrian injury rates as do census tracts with higher levels of poverty.

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INTRODUCTION

The roads in Virginia serve not only as pathways for various vehicles, including motorcycles, passenger cars, buses, trucks, and tractor-trailers, but also as crucial components of the economy, public health, and people's social interactions. Given these multifaceted functions, it is unnecessary to reiterate the importance of road safety in transportation management. Over the past decade, there has been a reduction in traffic fatalities across the country, benefiting both drivers and pedestrians, due to the collaboration between the government and the automotive industry (Harper et al. 2015; Raifman and Choma 2022). Safety projects such as hazard location treatments, road designs and audits, and school zones have significantly contributed to this decline in crash injuries and fatalities (Sung and Rios 2015). Improvements in vehicle engineering and innovation, emergency room care, and safety legislation has also played a critical role in ensuring safety on U.S. roads (Badger and Ingraham 2015). The downward trend in traffic fatalities and injuries is truly inspiring, as these incidents represent not just numbers but also the lives, families, and communities affected by them.

Despite these trends, research suggests that the decline in fatal crashes has not benefited all drivers equally (Fish 2021; Pizzigati 2020). For example, according to Harper et al. (2015), the most significant decline in traffic fatalities has occurred among educated people, while socioeconomically disadvantaged areas continue to face a higher rate of vehicle fatalities. The study highlights that between 1995 and 2010, vehicle fatalities among individuals aged 25 and older who have not completed high school increased, even though car fatalities were decreasing nationwide during the same time period. Another study shows that pedestrian fatalities are found to be higher in poor communities (Badger and Ingraham 2015). Additionally, a separate study indicates that traffic safety is significantly related with racial and income inequality (Dumbaugh et al. 2020). Undoubtedly, having a college degree does not necessarily imply better driving skills. Research has shown that lower education levels are associated with lower incomes (Herrera-Escobar et al. 2019), which may lead to residing in areas with more hazardous driving conditions and an increased likelihood of car crashes. Similarly, lower incomes are more likely to be linked with older cars that may have fewer safety features and lower crash-test ratings. Taken together, previous studies indicate that socioeconomic inequality exists with regard to roads, despite national trends showing improvements in traffic safety over the past decade.

The American Psychological Association (APA) defines socioeconomic status (SES) as "the position of an individual or group on the socioeconomic scale, which is determined by a combination of social and economic factors such as income, amount and kind of education, type and prestige of occupation, place of residence, and - in some societies or parts of society - ethnic origin or religious background" ("APA Dictionary of Psychology" 2023). Socioeconomic status encompasses various aspects such as educational attainment, financial security, quality of life, and opportunities within society. It is a pressing concern to address SES-related inequality as these disparities affect community cohesion, social mobility, and long-term economic growth. However, Pew Research finds that most Americans do not perceive it as a top priority (Horowitz et al. 2020).

It is reported that road crashes cost approximately 2% to 5% of the gross domestic product (GDP) (Sung and Rios 2015). If traffic crashes disproportionately occur in disadvantaged areas on Virginia roads, the social and economic losses may be even more severe to those areas. Therefore, it is crucial to explore the relationship between SES and traffic safety on Virginia roads. A SES-focused approach to understanding traffic fatalities and injuries is a meaningful strategy for fostering a better community in Virginia (Haghighi et al. 2020). Consequently, this study aimed to investigate the influence of socioeconomic inequality on traffic crashes within the context of Virginia's roads. By utilizing big data analytics and employing sophisticated research methods such as machine learning and longitudinal analysis, valuable insights into traffic safety on Virginia roads can be derived.

This study sheds light on socioeconomic disparities related to traffic crashes in a more holistic way, offering insights for Virginians, the Virginia Department of Transportation (VDOT), Metropolitan Planning Organizations (MPOs), Office of Intermodal Planning and Investment (OIPI), Planning District Commissions (PDCs), and legislators about previously unexplored areas of SES influences. By providing a deeper understanding of the impacts of SES on road crashes, this study will help improve the overall performance of road safety strategies in Virginia, as well as enhance the quality life for Virginians.

PURPOSE AND SCOPE

Purpose

The purpose of this study was to investigate the relationship between SES and crashes on Virginia roads. Given that socioeconomic inequality is a pervasive issue with far-reaching effects in areas such as healthcare, income, education, justice systems, and employment, it requires significant attention. Surprisingly, the impact of socioeconomic inequality on road crashes, particularly in Virginia, has not been systematically studied. This lack of research is noteworthy and calls for an in-depth examination. While the lack of a systematic study may lead one to believe that traffic crashes are unaffected or only slightly affected by SES, there is anecdotal evidence suggesting otherwise (Badger and Ingraham 2015; Dumbaugh et al. 2020; Harper et al. 2015). This study aimed to delve into the reality of socioeconomic disparities with regard to Virginia roads and shed light on their influence on road crashes. By conducting a comprehensive investigation, the study sought to make novel contributions to the understanding of this issue in the Commonwealth of Virginia. Specific objectives included the following:

- Determine how traffic fatalities and injuries differ between socioeconomically advantaged and disadvantaged areas in Virginia.

- Identify overall trends in traffic crash measures, including total crash rate, fatal crash rate, serious injury crash rate, people injury rate, pedestrian fatality rate, and pedestrian injury rate in Virginia.

- Assess how socioeconomic status influences traffic crash metrics in Virginia.

Scope

It is important to note that this study included two phases to address different spatial scales, as shown in Table 1. Phase 1 examined data at the county level, while Phase 2 focused on the census-tract level. The county-level analysis provides a broader understanding of socioeconomic inequality related to traffic crashes on Virginia roads. Going a step further, the census-tract analysis allows for a more nuanced examination of this important research topics. Both approaches are complementary, as the study aimed to comprehensively investigate crash disparities in Virginia. Overall, having both a big picture and nuanced picture understanding of the research stream will help Virginia develop effective solutions and polices by identifying specific areas where targeted interventions are needed to address disparities and improve outcomes. It should be noted that Phase 2 covered only four districts/areas, encompassing a majority of crashes in Virginia. Detailed information is provided in the Methods section.

Table 1. Overview of Phase 1 and Phase 2

	Data Source	Phase 1	Phase 2
		County Level	Census-Tract Level
1	Virginia Crash Data	2013 to 2020 (968,840 Crashes)	2015 to 2021 (865,818 Crashes)
2	Virginia Traffic Vehicle Miles Traveled (VMT) Data	2013 to 2020 (133 Counties/Cities)	
3	American Community Survey (ACS)	2012 to 2019 (133 Counties/Cities)	2014 to 2020 (1,485 Census Tracts)
4	County Health Rankings & Roadmaps (CHR&R)	2013 to 2020 (133 Counties/Cities)	

METHODS

Overview

To examine road safety and socioeconomic inequality with regard to Virginia roads, the study conducted a series of tasks to achieve the objectives of this study. The theoretical and empirical processes are organized as follows:

- Task 1: Conduct a literature review of SES and traffic crashes.
- Task 2: Perform descriptive analytics of variables used in this study.
- Task 3: Employ cluster analysis to group localities based on five SES variables.
- Task 4: Conduct longitudinal data analysis.

Through this structured approach, the study aimed to gain a comprehensive understanding of the relationship between socioeconomic factors and road safety on Virginia roads. The detailed descriptions of each task are presented in the next section.

Conduct a Literature Review

A literature review is a critical component of the research process, helping studies identify gaps, build a theoretical framework, and provide context and credibility to research. It also contributes significantly to the advancement of knowledge in a particular field by summarizing and synthesizing existing research. This study conducted a comprehensive literature review to examine prior studies in relation to SES variables in the context of traffic safety and healthcare. The extensive literature review conducted for this study highlights the crucial role of SES variables. Building upon the existing body of research, the current study aimed to contribute valuable insights into the relationship between SES and traffic crashes. By synthesizing and expanding on the findings from previous studies, this study endeavored to shed further light on the complexities of SES disparities with regard to traffic safety.

Data Description

This study constructed a large-scale panel dataset by integrating heterogenous big data from various sources at both the county and census-tract levels, as shown in Table 1. First, Virginia crash data integrate millions of traffic crashes with the geographic coordinates of crash locations in various localities across Virginia. The dataset enables the Commonwealth to explore problems and implement solutions regarding car crashes, injuries, and pedestrians on Virginia roads. Specifically, the dataset provides crash measures (i.e., total crashes, injury crashes, fatal crashes, people injured, pedestrians killed, and pedestrians injured), which are essential for this study. In this study, the crash metrics are recalculated using rate variables, adjusting them based on the population of each locality. When studying phenomena such as crashes or other events, using rate variables is often beneficial because it helps account for population differences between regions.

Second, VDOT shares data collected from sensors on secondary/primary roads and interstates to estimate the average number of vehicles and daily vehicle miles traveled (DVMT). The data are useful for assessing travel demands and understanding regional impacts, enabling advanced preparation for the future. Furthermore, analyzing local residents’ travel patterns, freight activity, and external travels provides insights into transportation operations, strategies, and trends in travel growth and decline. The data help differentiate between local residents’ travels and external travels in this study.

Third, the ACS is an ongoing survey that provides information on jobs, occupations, educational attainment, employment, home ownerships, poverty rate, and supplemental nutrition assistance program (SNAP) participation at the state, county/city, or census-tract levels. Conducted annually, this survey helps the government allocate resources for purposes such as hospitals, schools, school lunch programs, emergency services, and building construction, as well as creating new markets to enhance job effectiveness in the United States.

Fourth, County Health Rankings & Roadmaps, a program of the University of Wisconsin Population Health Institute, collects data on community health indicators, schools, and workplaces on an annual basis. It ranks counties and cities based on health outcomes and health factors at the county/city level, enabling stakeholders to assess health disparities among different racial and ethnic groups and work towards creating healthier communities. This study utilized these big data to examine access to healthcare and identify inequalities with regard to Virginia roads.

As summarized in Table 1, all of the rich datasets gave this study an opportunity to fulfill the study objective and utilize machine learning, geographical information systems (GIS), and causal relationships via longitudinal analysis to thoroughly examine socioeconomic disparities with regard to Virginia roads at both the county and census-tract levels.

Descriptive Analytics of SES Variables in Virginia

Table 2 provides a summary of SES variables, including their descriptions, sources, and years of data collection for Phase 1 (i.e., county level) and Phase 2 (i.e., census-tract level). Education is measured by the percentage of people with a bachelor's degree or higher among the population aged 25 years and older. Income refers to the median household income over the past 12 months. Poverty represents the percentage of the population living below the 100% poverty line. The SNAP participation rate indicates the percentage of households receiving food stamps or SNAP in the past 12 months. Last but not least, the Gini index is a calculated value used to measure income inequality. The Gini index is a statistical measure commonly used to assess wealth distribution within a population, ranging from 0 to 1. A value of 0 signifies perfect equality, where every individual has the same wealth. A value of 1 represents maximum inequality, with one individual possessing all the wealth while others have none. It is important to note that Phase 1 and Phase 2 of the analysis had different time periods, as they focused on different geographical units.

Table 2. Description of SES Variables Used for Cluster Analysis

Feature	Variable	Description	Source	Year(s)
SES Features	Education	Percentage of people with a bachelor's degree or higher for the population 25 years and older	American Community Survey, 5-year estimate	Phase 1 (2012-2019) Phase 2 (2014-2020)
	Income	Median household income over the past 12 months (inflation-adjusted dollars)		
	Poverty	Percentage of population living under the 100% poverty line		
	SNAP	Percentage of households receiving food stamps/SNAP in the past 12 months		
	Gini	Gini index of income inequality		

Prior to conducting the analysis of the impact of SES on traffic crash measures using machine learning, GIS, and longitudinal data analysis, it is necessary to present descriptive analytics for each SES variable used in both Phase 1 and Phase 2. This step helps provide an overview of the included SES factors. Given that Virginia is composed of 133 counties/cities and 1,485 census tracts within the scope of this project, presenting data for all these localities in relation to SES factors for Phase 1 and Phase 2 could be inefficient. To address this issue, the study provides several examples that represent areas with high, middle, and low values of variables. The higher criteria refer to localities that fall above the 75th percentile, while the lower criteria represent areas below the 25th quantile. The mid-criterion focuses on localities that hold average values for the SES variables. By presenting these examples, this study attempted to show the variations in SES across Virginia to serve as illustrative cases that highlight diverse SES landscape within the state. This approach enabled this study to capture the range of socioeconomic factors without overwhelming the analysis with excessive data from all localities.

Cluster Analysis to Group Localities Based on Five SES Variables

This study utilized cluster analysis to group localities based on SES variables. Cluster analysis is a method that groups observations into segments whose elements share similar characteristics. It is a popular and powerful machine learning technique used in unsupervised learning. Three approaches were used in this study: (1) hierarchical clustering with complete linkage, (2) hierarchical clustering with Ward’s linkage, and (3) k-means. Hierarchical clustering starts with each observation as a separate cluster and merges them iteratively by identifying two clusters that are closest together. Distances between two clusters are calculated by a straight line between clusters, commonly referred to as the Euclidean distance. The research method also needs to specify a linkage among a group of observations, and this study used two linkages (i.e., complete and Ward’s). Complete linkage uses the maximum distances between an observation in one cluster and an observation in another cluster. Ward’s linkage minimizes the total within-cluster variance by assessing the sum of squared errors from the mean vector (centroid). Different linkages can yield different results, so researchers need to select an appropriate linkage based on the data and context. With k-means, the exact number of clusters should be provided. The algorithm iterates until the data belong to one of the k-clusters by minimizing the within-cluster variation measured by the squared Euclidean distances. Due to the iteration process, k-means results may differ from the specified number of clusters.

For Phase 2, four districts or areas were selected for study: (1) VDOT’s Northern Virginia District, (2) the Hampton Roads area, (3) the Richmond area, and (4) VDOT’s Salem District, as shown Figures 1-5. These regions account for the majority of crashes in Virginia, representing a significant portion of the overall crash data. Converting crash locations and their coordinates to each census tract takes time, and for the sake of efficiency, the four districts/areas are chosen to provide a comprehensive representation of the state’s crash patterns. The selection of these specific districts allows for a more focused analysis of the socioeconomic factors contributing to road safety disparities.

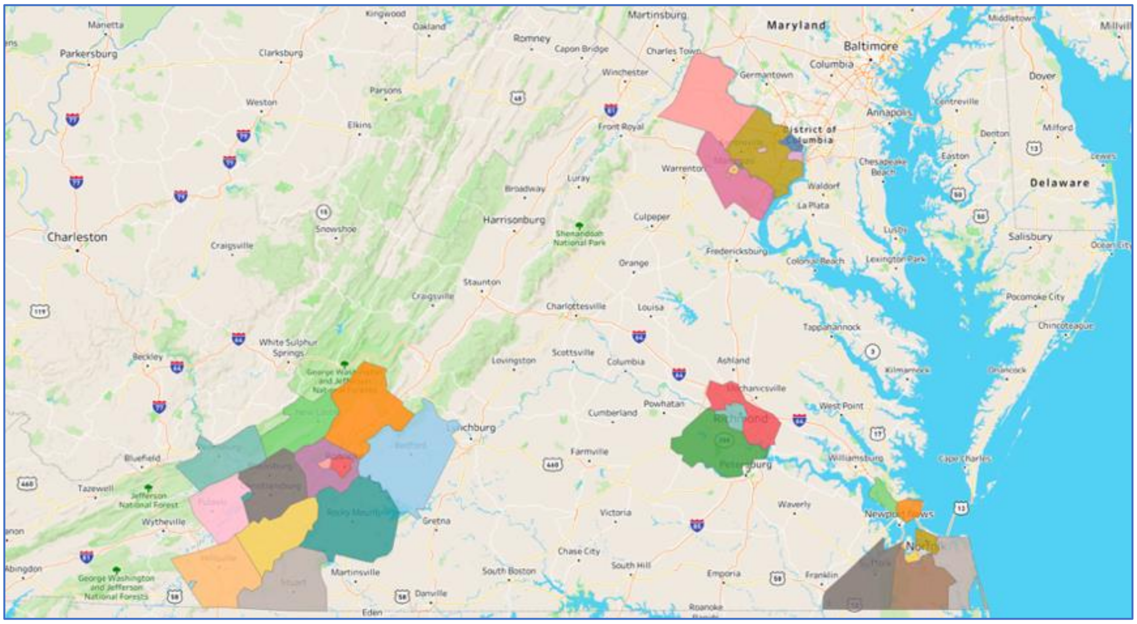

Figure 1. Four Districts and Areas Analyzed for Phase 2

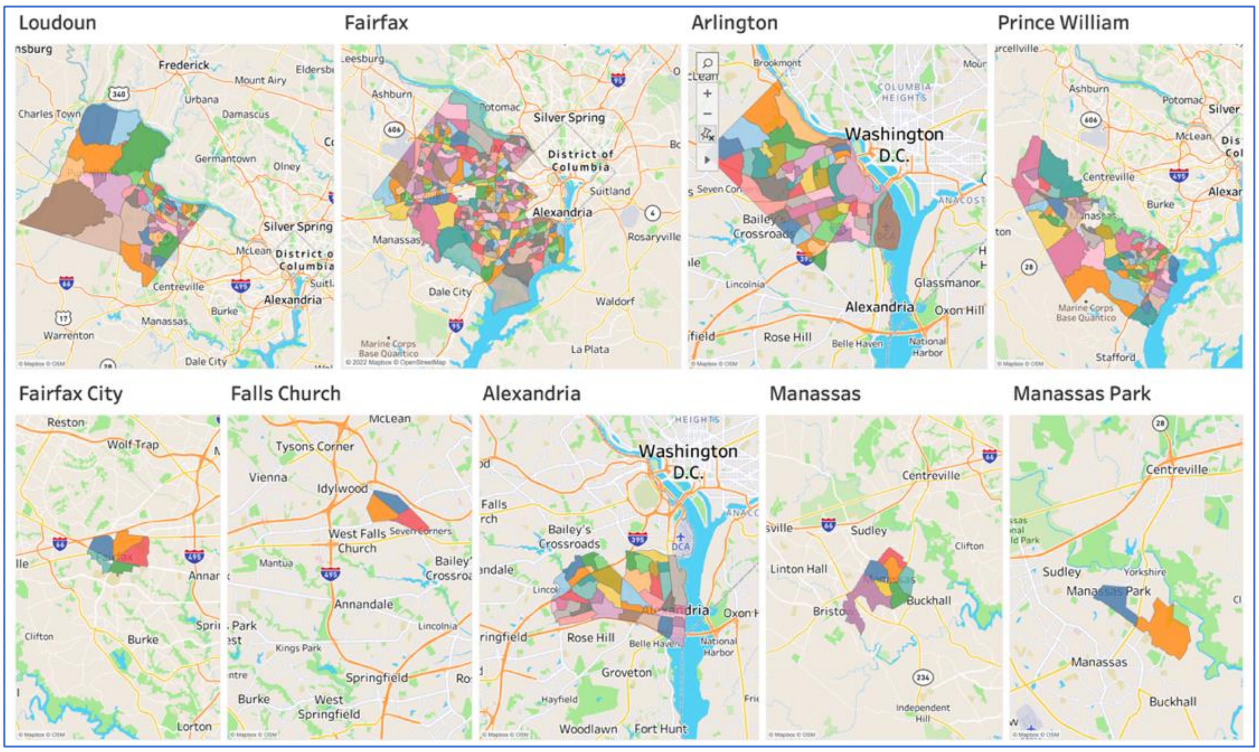

Figure 2. Census Tracts of VDOT's Northern Virginia District

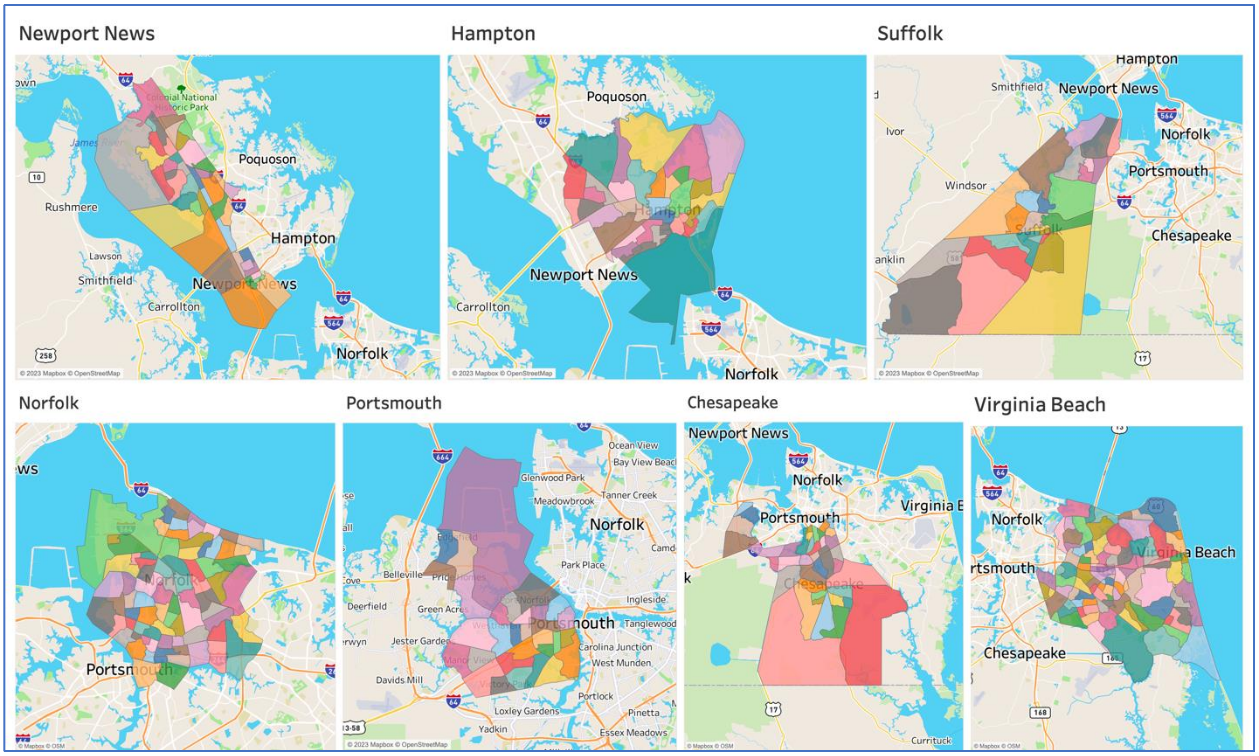

Figure 3. Census Tracts of the Hampton Roads Area

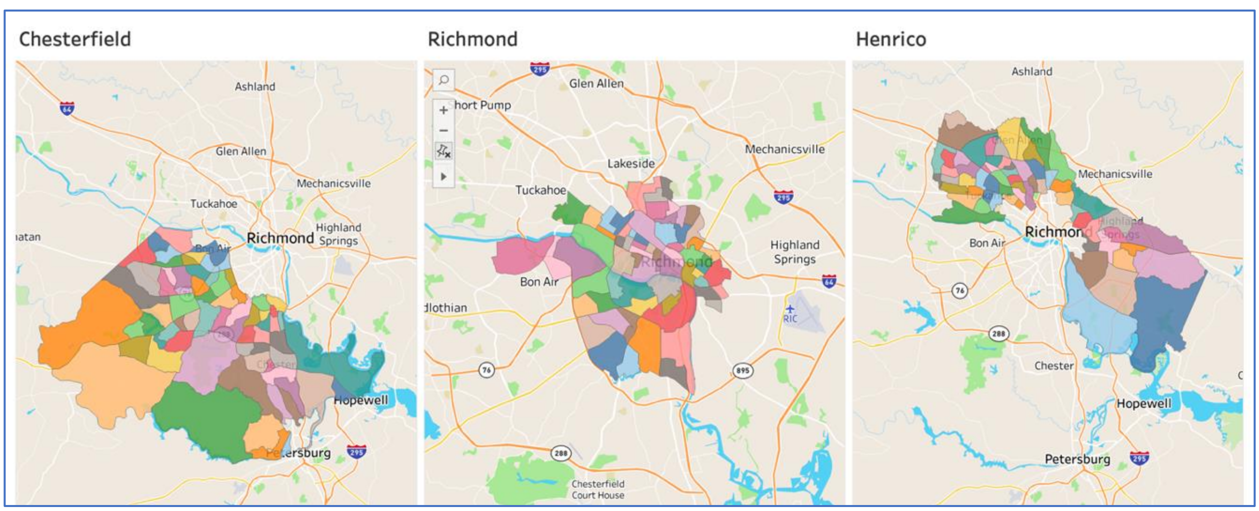

Figure 4. Census Tracts of the Richmond Area

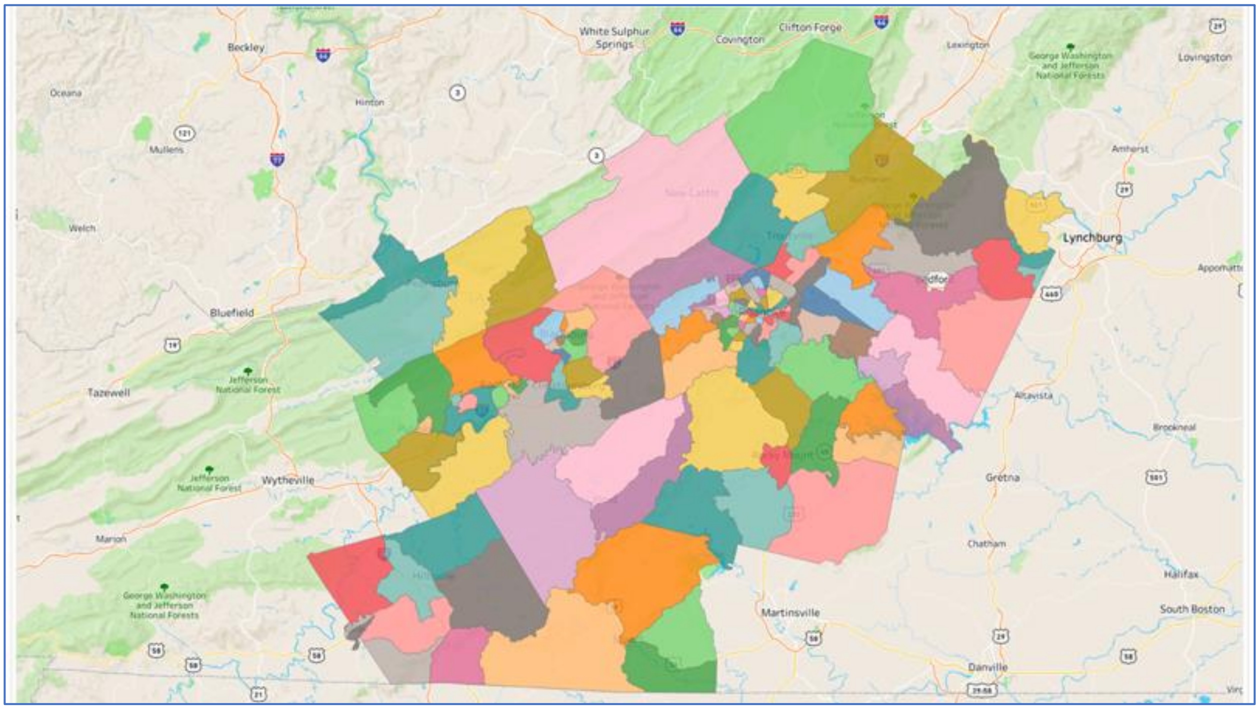

Figure 5. Census Tracts of VDOT's Salem District

Measures of Longitudinal Data Analysis

This study constructed a large-scale panel dataset, comprising 1,604 observations from 2013 and 2020 across 133 counties/cities in Virginia for Phase 1, and 8,068 observations from 2015 and 2021 across 1,485 census tracts in Virginia for Phase 2. The comprehensive dataset enabled this study to investigate long-term impacts and causal relationships when analyzing socioeconomic inequality with regard to Virginia's roads. As mentioned earlier, the county analysis provided a broader perspective, while the census-tract analysis offered a more detailed understanding. Table 3 outlines the six target variables that this study examined in relation to socioeconomic disparities. The traffic crash measures included total crash rate, fatal crash rate, serious injury crash rate, people injury rate, pedestrian fatality rate, and pedestrian injury rate. It is important to note that all of these variables were calculated as rates by dividing total number of cases by the locality's population and multiplying it by 1,000 people. It should be noted that the traffic crash metrics were based on a per 1,000 people rate, not on VMT. The categorization of all non-interstate roads, urban roads, and secondary roads was based on Virginia crash data.

Table 3. Descriptions of Target Variables

Name	Description	Formula
Total Crash Rate	Total number of total crashes is divided by the population of the locality and multiplied by 1,000.	$\frac{Total\ Crashes}{Population} \times 1{,}000\ people$
Fatal Crash Rate	Total number of fatal crashes is divided by the population of the locality and multiplied by 1,000.	$\frac{Fatal\ Crashes}{Population} \times 1{,}000\ people$
Serious Injury Crash Rate	Total number of serious injury crashes is divided by the population of the locality and multiplied by 1,000.	$\frac{Seriou\ Injury\ Crashes}{Population} \times 1{,}000\ people$
People Injury Rate	Total number of people injured is divided by the population of the locality and multiplied by 1,000.	$\frac{People\ Injured}{Population} \times 1{,}000\ people$
Pedestrian Fatality Rate	Total number of pedestrians killed is divided by the population of the locality and multiplied by 1,000.	$\frac{Pediestrian\ Killed}{Population} \times 1{,}000\ people$
Pedestrian Injury Rate	Total number of pedestrians injured is divided by the population of the locality and multiplied by 1,000.	$\frac{Pedestrian\ Injured}{Population} \times 1{,}000\ people$

The predictors utilized for this study are explained in Table 4. For Phase 1, they were grouped by SES, time, VMT, and access to healthcare. Socioeconomic status included education, income, poverty, SNAP, and Gini index. The time variable was useful for detecting trends in traffic crashes from 2013 to 2020. Vehicle Miles Traveled (VMT) included secondary streets, primary roads, and interstates. Access to healthcare involved the insurance rate, the rate of primary care physicians, and the rate of preventable hospital stays. Detailed information such as variable names, sources, and years are also delineated in Table 4. The predictors were chosen based on the literature review, theoretical reasoning, and data availability when exploring the impact of the six response variables for socioeconomic disparities on Virginia roads.

Table 4. Summary of Predictors for Phase 1

Feature	Variable	Description	Source	Year(s)
SES	Education	Percentage of the population aged 25 years and older with a bachelor's degree or higher	American Community Survey, 5-year estimate	2012-2019
	Income	Median household income over the past 12 months (inflation-adjusted dollars)		
	Poverty	Percentage of the population living below the 100% poverty line		
	SNAP	Percentage of households receiving food stamps/SNAP in the past 12 months		
	Gini	Gini index of income inequality		
Time	Wave	A numerical value was created, with the year 2013 assigned the value of 1, the year 2014 assigned the value of 2, and so on, until the year 2020, which is assigned the value of 8		2013-2020
VMT	DVMT_S	Daily vehicle miles traveled per 1,000 people on secondary roads	VDOT Traffic Data	2013-2020
	DVMT_P	Daily vehicle miles traveled per 1,000 people on primary roads		
	DVMT_I	Daily vehicle miles traveled per 1,000 people on interstates		
Access to Healthcare	Uninsured	Percentage of the population under age 65 without health insurance	CHR&R, Small Area Health Insurance Estimates	2010-2017
	PCP	Rate of primary care physicians per 1,000 people	CHR&R, Area Health Resource File/American Medical Association	2010-2017
	PHS	Preventable hospital stays. Rate of hospital stays for ambulatory-care sensitive conditions per 1,000 Medicare enrollees	CHR&R, Mapping Medicare Disparities Tool	2010-2017

The Phase 2 variables are detailed in Table 5, and cover the same aspects as Phase 1, such as SES and time. Notably, Phase 2 data spanned more recent years (i.e., 2015 to 2021), including the period of COVID-19 lockdowns in 2020. The inclusion of the COVID-19 variable as a control allowed this study to account for its impact on traffic crash measures more accurately. Automobile ownership is often linked to socioeconomic factors and demographic characteristics. This study included these factors to analyze how automobile ownership varies across geographic areas, which helped identify disparities in road safety. Understanding the role of race in traffic studies is crucial as it can illuminate potential disparities, biases, and inequalities in various aspects of transportation and road safety. It should be noted that the race category of White was not included in the analysis due to concerns regarding multicollinearity. Moreover, population density can impact road safety, particularly in areas with high population density where pedestrian activity and vehicle-to-vehicle interactions are more pronounced. Addressing these factors is especially vital for promoting transportation equity and ensuring that all communities have access to safe and reliable transportation options.

Table 5. Summary of Predictors for Phase 2

Feature	Variable	Description	Source	Year(s)
SES	Education	Percentage of the population aged 25 years and older with a bachelor's degree or higher	American Community Survey, 5-year estimate	2014-2020
	Income	Median household income over the past 12 months (inflation-adjusted dollars)		
	Poverty	Percentage of population living below the 100% poverty line		
	SNAP	Percentage of households receiving food stamps/SNAP in the past 12 months		
	Gini	Gini index of income inequality		
Time	Wave	A numerical value was created, with the year 2015 assigned the value of 1, the year 2016 assigned the value of 2, and so on, until the year 2021, which is assigned the value of 7		2015-2021
COVID-19	COVID-19	Dummy variable is 0 if the crash occurred before 2020; otherwise, it is 1.		
Automobile Ownership	ZeroVeh	Percentage of households without a vehicle	American Community Survey, 5-year estimate	2014-2020
	TwoMoreVeh	Percentage of households with two or more vehicles		
Race	Black	Percentage of the Black or African-American population in the locality	American Community Survey, 5-year estimate	2014-2020
	Asian	Percentage of the Asian population in the locality		
	Hispanic	Percentage of the Hispanic/Latino population in the locality		
Population Density	PopDensity	Population density was calculated by dividing the number of people by the land area in the locality.	American Community Survey, 5-year estimate	2014-2020

Models Derived from Longitudinal Data

Longitudinal data, also known as panel data, involve repeated observations of the same variable at different points in time. This type of data allows investigators to examine the temporal order of events for individual subjects, thereby strengthening causal inferences. Panel data provide advantages over pure time series and cross-sectional data as they offer more information and variability, enabling researchers and practitioners to investigate statistical impacts with greater precision. Given that the present study incorporates heterogeneous big data from the previous years, analyzing the longitudinal data is an appropriate approach for exploring socioeconomic disparities with regard to Virginia roads. This study integrated data from localities (i.e., counties and census tracts) and treated these localities as fixed factors in the empirical models.

Fixed effects regression models are commonly used in panel data because they are well-suited for panel data analysis, allowing researchers to account for individual-specific or region-specific effects that remain constant over time. These models effectively control for unobservable factors, isolating the impact of the variables of interest. In this study, the researcher utilized fixed effects regression models, for which the research models are presented below. For

Phase 1, which involved county-level analysis, Equations (1) and (2) were employed. During the analysis, the variable of education sometimes produced conflicting results, leading the researcher to conduct additional tests using Equation (2) to reinforce the understanding of socioeconomic inequalities with regard to Virginia roads. For Phase 2, the analysis shifted to the census-tract level, and Equations (3) and (4) were utilized. Equation (3) served as the primary model for all analyses, but Equation (4) was applied when examining area-specific data. The cluster analysis with socioeconomic factors helped identify disadvantaged and advantaged areas. While SES factors were not included in Equation (4), they already played a crucial role in identifying distinct clusters. In Phase 2, which aimed to investigate the detailed circumstances of socioeconomic situations on the road, the research examined crash measures based on road type (e.g., all crashes with no interstates, secondary roads only, rural roads only, and urban roads only) and by area (e.g., disadvantaged areas, intermediate areas, and advantaged areas). This approach allowed the researcher to gain deeper insights into the impact of socioeconomic conditions on road safety and traffic incidents.

$$\begin{aligned}
CrashMeasure_{it+1} = {} & \\
& \beta_0 + \beta_1 Edu_{it} + \beta_2 Income_{it} + \beta_3 Poverty_{it} + \beta_4 SNAP_{it} + \beta_5 Gini_{it} + \\
& \beta_6 Wave_t + \\
& \beta_7 DVMT_S_{it} + \beta_8 DVMT_P_{it} + \beta_9 DVMT_I_{it} + \\
& \beta_{10} UnInsured_{it} + \beta_{11} PCP_{it} + \beta_{12} PHS_{it} + \alpha_i + \varepsilon_{it}
\end{aligned} \tag{1}$$

$$\begin{aligned}
CrashMeasure_{it+1} = {} & \\
& \beta_0 + \beta_1 Income_{it} + \beta_2 Poverty_{it} + \beta_3 SNAP_{it} + \beta_4 Gini_{it} + \\
& \beta_5 Wave_t + \\
& \beta_6 DVMT_S_{it} + \beta_7 DVMT_P_{it} + \beta_8 DVMT_I_{it} + \\
& \beta_9 UnInsured_{it} + \beta_{10} PCP_{it} + \beta_{11} PHS_{it} + \alpha_i + \varepsilon_{it}
\end{aligned} \tag{2}$$

$$\begin{aligned}
CrashMeasure_{it+1} = {} & \\
& \beta_0 + \beta_1 Edu_{it} + \beta_2 Income_{it} + \beta_3 Poverty_{it} + \beta_4 SNAP_{it} + \beta_5 Gini_{it} + \\
& \beta_6 Wave_t + \\
& \beta_7 CovidDummy + \\
& \beta_8 ZeroVeh_{it} + \beta_9 TwoMoreVeh_{it} + \\
& \beta_{10} Black_{it} + \beta_{11} Asian_{it} + \beta_{12} Hispanic_{it} + \\
& \beta_{13} PopDensity_{it} + \alpha_i + \varepsilon_{it}
\end{aligned} \tag{3}$$

$$\begin{aligned}
CrashMeasure_{it+1} = {} & \\
& \beta_1 Wave_t + \\
& \beta_2 CovidDummy + \\
& \beta_3 ZeroVeh_{it} + \beta_4 TwoMoreVeh_{it} + \\
& \beta_5 Black_{it} + \beta_6 Asian_{it} + \beta_7 Hispanic_{it} + \\
& \beta_8 PopDensity_{it} + \alpha_i + \varepsilon_{it}
\end{aligned} \tag{4}$$

where i refers to the locality and t refers to the yearly observation. The traffic crash measure, denoted as $CrashMeasure_{it+1}$, represents a traffic crash measure for a particular locality i in year t. It should be noted that the six crash measures are total crash rate, fatal crash rate, serious injury crash rate, people injury rate, pedestrian fatality rate, and pedestrian injury rate. The variable Edu_{it} represents the percentage of the population aged 25 years and older with a bachelor's degree or higher for particular locality i in year t. Further details on predictors can be found in Tables 4 and 5. In addition, α_i is time-invariant unobservable characteristics of locality i, and ε_{it} represents the error term. To compare the model fit of different models, the present study used Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

RESULTS

Literature Review of Socioeconomic Status in the Context of Road Safety

As mentioned above, SES is described as a comprehensive measure of social and economic indicators used to assess an individual's or their family's access to resources and opportunities within a community or society (Baker 2014). These SES indicators have been employed to understand and analyze inequalities and disparities as they significantly influence overall individual well-being (Lym et al. 2022; Shults et al. 2021; Zhang et al. 2021). Considering that this study aimed to analyze the effects of socioeconomic inequality on safety on Virginia roads, the literature review on SES impacts focused on this area and public health outcomes and is summarized outlined in Table 6. Extensive research indicates that SES has played a significant role in traffic crashes and poorer health outcomes, highlighting the importance of considering SES factors to better understand road safety in Virginia.

This research stream of SES emphasizes social and economic progress that impacts all sections of society, recognizing the critical need to maintain each person's quality of life. By providing relatively equal opportunities, individuals are better able to realize their potential and contribute to social and economic growth in communities.

Descriptive Analytics for SES, Predictors, and Target Variables

The results of the descriptive analytics between 2012 and 2019 for Phase 1, as depicted in Appendix A (i.e., SES Examples of Counties/Cities), indicated a notable increase in the number of individuals attaining a bachelor's degree or higher in Virginia. During this period, there was a clear upward trajectory in educational attainment. Additionally, there was an improvement in median household income during the same time frame. These data revealed that not only were more people achieving higher levels of education, but they were also experiencing an increase in their median income. These findings are promising for the overall economic well-being of Virginians. However, unlike the consistent upward trends observed in education and income, patterns related to the poverty rate, SNAP participation rate, and Gini index were elusive. These indicators showed fluctuating patterns that made it challenging to predict changes over time. Certain localities within Virginia exhibited rapid fluctuations in these variables, rendering their trends less predictable and highlighting the need for further investigation into the underlying factors driving these fluctuations. In addition, the descriptive statistics for the variables used for Phase 1 are presented in Appendix B (i.e., Descriptive Statistics for Predictors Used in Phase 1). This provides a comprehensive overview of the key variables used in the analysis, offering valuable insights into their distributions and characteristics.

Table 6. Literature Review of SES in Relation to Traffic Crashes and Healthcare

Author(s)	Journal	SES Measure	Context	Findings
Lym et al. (2022)	Journal of Transport Geography	• Income • Poverty • Unemployment	The influence of urbanicity and built environment on the frequency of distracted driving-related crashes in multiple states.	The frequency of driving-related crashes is influenced by factors such as population density, land use, and road network characteristics.
Shults et al. (2021)	Journal of Transport & Health	• Grades • School meal program (free or reduced school meals)	Does geographic location matter for transportation risk behaviors among U.S. public high school students?	Regardless of location, teen transportation risk behaviors remain high.
Zhang et al. (2021)	BMJ	• Income • Occupation and employment status • Education • Health insurance	Associations of healthy lifestyle and socioeconomic status with mortality and incident cardiovascular disease	Low SES in both the U.S. and U.K. was found to be linked to higher risks of mortality and cardiovascular disease.
Wolfe et al. (2020)	American Journal of Public Health	• Education • Income • Poverty • Health insurance • Employment	Transportation barriers to health care in the U.S.: findings from the National Health Interview Survey, 1997–2017	Transportation barriers to health care have a disproportionate impact on individuals who are poor and who have chronic conditions.
Haghighi et al. (2020)	BMC Public Health	• Gini index • Unemployment • Education • Income	Social, economic, and legislative factors and global road traffic fatalities	Any increase in the human development index (i.e.., measure of long and healthy life, knowledge, and a decent standard of living) was associated with a reduction in road traffic fatalities.
Owsley et al. (2020)	American Journal of Public Health	• Below poverty • Health insurance • Income • Unemployment • College degree	The growing divide in the composition of public health delivery systems in U.S. rural and urban communities, 2014–2018	Urban public health systems have enhanced their scope of activities and organizational networks since 2014, whereas rural systems have lost capacity.
Tajeu et al. (2020)	American Journal of Public Health	• Education • Income • Health insurance	Black–White differences in cardiovascular disease mortality: A prospective U.S. study, 2003–2017	Cardiovascular disease mortality rates were higher among Black adults compared to White adults.
Fitzpatrick and Willis (2020)	International Journal of Environmental Research and Health	• Gini index • SNAP • Lower high school education • Weight (obesity)	Chronic disease, the built environment, and unequal health risks in the 500 largest U.S. cities	Chronic disease (diabetes type 2, strokes, and high blood pressure) is a leading cause of death in the U.S.

Vierboom (2020)	Population Research and Policy Review	• Education	Trends in alcohol-related mortality by educational attainment in the U.S., 2000–2017	Alcohol-related mortality rates increased at all levels of educational attainment.
Marshall and Ferenchak (2019)	Journal of Transport & Health	• Income	Why cities with high bicycling rates are safer for all road users	Better safety outcomes are associated with a greater prevalence of bike facilities.
Monnat et al. (2019)	American Journal of Public Health	• Unemployment • No college education • Median household income • Poverty • Gini index	Using census data to understand county-level differences in overall drug mortality and opioid-related mortality by opioid type	Drug mortality rates are higher in counties that are more economically disadvantaged, have more blue-collar/service. employment, and have higher opioid prescription rates.
Duranton and Turner (2018)	Journal of Urban Economics	• Income • Education • Employment	Urban form and driving: Evidence from U.S. cities	Increases in density cause small decreases in individual driving. Plausible densification policies cause decreases in aggregate driving that are small, from gas taxes or congestion pricing.
Engelberg et al. (2015)	Journal of Transport & Health	• Income	Distracted driving behaviors related to cell phone use among middle-aged adults	Talking on the phone or texting while driving were significant predictors of distracted driving.
Harper et al. (2015)	American Journal of Epidemiology	• Education	Trends in socioeconomic inequalities in motor vehicle crash deaths in the United States, 1995–2010	Larger mortality decreases among the more highly educated and mortality increases among the least educated.

As discussed, six target variables were employed to examine socioeconomic inequality with regard to Virginia roads. Table 7 explains their descriptive statistics, providing detailed information on each variable’s mean, median, standard deviation, and other relevant statistical measures. These statistics serve as a foundation for understanding the socioeconomic landscape in Virginia.

Table 7. Descriptive Analytics of Target Variables at the County Level

Target Variable		Year							
		2013	2014	2015	2016	2017	2018	2019	2020
Total Crash Rate (Total Crash per 1,000 People)	Minimum	2.54	2.69	0.6	0.6	0.15	0.31	0	0.15
	Maximum	33.67	36.71	34.21	36.28	35.69	37.11	34.92	24.56
	Average	14.03	13.59	14.21	14.37	14.3	15.05	14.49	10.35
	Median	12.99	12.65	12.86	13.19	13.32	13.91	13.34	9.73
	SD	5.09	5.14	5.34	5.46	5.51	5.97	5.58	4.34
	N	133	133	133	133	133	133	133	133
Fatal Crash Rate (Fatal Crash per 1,000 People)	Minimum	0	0	0	0	0	0	0	0
	Maximum	0.67	0.47	0.48	0.67	0.56	0.52	0.58	0.71
	Average	0.12	0.12	0.14	0.14	0.13	0.13	0.14	0.12
	Median	0.1	0.1	0.11	0.09	0.11	0.12	0.11	0.1
	SD	0.11	0.11	0.12	0.13	0.11	0.11	0.12	0.11
	N	133	133	133	133	133	133	133	133
Serious Injury Crash Rate (Serious Injury Crash per 1,000 People)	Minimum	0	0	0	0	0	0	0	0
	Maximum	5	3.85	3.99	3.5	4	3.21	3.48	3.12
	Average	1.41	1.19	1.31	1.25	1.24	1.13	1.14	0.93
	Median	1.2	1.15	1.21	1.21	1.18	1.06	1.02	0.83
	SD	0.87	0.69	0.78	0.68	0.73	0.69	0.67	0.61
	N	133	133	133	133	133	133	133	133
People Injury Rate (People Injury per 1,000 People)	Minimum	0.6	0.45	0.15	0.3	0	0.15	0	0
	Maximum	28.5	24.64	28.42	31.9	35.62	34.48	36.5	27.38
	Average	7.56	7.35	7.5	7.65	7.57	7.6	7.48	5.39
	Median	7.21	6.52	6.71	6.87	6.41	6.39	6.3	4.47
	SD	3.3	3.52	3.65	3.93	4.42	4.56	4.51	3.7
	N	133	133	133	133	133	133	133	133
Pedestrian Fatality Rate (Pedestrian Fatality per 1,000 People)	Minimum	0	0	0	0	0	0	0	0
	Maximum	0.07	0.17	0.15	0.16	0.3	0.45	0.14	0.09
	Average	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01
	Median	0	0	0	0	0	0	0	0
	SD	0.01	0.02	0.02	0.03	0.03	0.05	0.02	0.02
	N	133	133	133	133	133	133	133	133
Pedestrian Injury Rate (Pedestrian Injury per 1,000 People)	Minimum	0	0	0	0	0	0	0	0
	Maximum	0.71	1.21	0.76	0.88	0.77	0.74	0.66	0.55
	Average	0.15	0.15	0.14	0.13	0.12	0.13	0.12	0.09
	Median	0.08	0.07	0.08	0.08	0.07	0.08	0.08	0.05
	SD	0.17	0.19	0.18	0.16	0.16	0.16	0.15	0.11
	N	133	133	133	133	133	133	133	133

SD = standard deviation.

Phase 2 of the study focused on census-tract analysis, utilizing 1,485 census tracts in Virginia. Once again, presenting all these localities would be inefficient. Therefore, for Phase 2, a representative major place for each research area was selected to demonstrate fluctuations in the SES variables. Table 8 highlights significant disparities within selected counties, providing an overview of SES at the census-tract level. As shown, census tracts within a county exhibited significant differences in SES variables. For example, in the City of Richmond, the highest median household income in 2020 in a census tract was $250,001, while the lowest was $13,458. Appendix C (i.e., Descriptive Statistics for Predictors Used in Phase 2) examines the descriptive statistics of the variables used for Phase 2.

Table 8. 2020 Census-Tract SES in 2020

City of Richmond (Sorted by Income)							
	Tract	Population	College	Income	Poverty	SNAP	Gini
Top Five	Census Tract 506	2,849	87.1%	$250,001	0.00%	0.63%	0.47
	Census Tract 504	2,615	84.4	173,375	0.00	1.53	0.44
	Census Tract 410	2,411	82.5	135,000	1.07	6.68	0.49
	Census Tract 505	5,124	80.2	116,678	2.64	2.57	0.53
	Census Tract 502	3,069	80.0	114,688	0.00	1.14	0.35
Bottom Five	Census Tract 103	1,871	4.8%	$17,928	66.22%	52.92%	0.46
	Census Tract 202	4,200	7.8	17,602	72.93	62.10	0.48
	Census Tract 204	4,452	6.0	15,703	62.20	50.49	0.57
	Census Tract 710.04	2,059	1.7	15,632	64.44	50.90	0.53
	Census Tract 301	2,514	2.4	13,458	79.88	63.80	0.44
Loudoun County (Sorted by Income)							
Top Five	Census Tract 6110.29	5,458	70.43%	$250,001	1.48%	2.36%	0.41
	Census Tract 6112.08	4,846	77.99	250,001	0.43	0.68	0.44
	Census Tract 6110.09	5,390	74.60	245,515	2.28	2.86	0.31
	Census Tract 6110.28	6,537	76.50	243,750	0.26	2.80	0.28
	Census Tract 6119.02	5,598	83.41	227,778	0.38	2.36	0.28
Bottom Five	Census Tract 6110.18	3,151	53.94%	87,845	4.72%	0	0.38
	Census Tract 6106.03	3,802	48.10	75,848	2.37	5.75%	0.37
	Census Tract 6110.10	1,923	55.97	74,375	2.70	2.91	0.43
	Census Tract 6115.01	3,914	41.09	70,609	12.19	14.20	0.43
	Census Tract 6105.05	6,534	26.64	61,195	4.21	11.55	0.43
City of Norfolk (Sorted by Income)							
Top Five	Census Tract 23	2,172	83.88%	$115,250	11.37%	2.98%	0.45
	Census Tract 24	3,613	73.99	110,735	9.63	0	0.36
	Census Tract 22	1,634	65.88	106,852	2.76	0	0.44
	Census Tract 40.01	1,297	80.98	105,000	4.55	0	0.37
	Census Tract 21	1,338	54.54	98,160	8.37	1.37	0.57
Bottom Five	Census Tract 26	4,135	57.09%	$26,615	52.01%	17.39%	0.48
	Census Tract 43	3,502	19.64	22,656	34.67	35.55%	0.47
	Census Tract 42	1,385	5.67	13,685	60.66	75.27	0.49
	Census Tract 48	2,057	3.27	13,442	73.23	86.08	0.42
	Census Tract 41	2,054	3.53	11,581	74.83	59.29	0.48
Bedford County (Sorted by Income)							
Top Five	Census Tract 302.03	4,690	58.44%	$111,075	0.99%	0	0.34
	Census Tract 301.01	7,251	55.86	103,151	2.50	0.69%	0.38
	Census Tract 301.03	7,418	53.16	77,200	5.13	3.30	0.41
	Census Tract 305.04	2,836	27.71	72,617	4.52	8.40	0.44
	Census Tract 302.02	5,175	29.92	70,417	3.53	5.32	0.43
Bottom Five	Census Tract 305.01	4,201	10.53%	$54,141	9.57%	4.92%	0.31
	Census Tract 304.03	3,136	17.39	53,973	7.02	6.67	0.35
	Census Tract 304.01	3,292	24.63	53,021	7.62	1.01	0.41
	Census Tract 501.02	2,994	30.77	52,609	15.43	11.00	0.35
	Census Tract 501.01	3,313	4.45	33,523	32.36	28.32	0.44

In addition, the descriptive statistics of target variables for Phase 2 are presented. It is worth noting that due to the geographical differences between the county level and census-tract level, their descriptions are distinct. Census tracts offer a more granular view of the data, allowing for a detailed analysis of socioeconomic trends. The breakdown of the six target variables for Phase 2 is provided in Table 9, which offers a comprehensive overview of these variables within the selected major places, further enhancing the understanding of socioeconomic disparities at the census-tract level.

Table 9. Descriptive Analytics of Target Variables at the Census-Tract Level

Target Variables		Year						
		2015	2016	2017	2018	2019	2020	2021
Total Crash Rate (Total Crash per 1,000 People)	Minimum	0.11	0.19	0.17	0.11	0.14	0.14	0.12
	Maximum	101.88	97.82	113.68	114.86	94.87	68.49	100.63
	Average	12.19	12.55	12.2	12.26	12.12	9.75	10.86
	Median	9.37	9.54	8.82	8.96	8.82	6.88	7.77
	SD	11	11.39	11.38	11.8	11.54	9.44	10.91
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Fatal Crash Rate (Fatal Crash per 1,000 People)	Minimum	0	0	0	0	0	0	0
	Maximum	2.78	2.07	1.62	1.66	2.29	2.09	1.38
	Average	0.04	0.05	0.06	0.06	0.06	0.06	0.06
	Median	0	0	0	0	0	0	0
	SD	0.14	0.14	0.16	0.16	0.16	0.16	0.16
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Serious Injury Crash Rate (Serious Injury Crash per 1,000)	Minimum	0	0	0	0	0	0	0
	Maximum	5.74	6.37	9.1	9.05	10.8	11.07	8.29
	Average	0.66	0.68	0.59	0.58	0.6	0.57	0.63
	Median	0.4	0.43	0.33	0.28	0.31	0.26	0.29
	SD	0.83	0.82	0.81	0.88	0.89	1.01	1.01
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
People Injury Rate (People Injury Crash per 1,000)	Minimum	0	0	0	0	0	0	0
	Maximum	59.8	54.62	55.93	64.54	59.51	65.48	107.78
	Average	6.84	7.02	6.69	6.59	6.76	5.48	6.02
	Median	5.05	5.18	4.66	4.44	4.59	3.19	3.67
	SD	6.47	6.96	7.06	7.31	7.51	6.9	7.93
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Pedestrian Fatality Rate (Pedestrian Fatality per 1,000 People)	Minimum	0	0	0	0	0	0	0
	Maximum	0.7	0.69	0.58	0.95	1.32	0.84	0.79
	Average	0.01	0.01	0.01	0.01	0.02	0.01	0.02
	Median	0	0	0	0	0	0	0
	SD	0.05	0.06	0.06	0.08	0.08	0.06	0.07
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Pedestrian Injury Rate (Pedestrian Injury per 1,000	Minimum	0	0	0	0	0	0	0
	Maximum	8.14	6.4	4.09	5.39	4.43	3.45	4.43
	Average	0.28	0.26	0.24	0.25	0.25	0.18	0.21
	Median	0	0	0	0	0	0	0
	SD	0.6	0.5	0.41	0.46	0.47	0.33	0.38
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485

Note: All the results were crashes that occurred on non-interstate roads. SD = standard deviation.

Tables 7 and 9 showed that some target variables had rather skewed distributions, with minimum and median values equal to zero. To address this concern, this study standardized the independent variables, which should not introduce bias into the results. In fact, it may improve the interpretability of regression coefficients, as they represent the change in the dependent variable. Additionally, this study used fixed effects models, which do not necessarily assume a normal distribution in dependent variables.

Results of Cluster Analysis

As described in the Methods section, this study employed three different approaches. Hierarchical clustering using complete linkage indicated the presence of 3 clusters in Phase 1 and 4 clusters in Phase 2. On the other hand, hierarchical clustering with Ward's linkage resulted in 3 clusters for both Phase 1 and Phase 2. Utilizing the k-means algorithm led to the identification of 2 clusters in Phase 1 and 3 clusters in Phase 2. Taking into account the more concise results yielded by the k-means approach, it was selected for this study. To put it another way, the county-level analysis aimed to adopt a broader perspective, ultimately leading to the conclusion that two clusters would be more suitable for achieving this specific purpose. Meanwhile, the census-tract analysis aimed to uncover more intricate insights. Both the k-means and hierarchical clustering with Ward's linkage approaches consistently revealed that 3 clusters were predominant. In order to maintain consistency with Phase 1 and Phase 2, this study opted to proceed with the k-means algorithm.

Phase 1

Based on the majority rule, the results of the cluster analysis using k-means indicated the existence of two clusters, as illustrated in Figure 6. It is important to highlight that disadvantaged areas are represented by red, while advantaged areas are depicted in gray. By employing cluster analysis with the five socioeconomic variables, a comprehensive classification was performed, resulting in a total of 70 counties/cities being assigned to the disadvantaged group, and 63 counties/cities to the advantaged group. For a more in-depth understanding of the classification process, Appendix D (i.e., Detailed Results of Cluster Analysis at the County Level) offers detailed information on the categorization of each locality, providing valuable insights.

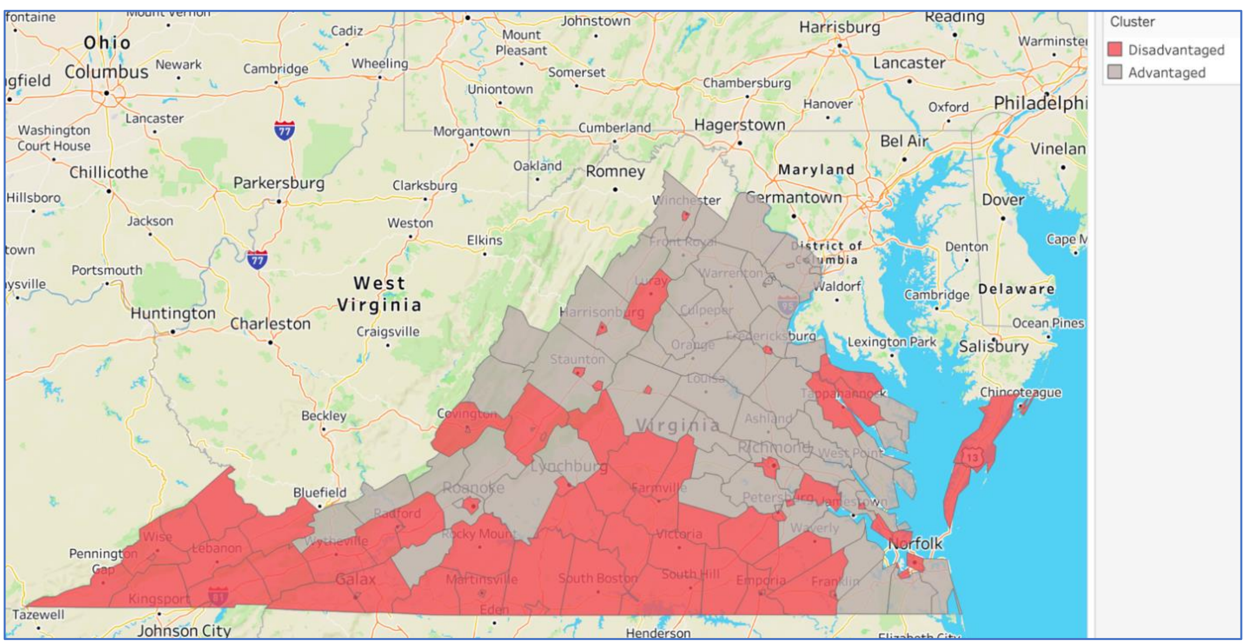

Figure 6. Cluster Analysis Results at the County Level

Phase 2

Continuing in the same vein, the census-tract analysis was conducted using the unsupervised machine learning technique. This analysis resulted in the generation of three clusters, as illustrated in Figure 7. It is noteworthy that the cluster in red represents disadvantaged areas, the cluster in gray advantaged areas, and the cluster in green highlights the intermediate areas. Figure 7 encompasses all of Virginia’s census tracts. For a more targeted investigation, Figures 8-11 showcase the results of the cluster analysis within the specific research scope areas. Given the extensive nature of the results, a detailed breakdown is provided as supplemental materials. These additional materials examine the specific composition and characteristics of each cluster within the census-tract analysis.

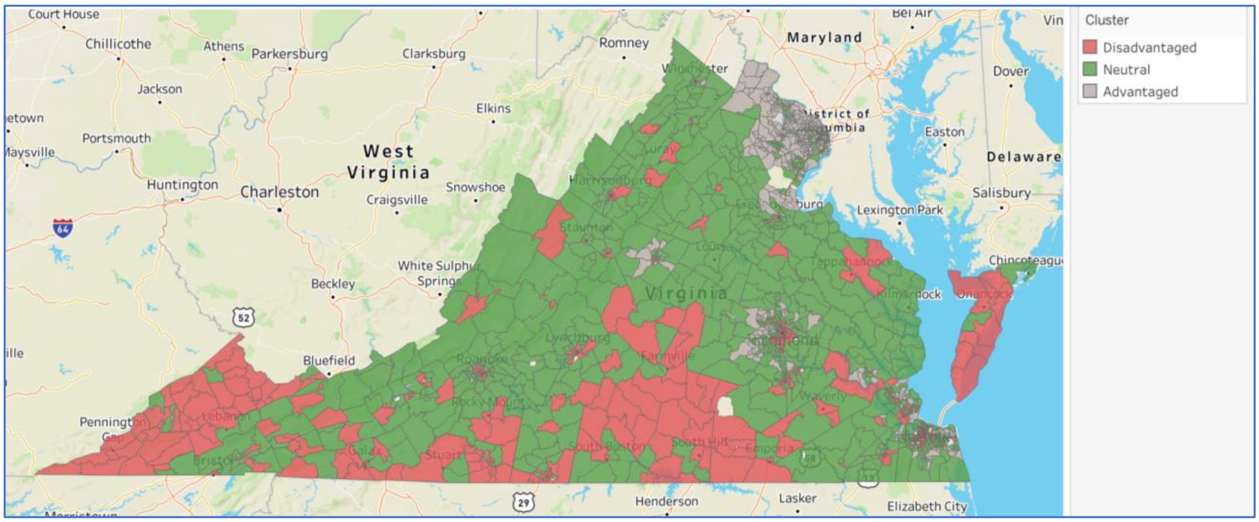

Figure 7. Cluster Analysis Results with All Census Tracts in Virginia. The cluster in red represents disadvantaged areas, the cluster in gray represents advantaged areas, and the cluster in green highlights the intermediate areas.

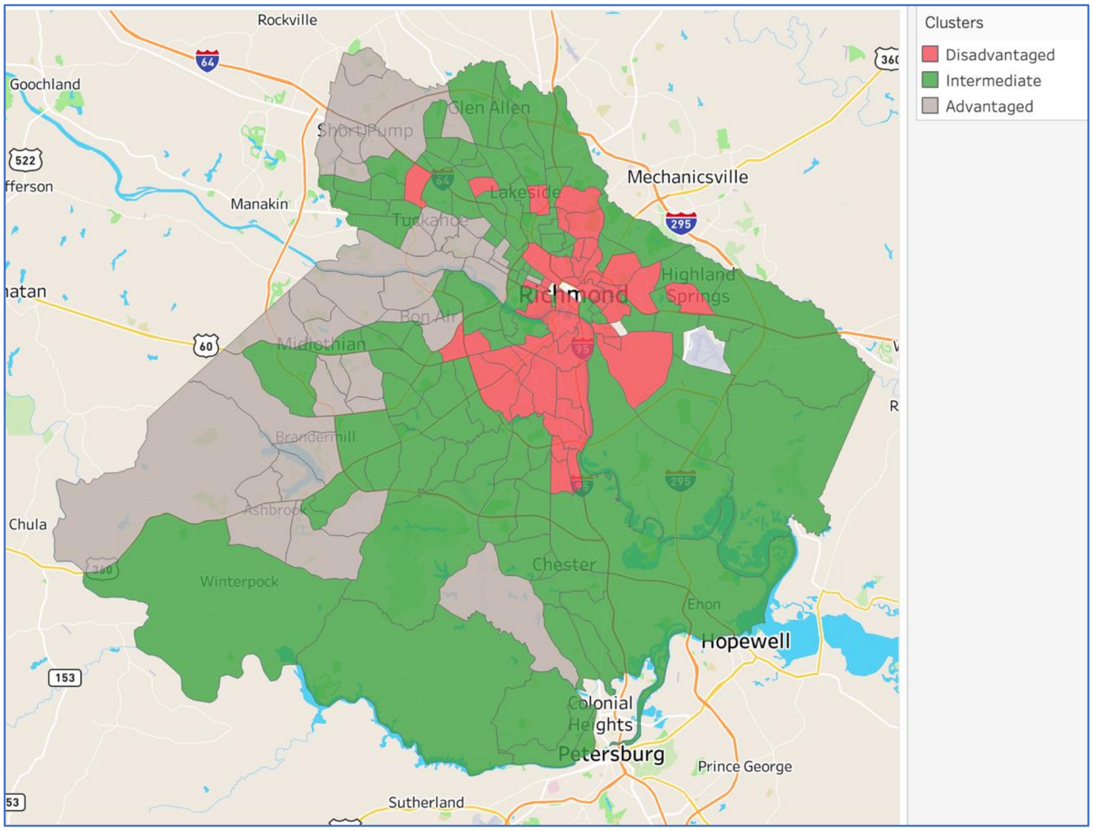

Figure 8. Cluster Analysis Results in the Richmond Area

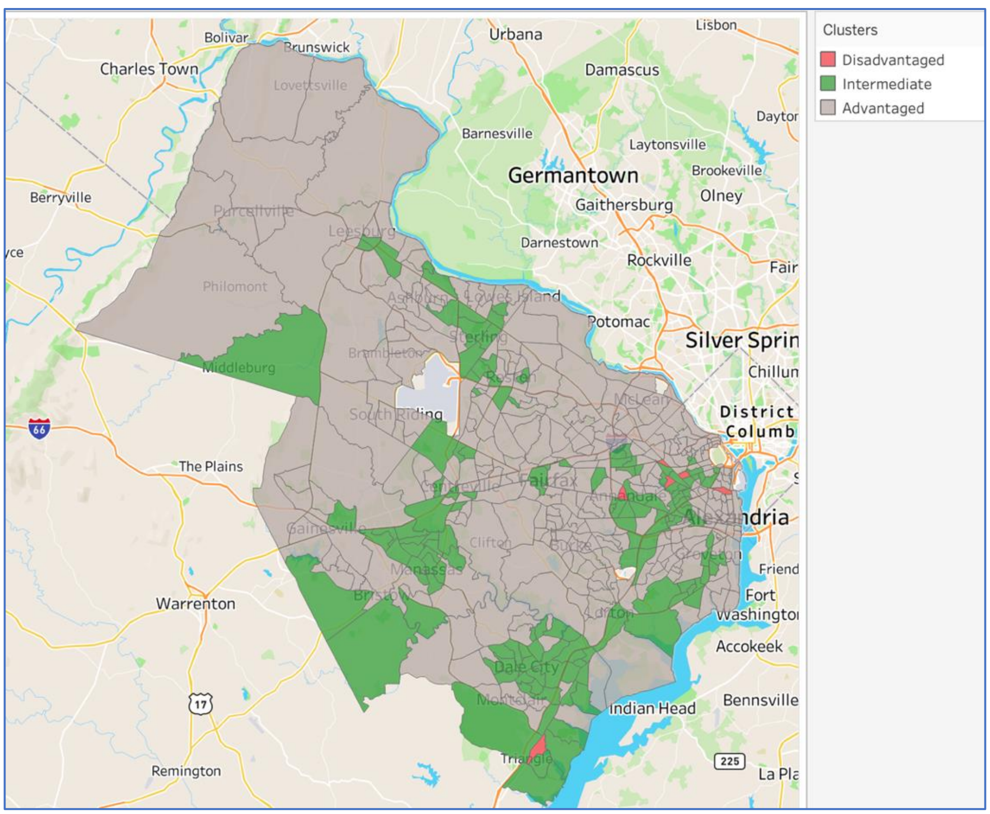

Figure 9. Cluster Analysis Results in the NOVA District

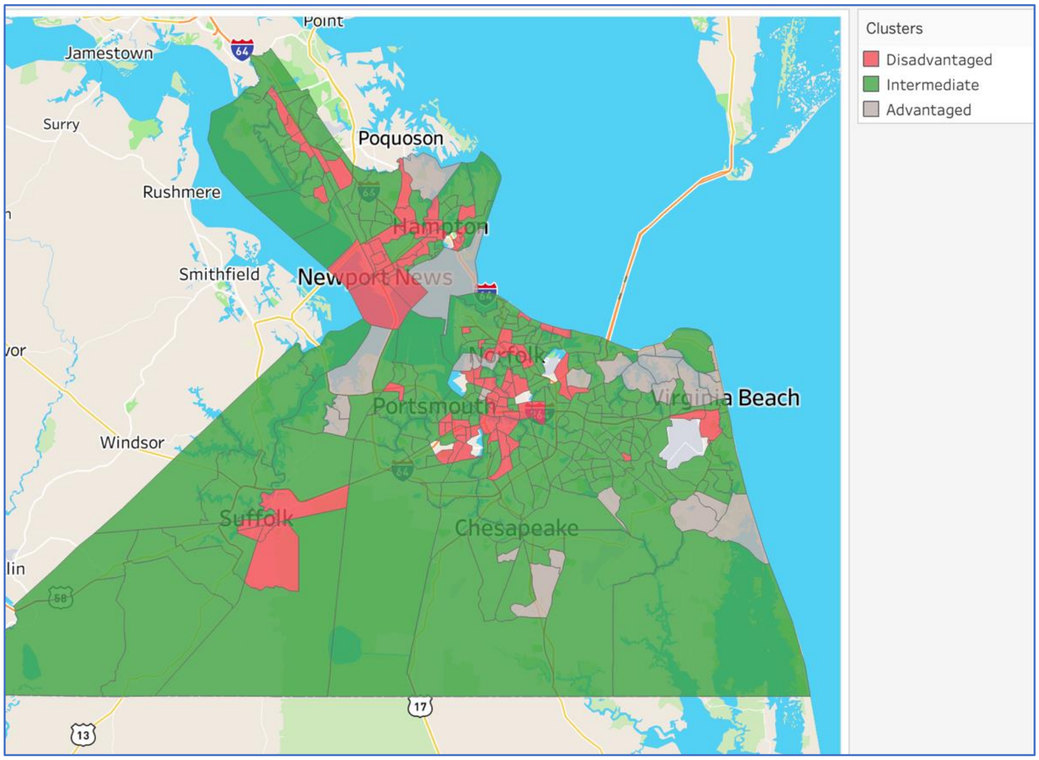

Figure 10. Cluster Analysis Results in the Hampton Roads Area

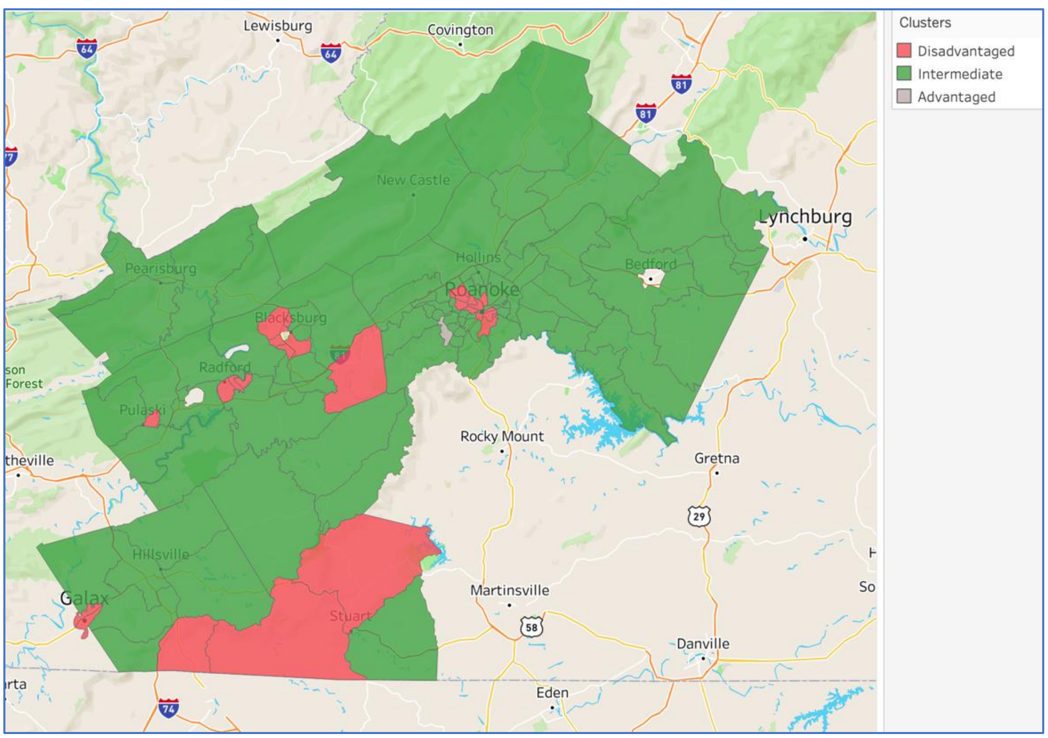

Figure 11. Cluster Analysis Results in the Salem District

As a result of the cluster analysis, 212 census tracts were identified as disadvantaged areas (cluster 1) while 535 census tracts were categorized as advantaged areas (cluster 3). Additionally, 738 census tracts (cluster 2) were placed in the intermediate areas. The descriptive analytics of these areas using boxplots are shown in Figures 12-16.

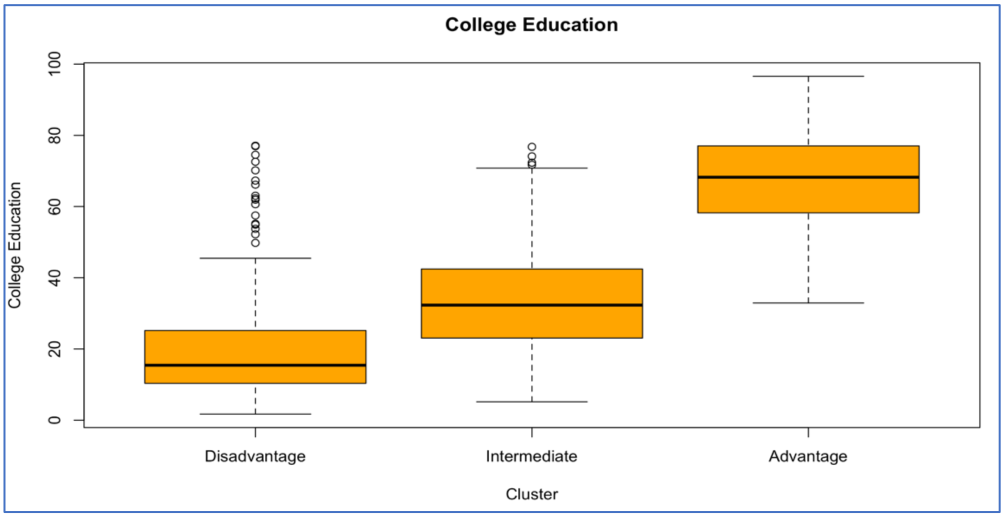

Figure 12. Boxplots for College Education at the Census-Tract Level

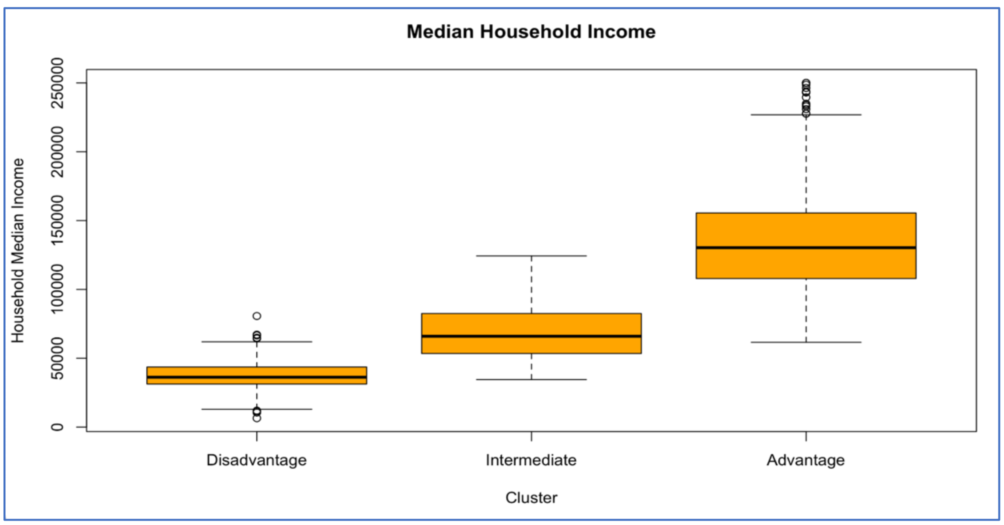

Figure 13. Boxplots for Median Household Income at the Census-Tract Level

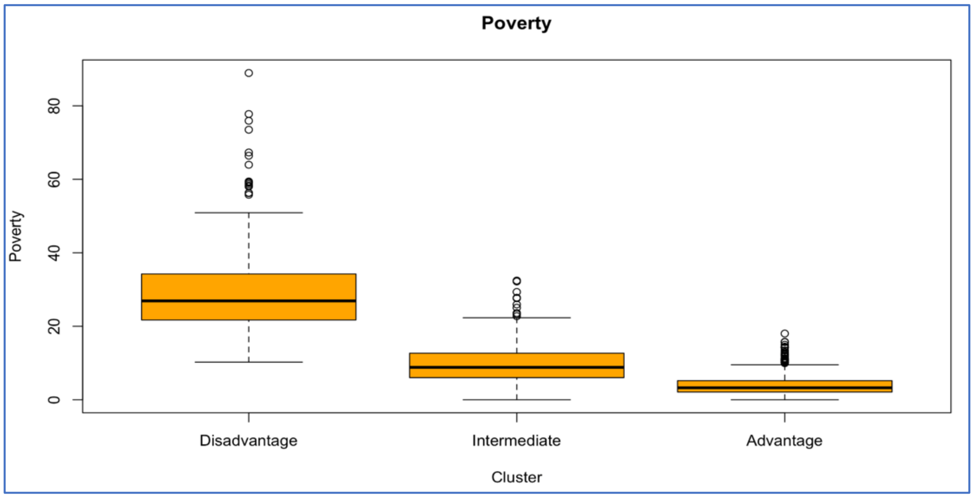

Figure 14. Boxplots for Poverty at the Census-Tract Level

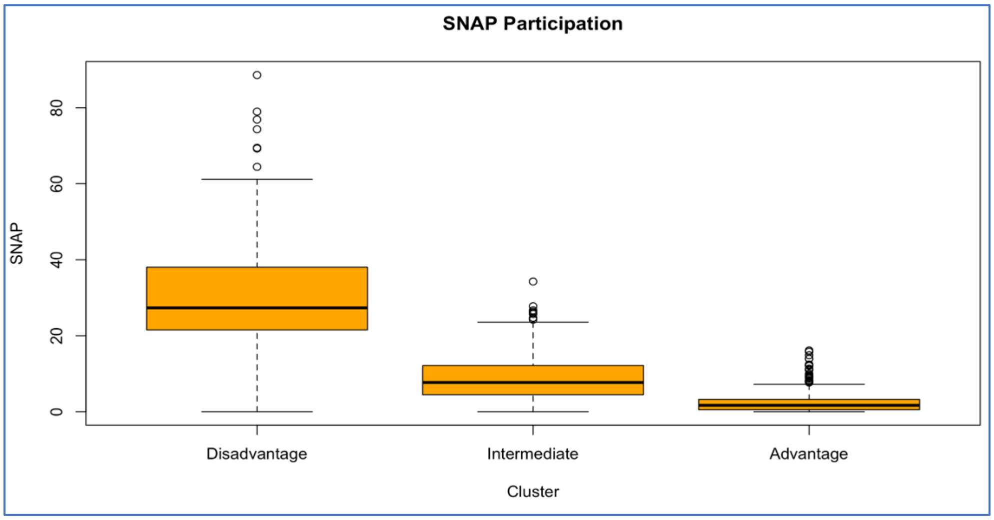

Figure 15. Boxplots for SNAP Participation Rate at the Census-Tract Level

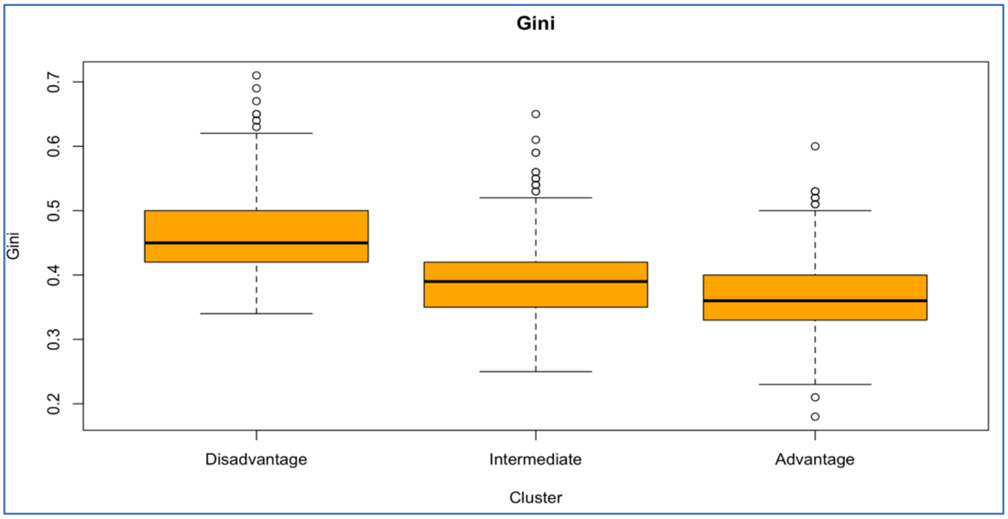

Figure 16. Boxplots for the Gini Index at the Census-Tract Level

Results of Longitudinal Data Analysis

Total Crash Rate

Before delving into an explanation of the six traffic crash measure results, it is appropriate to outline the structure of the longitudinal test findings. First, each crash measure at the county level (i.e., Phase 1) and at the census-tract level (i.e., Phase 2) was sequentially examined. Additionally, fixed effects regression was conducted for Phase 1, both with and without education as a variable, and denoted as Model 1 and Model 2, respectively. As mentioned earlier, the education variable yielded conflicting results, thus presenting the results without the variable provided more accurate insights. For readability in Tables 10-15, significant results with different colors were added to the detailed results, using green for supporting results and orange for conflicting (non-intuitive) results,

For Phase 2, the results were analyzed based on four different roads (i.e., all non-interstate roads, secondary roads only, rural roads only, and urban roads only). This approach aimed to facilitate a more precise understanding of the impacts of SES. Following detailed results, significant results were presented only to allow for a quick overview of the impacts. Following the individual explanation of the results of the six traffic crash measures, the Discussion section provides more comprehensive implications, focusing primarily on the impact of SES on traffic crashes in Virginia.

Total Crash Rate at the County Level

Table 10 presents the longitudinal test results of the total crash rate at the county level. It is noteworthy that median household income ($\beta = -2.62, p < 0.01\ for\ Model\ 1$; $\beta = -1.39, p < 0.01\ for\ Model\ 2$) had a negative influence on the total crash rate across the two models. In other words, localities with higher incomes had lower total crash rates, indicating socioeconomic disparities. Additionally, the SNAP participation rate ($\beta = 0.73, p < 0.01\ for\ Model\ 1$; $\beta = 0.65, p < 0.01\ for\ Model\ 2$) had a positive influence on the target variable, implying that poorer counties had higher car crash rates. While poverty rate showed statistical insignificance, the Gini index ($\beta = 0.31, p < 0.05\ for\ Model\ 2$) had a positive impact on the total crash rate. Taken together, the total crash rate on Virginia roads suffered from socioeconomic disparities based on the SES criteria at the county level.

As mentioned above, Table 10 illustrates the conflicting results that education ($\beta = 2.41, p < 0.01\ for\ Model\ 1$) had a significant and positive impact on the total crash rate. In other words, localities with a higher proportion of people with college degrees and above had higher traffic crash rates. It is known that an area with a higher number of residents who have college degrees may have higher incomes. Therefore, education and income may have similar impacts on target variables in SES studies. The statistical results of this study, however, showed conflicting results. It should be noted that the variance inflation factors (VIF) of all variables were less than 7.03, indicating no concern of multicollinearity. Accordingly, this study tested the impact of socioeconomic factors without education, as shown in Table 10, to gain insights into socioeconomic influences in the empirical results. In general, decreasing median household income ($\beta = -1.39, p < 0.01\ for\ Model\ 2$), increasing SNAP participation rate ($\beta =$

$0.65, p < 0.05$ *for Model* 2), and increasing Gini index ($\beta = 0.31, p < 0.05$ *for Model* 2) showed significant and positive impacts on the total crash rate.

The coefficients of time (Wave) showed negative influences across models, indicating that total crash rates decreased between 2013 and 2020 at the county level. However, the benefits were not evenly distributed among all areas. Localities with lower median household incomes and higher SNAP participation rates recorded more traffic crashes, implying the presence of socioeconomic disparities with regard to Virginia roads. Although education showed positive impacts in Table 10, the multitude of coefficients showed that income had a stronger impact on total crash rates. In the category of healthcare access, the number of primary care physicians and preventable hospital stays were insignificant in explaining the variance in the total crash rate. Interestingly, the uninsured variable (the percentage of people without health insurance) showed statistically negative impacts on the total crash rate. This seems to be likely correlated with income and SNAP participation rate.

Table 10. Detailed and Significant Results of the Total Crash Rate at the County Level

Response Variable: Total Crash Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	2.41**			Education	2.41**	
	Income	-2.62**	-1.39**		Income	-2.62**	-1.39**
	Poverty	-0.13	-0.10		Poverty		
	SNAP	0.73**	0.65*		SNAP	0.73**	0.65*
	Gini	0.09	0.31*		Gini		0.31*
Time	Wave	-0.39**	-0.40**		Wave	-0.39**	-0.40**
Access to Healthcare	Uninsured	-1.06**	-1.06**		Uninsured	-1.06**	-1.06**
	PCP	0.24	0.27		PCP		
	PHS	-0.06	-0.12		PHS		
VMT	DVMT_S	2.35**	2.40**				
	DVMT_P	2.03**	1.91**				
	DVMT_I	3.33**	3.43**				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	4871.17	4896.20				
	BIC	4945.71	4965.77				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. p < 0.05; ** p < 0.01.

Total Crash Rate at the Census-Tract Level

Tables 11 and 12 show the longitudinal results of the total crash rate at the census-tract level. In general, education and median household income had statistically significant and negative coefficients, indicating socioeconomic inequality on different types of roads in Virginia. For example, median household income ($\beta = -1.28, p < 0.01$) on all non-interstate roads and education ($\beta = -0.011, p < 0.01$) on the secondary roads only were statistically significant and negative. In other words, localities with higher income and education exhibited lower crash rates.

Evidence of socioeconomic inequality was also found with the zero-vehicle variable $(\beta = 0.005, p < 0.05; \beta = 0.49, p < 0.01)$. The coefficients were statistically positive, implying higher crash rates in localities with a higher proportion of households without a vehicle. The absence of a vehicle is associated with poverty, and it highlights another aspect of socioeconomic inequality.

With regard to trends in the total crash rate, secondary roads only $(\beta = 0.002, p < 0.01)$ and rural roads only $(\beta = 0.17, p < 0.01)$ had an increasing pattern of crash rates. In terms of race, there were no observed socioeconomic disparities. More populated areas $(for\ example, \beta = -2.82, p < 0.01\ for\ all\ non-highway\ roads)$ had lower car crash rates. It could be that people traveled shorter distances in their cars, crashes happened in congestion and were not reported to the police because they were property damage only and below damage thresholds for reportable crashes, or travel speeds were lower due to greater density of access to property.

Regarding SES variables for Phases 1 and 2, it seems that household median income is a significant factor influencing the total crash rate. While the overall county-level total crash rate has decreased, a notable increasing trend has been observed at the census-tract level, especially on secondary and rural roads.

Table 11. Detailed Results of the Total Crash Rate at the Census-Tract Level

Response Variable: Total Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	0.30	-0.011**	-1.23**	0.04
	Income	-1.28**	0.001	-0.19	-1.86**
	Poverty	-0.17	-0.006*	-0.25	-0.39*
	SNAP	-0.09	0.001	0.27	-0.27
	Gini	-0.42*	0.001	-0.16	0.04
Time	Wave	0.02	0.002**	0.17**	-0.02
COVID-19	COVID-19	-2.04**	-0.007*	-1.34**	-1.79**
Automobile Ownership	ZeroVeh	0.03	0.005*	-0.13	0.49**
	TwoMoreVeh	-2.46**	0.003	0.02	-0.76**
Race	Black	0.29	-0.003	-0.95**	-0.37
	Asian	-0.42*	-0.002	0.03	-0.49**
	Hispanic/Latino	-0.40	-0.003*	0.04	-0.29*
Population Density	PopDensity	-2.82**	-0.003	-1.55**	-2.55**
Locality – Fixed Effects		Y	Y	Y	Y
Model Fit	AIC	45677.77	-15999.22	3323.19	46518.39
	BIC	45789.7	-15887.49	3396.35	46629.84
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* p < 0.05; ** p < 0.01.

Table 12. Significant Results of the Total Crash Rate at the Census-Tract Level

Response Variable: Total Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education		-0.011**	-1.23**	
	Income	-1.28**			-1.86**
	Poverty		-0.006*		-0.39*
	SNAP				
	Gini	-0.42*			
Time	Wave		0.002**	0.17**	
COVID-19	COVID-19	-2.04**	-0.007*	-1.34**	-1.79**
Automobile Ownership	ZeroVeh		0.005*		0.49**
	TwoMoreVeh	-2.46**			-0.76**
Race	Black			-0.95**	
	Asian	-0.42*			-0.49**
	Hispanic/Latino		-0.003*		-0.29*
Population Density	PopDensity	-2.82**		-1.55**	-2.55**

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Fatal Crash Rate

Fatal Crash Rate at the County Level

The fatal crash rate, a critical indicator of road safety, involves crashes that result in the loss of human life. It is essential for traffic safety analysts to closely examine the factors that contribute to the fatal crash rate to develop effective prevention strategies. As shown in Table 13, in the analysis with education, education ($\beta = -0.02, p < 0.05\ for\ Model\ 1$) had a significant and negative effect on the fatal crash rate, implying that localities with a higher level of college graduates and above showed lower fatal crash rates. No other socioeconomic variable had an impact on fatal crash rates. In the analysis without education, median household income ($\beta = -0.02, p < 0.01\ for\ Model\ 2$) had a significant and negative impact on fatal crash rates. The response variable showed that the fatal crash rate increased in recent years slightly, particularly in the analysis without education, as shown in Wave ($\beta = 0.005, p < 0.05\ for\ Model\ 2$). Harper et al. (2015) reported that the biggest declines in traffic fatalities occurred among the most educated portion of the population, based on data from 1995 to 2010. This study demonstrated that this trend was reflected in Virginia based on county-level data from 2013 to 2020. With regard to access to healthcare, the percentage of people without health insurance ($\beta = 0.01, p < 0.05\ for\ Model\ 2$) had a positive impact on fatal crash rates only in the analysis without education.

Table 13. Detailed and Significant Results of the Fatal Crash Rate at the County Level

Response Variable: Fatal Crash Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	-0.02*			Education	-0.02*	
	Income	0.00	-0.02**		Income		-0.02**
	Poverty	0.00	-0.01		Poverty		
	SNAP	-0.01	0.00		SNAP		
	Gini	0.00	-0.01		Gini		
Time	Wave	0.003	0.005*		Wave		0.005*
Access to Healthcare	Uninsured	0.01	0.01*		Uninsured		0.01*
	PCP	-0.01	-0.01*		PCP		-0.01*
	PHS	0.00	0.00		PHS		
VMT	DVMT_S	0.01**	0.02**				
	DVMT_P	0.04**	0.04**				
	DVMT_I	0.02**	0.03**				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	-2056.40	-2052.46				
	BIC	-1981.85	-1982.89				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Fatal Crash Rate at the Census-Tract Level

Consistent with the county-level analysis, education was a major contributing factor in the fatal crash rate for all different road types, as shown in Tables 14 and 15. For instance, the beta coefficient ($\beta = -0.03, p < 0.05$) was statistically significant and negative on all non-interstate roads. In other words, census tracts with a higher proportion of people with college degrees or higher exhibited a lower fatal crash rate. Unfortunately, the fatal crash rate increased from 2015 to 2021 in nearly all road types. The coefficient ($\beta = 0.002, p < 0.01$) was positive on secondary roads only. The number of fatalities is not simply numbers but represents the lives of families. Interestingly, the impact of COVID-19 did not decrease the fatality rate. Despite the widespread assumption that the COVID-19 pandemic would lead to a reduction in traffic-related fatalities, it was surprising to find that the fatality rate remained unaffected during this period. The variables fatal crash rate did not reveal any other systematic socioeconomic patterns.

Table 14. Detailed Results of the Fatal Crash Rate at the Census-Tract Level

Response Variable: Fatal Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.03**	0.08	-0.03*	-0.02**
	Income	0.00	-1.00**	0.00	0.00
	Poverty	0.00	-0.31**	0.02	-0.01*
	SNAP	0.00	-0.7*	-0.01	0.00
	Gini	0.00	-0.02	0.00	0.00
Time	Wave	0.004**	-0.04	0.00	0.004**
COVID-19	Covid Dummy	0.00	-0.95**	0.01	-0.01
Automobile Ownership	ZeroVeh	0.00	0.11	-0.03**	0.01
	TwoMoreVeh	-0.01	-0.39**	0.01	-0.01*
Race	Black	-0.01**	0.18	-0.01	0.00
	Asian	-0.01**	-0.08	0.00	0.00
	Hispanic/Latino	-0.01**	0.02	-0.02	0.00
Population Density	PopDensity	-0.01**	-1.21**	-0.02	-0.01**
Locality – Fixed Effects		Y	Y	Y	Y
Model Fit	AIC	-7762.70	38432.16	-513.66	-8007.01
	BIC	-7650.77	38543.9	-440.50	-7895.56
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* p < 0.05; ** p < 0.01.

Table 15. Significant Results of the Fatal Crash Rate at the Census-Tract Level

Response Variable: Fatal Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.03*	-0.011**	-0.03*	-0.02**
	Income				
	Poverty		-0.006*		-0.01*
	SNAP				
	Gini				
Time	Wave	0.004**	0.002**		0.004**
COVID-19	COVID-19				
Automobile Ownership	ZeroVeh		0.005*	-0.03**	
	TwoMoreVeh				-0.01*
Race	Black	-0.01**			
	Asian	-0.01**			
	Hispanic	-0.01**	-0.003*		
Population Density	PopDensity	-0.01**			-0.01**

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

It is noteworthy that the fatal crash rates have shown a general increase, both at the county level and within census tracts. Furthermore, education plays a critical role in reducing the fatal crash rate at both of these levels.

Serious Injury Crash Rate

Crashes resulting in serious injuries have a more significant and long-lasting impact on the individuals involved, as compared to those with minor injuries. The cost of treating serious injuries can be substantial, placing a considerable financial strain on healthcare systems and causing financial hardships for those affected. The ripple effects of serious injuries extend beyond the immediate victims, impacting their social circles and communities through lost productivity and emotional distress. As such, in the context of road safety initiatives, preventing serious injuries is a paramount concern, potentially saving lives and reducing the overall societal impact.

Serious Injury Crash Rate at the County Level

Among the SES variables, median household income ($\beta = -0.23, p < 0.05\ for\ Model\ 1;\ \beta = -0.20, p < 0.05\ for\ Model\ 2$) had statistically significant and negative impacts on the serious injury crash rate, as shown in Table 16. It implies that counties with higher incomes had lower serious injury crash rates. However, there were conflicting results regarding the impact of the SNAP participation rate on the serious injury crash rate among the SES variables. Furthermore, the analysis revealed that the serious injury crash rate has decreased in recent years, as indicated by the time variable ($\beta = -0.02, p < 0.05\ for\ Model\ 2$). In terms of access to healthcare, none of the variables related to healthcare had significant effects on the serious injury crash rate.

Table 16. Significant Results of the Serious Injury Crash Rate at the County Level

Response Variable: Serious Injury Crash Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	0.04			Education		
	Income	-0.23*	-0.20*		Income	-0.23*	-0.20*
	Poverty	-0.02	-0.01		Poverty		
	SNAP	-0.1*	-0.11*		SNAP	-0.1*	-0.11*
	Gini	-0.06	-0.05		Gini		
Time	Wave	-0.02	-0.02*		Wave		-0.02*
Access to Healthcare	Uninsured	0.02	0.02		Uninsured		
	PCP	-0.02	-0.01		PCP		
	PHS	0.05	0.05		PHS		
VMT	DVMT_S	0.14*	0.14*				
	DVMT_P	0.25*	0.25*				
	DVMT_I	0.18*	0.18*				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	1554.16	1552.53				
	BIC	1628.71	1622.11				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Serious Injury Crash Rate at the Census-Tract Level

Following the county analysis, the census-tract analysis provided more nuanced insights into the serious injury crash rate. As demonstrated in Tables 17 and 18, education, similar to the county-level analysis, exhibited a negative impact on the serious injury crash rate across all different types of roads. For example, consider the impact of education ($\beta = -0.23, p < 0.01$) on all-but-interstate roads. This implies that census-tract areas with higher levels of education experienced lower serious injury crash rates, highlighting the presence of socioeconomic disparities. Notably, the analysis revealed no conflicting results among SES variables. Consistent with the county-level findings, the analysis showed a general decrease in the serious injury crash rate in recent years. Furthermore, similar to other analyses, households with a higher number of vehicles and densely populated areas displayed lower rates of serious injury crashes. With regard to race in the context of road safety, census tracts with a higher proportion of Black residents showed an increase in serious injury crash rate on secondary roads ($\beta = 0.04, p < 0.01$) and urban roads ($\beta = 0.12, p < 0.01$). Additionally, the statistical analysis revealed a correlation between increases in the Hispanic population and lower rates of serious injury crashes across all road types (for example, on secondary roads ($\beta = -0.04, p < 0.01$)).

Table 17. Detailed Results of the Serious Injury Crash Rate at the Census-Tract Level

Response Variable: Serious Injury Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.23**	-0.09**	-0.30**	-0.12**
	Income	0.04	0.01	-0.02	0.00
	Poverty	0.01	0.00	0.07	-0.01
	SNAP	0.01	-0.02	0.02	-0.01
	Gini	0.01	0.00	-0.04	0.00
Time	Wave	-0.02**	-0.01*	-0.01	-0.02**
COVID-19	Covid Dummy	0.04	0.002	0.02	0.05
Automobile Ownership	ZeroVeh	0.01	0.02	-0.02	0.03
	TwoMoreVeh	-0.14**	-0.05**	0.10	-0.15**
Race	Black	0.03	0.04**	-0.11**	0.12**
	Asian	-0.04*	0.00	0.02	-0.02
	Hispanic/Latino	-0.11**	-0.04**	-0.08**	-0.04**
Population Density	PopDensity	-0.14**	-0.06**	-0.12**	-0.15**
Locality – Fixed Effects		Y	Y	Y	Y
Model Fit	AIC	16511.87	9377.66	1397.75	16059.73
	BIC	16623.8	9489.39	1470.91	16171.18
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* p < 0.05; ** p < 0.01.

Table 18. Significant Results of the Serious Injury Crash Rate at the Census-Tract Level

RV: Serious Injury Crash Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.23**	-0.09**	-0.30**	-0.12**
	Income				
	Poverty				
	SNAP				
	Gini				
Time	Wave	-0.02**	-0.01*		-0.02**
COVID-19	COVID-19				
Automobile Ownership	ZeroVeh				
	TwoMoreVeh	-0.14**	-0.05**		-0.15**
Race	Black		0.04**	-0.11**	0.12**
	Asian	-0.04*			
	Hispanic	-0.11**	-0.04**	-0.08**	-0.04**
Population Density	PopDensity	-0.14**	-0.06**	-0.12**	-0.15**

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

The analysis conducted at the county level revealed that household median income stands as a significant variable, contributing to the reduction of serious injury crash rates in both of the employed models. On a more localized scale, within census tracts, education emerged as a key variable affecting serious injury crash rates across all types of roads. These findings highlight the multifaceted nature of factors influencing road safety and point to the importance of tailoring interventions based on specific geographic contexts.

People Injury Rate

A single collision has the potential to cause injuries to multiple individuals, and analyzing the number of people injured in crashes can be an important factor in understanding socioeconomic disparities. Certain areas and populations may be disproportionately affected by higher injury rates. This knowledge can guide efforts to address these inequalities and promote equitable road safety outcomes.

People Injury Rate at the County Level

The fixed effects regression analysis revealed similar patterns in the total crash rate. As shown in Table 19, over time the people injury rate decreased ($\beta = -0.23, p < 0.01\ for\ Model\ 1;\ \beta = -0.26, p < 0.01\ for\ Model\ 2$). However, significant socioeconomic disparities exist, particularly as indicated by median household income ($\beta = -2.18, p < 0.01\ for\ Model\ 1;\ \beta = -0.98, p < 0.01\ for\ Model\ 2$). Although the results for education ($\beta = 2.02, p < 0.01\ for\ Model\ 1$) presented conflicting findings, the magnitude of the coefficients suggested that income had a greater impact on the people injury rate. Furthermore, when excluding the education variable from Model 1, the impact of income on the people injury rate became more evident, highlighting income as the sole variable to influence the people injury rate. As for access to healthcare, the uninsured rate ($\beta = -0.54, p < 0.01\ for\ Model\ 1;\ \beta = -0.56, p < 0.01\ for\ Model\ 2$) displayed a negative association with the injured people rate.

Table 19. Detailed and Significant Results of the People Injury Rate at the County Level

Response Variable: People Injury Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	2.02**			Education	2.02**	
	Income	-2.18**	-0.98**		Income	-2.18**	-0.98**
	Poverty	-0.03	0.04		Poverty		
	SNAP	0.04	-0.06		SNAP		
	Gini	-0.25	-0.04		Gini		
Time	Wave	-0.23**	-0.26**		Wave	-0.23**	-0.26**
Access to Healthcare	Uninsured	-0.54**	-0.56**		Uninsured	-0.54**	-0.56**
	PCP	0.02	0.09		PCP		
	PHS	-0.02	-0.10		PHS		
VMT	DVMT_S	1.07**	0.98**				
	DVMT_P	0.88**	0.69*				
	DVMT_I	1.05**	0.97**				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	4617.40	4643.33				
	BIC	4691.95	4712.90				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

People Injury Rate at the Census-Tract Level

The census-tract analysis provides a more sophisticated understanding of the impact of SES and injuries. The analysis revealed significant and negative impacts from education and income on the overall people injury rate, as depicted in Tables 20 and 21. For instance, in the case of secondary roads, areas with higher medium household incomes ($\beta = -0.42, p < 0.01$) exhibited a decrease in the people injury rate. Furthermore, specifically on rural roads, census tracts with a higher level of education ($\beta = -0.71, p < 0.01$) demonstrated lower rates in people injury. Moreover, the study also examined the effects of automobile ownership and population density, which yielded similar results. With regard to race and road safety, notable findings emerged, indicating that neighborhoods with a higher proportion of Black population experienced higher rates of people injuries across three different road types: (1) all-but-interstate roads ($\beta = 0.81, p < 0.01$), (2) secondary roads only ($\beta = 0.56, p < 0.01$),and (3) urban roads only ($\beta = 0.65, p < 0.01$).

Table 20. Detailed Results of the People Injury Rate at the Census-Tract Level

Response Variable: People Injury Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.33	-0.01	-0.71*	-0.23
	Income	-0.52	-0.43**	-0.12	-0.80**
	Poverty	0.08	-0.11	0.16	-0.11
	SNAP	0.07	0.01	0.02	-0.12
	Gini	-0.16	0.02	-0.13	0.07
Time	Wave	-0.02	-0.02	-0.02	-0.03
COVID-19	Covid Dummy	-0.93**	-0.46**	-0.60**	-0.82**
Automobile Ownership	ZeroVeh	0.02	-0.08	-0.10	0.16
	TwoMoreVeh	-1.58**	-0.39**	0.33*	-0.99**
Race	Black	0.81**	0.56**	-0.39*	0.65**
	Asian	-0.15	0.045	0.15	-0.19
	Hispanic/Latino	-0.18	0.082	-0.04	-0.02
Population Density	PopDensity	-1.64**	-0.651**	-0.79**	-1.54**
Locality – Fixed Effects		Y	Y	Y	Y
Model Fit	AIC	43419.05	35637.52	2872.20	43189.22
	BIC	43530.98	35749.25	2945.36	43300.67
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* $p < 0.05$; ** $p < 0.01$.

Table 21. Significant Results of the People Injury Rate at the Census-Tract Level

Response Variable: People Injury Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education			-0.71**	
	Income		-0.43**		-0.80**
	Poverty				
	SNAP				
	Gini				
Time	Wave				
COVID-19	COVID-19	-0.93**	-0.46**	-0.60**	-0.82**
Automobile Ownership	ZeroVeh				
	TwoMoreVeh	-1.58**	-0.39**	0.33*	-0.99**
Race	Black	0.81**	0.56**	-0.39*	0.65**
	Asian				
	Hispanic				
Population Density	PopDensity	-1.64**	-0.65**	-0.79**	-1.54**

Green indicates supporting results while orange implies conflicting results. * $p < 0.05$; ** $p < 0.01$.

The results indicate that the people's injury rate generally had household median income as a variable, aiming to decrease the variable at both the county and census-tract levels. However, this approach was not applied uniformly across all cases, warranting careful consideration. Additionally, while the people's injury rate has decreased at the county level, there was no statistical significance observed for the census-tract level.

Pedestrian Fatality Rate

The following two response variables underscore the significance of pedestrians as vulnerable road users in traffic crashes. Vulnerable road users encompass individuals who face a greater risk of injury and fatality when involved in traffic crashes, primarily due to their lack of protection in comparison to occupants of motor vehicles. In light of the importance of pedestrian safety and the aim of addressing socioeconomic disparities within this context, this study investigated the impact of SES on road safety in Virginia. By examining the relationship between SES and pedestrian-related incidents, VDOT can gain insights into how socioeconomic factors might influence the occurrence and severity of such crashes.

Pedestrian Fatality Rate at the County Level

As highlighted in Table 22, education ($\beta = 0.007, p < 0.01\ for\ Model\ 1$) demonstrated a significant and positive impact on the pedestrian fatality rate. In simpler terms, counties with higher levels of education exhibited higher pedestrian fatality rates. It should be noted that the analysis was conducted while including the education variable, and it is different from the results of other response variables. However, socioeconomic inequality was evident by the SNAP participation rate ($\beta = 0.006, p < 0.01\ for\ Model\ 1$; $\beta = 0.004, p < 0.01\ for\ Model\ 2$) in both models. By combining these two results, it could be suggested that higher pedestrian fatality rates were observed in both affluent and disadvantaged neighborhoods. In regard to access to healthcare, the percentage of people without health insurance ($\beta = 0.002, p < 0.05\ for\ Model\ 1$; $\beta = 0.002, p < 0.05\ for\ Model\ 2$) exhibited significant and positive impacts. In other words, counites with a higher percentage of individuals lacking health insurance displayed higher pedestrian fatality rates. These findings align with a previous study that suggested pedestrian fatalities were more prevalent in disadvantaged communities (DACs) (Badger and Ingraham 2015). Therefore, the results obtained in the present study, based on the criterion of SNAP participation rates, are consistent with existing literature regarding Virginia roads.

Table 22. Detailed Results of the Pedestrian Fatality Rate at the County Level

Response Variable: Pedestrian Fatality Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	0.007**			Education	0.007**	
	Income	-0.003	0.003		Income		
	Poverty	-0.003	0.000		Poverty		
	SNAP	0.006**	0.004**		SNAP	0.006**	0.004**
	Gini	-0.002	0.000		Gini		
Time	Wave	0.001*	0.001		Wave	0.001*	
Access to Healthcare	Uninsured	0.002*	0.002*		Uninsured	0.002*	0.002*
	PCP	-0.001	-0.001		PCP		
	PHS	0.000	0.000		PHS		
VMT	DVMT_S	0.001	0.001				
	DVMT_P	0.003**	0.003**				
	DVMT_I	0.004**	0.004**				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	-4604.54	-4604.54				
	BIC	-4529.99	-4529.99				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Pedestrian Fatality Rate at the Census-Tract Level

With regard to the impact of SES on the pedestrian fatality rate at the census tract level, no significant variables were found across all different road types at the census-tract level. However, a slight increase in this pedestrian fatality rate was observed on all-but-interstate roads ($\beta = 0.002, p < 0.01$) and on urban roads ($\beta = 0.002, p < 0.01$), as shown Tables 23 and 24. When considering automobile ownership, the results followed similar patterns to other metrics. Census tracts with a high proportion of households with no available vehicle exhibited a higher pedestrian fatality rate ($\beta = 0.002, p < 0.05$), particularly on secondary roads. Conversely, census tracts with higher proportions of two or more vehicles had a lower pedestrian fatality rate ($\beta = -0.006, p < 0.01$) on all-but-interstate roads. In a sense, the absence of vehicles is associated with poverty, and the higher pedestrian fatality rate in areas with high numbers of households with no cars on secondary roads indicates the presence of socioeconomic inequality. In terms of race and road safety, census tracts with a higher population of Hispanic individuals, particularly on all-but-interstate roads ($\beta = 0.003, p < 0.05$) and on urban roads ($\beta = 0.002, p < 0.05$), showed an association with a higher pedestrian fatality rate. Detailed implications of these findings will be further explored with other metrics in the discussion section. In general, densely populated areas showed a lower pedestrian fatality rate ($\beta = -0.004, p < 0.01;\ \beta = -0.004, p < 0.01$).

Table 23. Detailed Results of the People Injury Rate at the Census-Tract Level

Response Variable: Pedestrian Fatality Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	-0.001	0.000	0.000	0.000
	Income	0.001	0.001	0.000	-0.001
	Poverty	0.001	-0.001	0.001	-0.001
	SNAP	-0.002	0.001	-0.001	0.000
	Gini	0.000	0.000	-0.002	0.000
Time	Wave	0.002**	0.001	0.000	0.002**
COVID-19	Covid Dummy	-0.005*	-0.003*	-0.001	-0.005*
Automobile Ownership	ZeroVeh	0.001	0.002*	-0.001	0.001
	TwoMoreVeh	-0.006**	-0.001	0.000	-0.005**
Race	Black	0.002	0.001	0.000	0.002
	Asian	-0.001	0.000	0.000	0.000
	Hispanic/Latino	0.003*	0.001	-0.001	0.002*
Population Density	PopDensity	-0.004**	0.000	-0.001	-0.004**
Model Fit	AIC	-20995.66	-30078.45	-3184.44	-20102.08
	BIC	-20883.73	-29966.72	-3111.28	-19990.63
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* p < 0.05; ** p < 0.01.

Table 24. Significant Results of the Pedestrian Fatality Rate at the Census-Tract Level

RV: Pedestrian Fatality Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education				
	Income				
	Poverty				
	SNAP				
	Gini				
Time	Wave	0.002**			0.002**
COVID-19	COVID-19	-0.005*	-0.003*		-0.005*
Automobile Ownership	ZeroVeh		0.002*		
	TwoMoreVeh	-0.006**			-0.005**
Race	Black				
	Asian				
	Hispanic	0.003*			0.002*
Population Density	PopDensity	-0.004**			-0.004**

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

The pedestrian fatality rate at the county level reveals that variables like education and SNAP have an impact on this rate. In simpler terms, both affluent and poor neighborhoods might experience higher pedestrian fatality rates. However, the analysis conducted at the census-tract level does not show similar patterns. In the Discussion section, areas were classified into disadvantaged, intermediate, and advantaged categories based on cluster analysis, aiming for a more in-depth investigation. The results indicated that both types of areas exhibited a pedestrian fatality rate on Virginia roads. Further details are provided in the Discussion section.

Pedestrian Injury Rate

Pedestrian Injury Rate at the County Level

The pedestrian injury rate, as shown in Table 25, revealed interesting results that both affluent and poor areas had a higher pedestrian injury rate in the county-level analysis. In Model 1, education ($\beta = 0.08, p < 0.01$) and SNAP ($\beta = 0.03, p < 0.01$) had statistically significant and positive impacts on the pedestrian injury rate. Additionally, Model 2 demonstrated that income ($\beta = 0.05, p < 0.01$), poverty ($\beta = 0.03, p < 0.01$), SNAP ($\beta = 0.02, p < 0.05$), and the Gini index ($\beta = 0.02, p < 0.01$) showed statistically significant and positive impacts on the pedestrian injury rate. In other words, advantaged areas with higher education and income had higher pedestrian injury rates, and disadvantaged areas with higher poverty, SNAP, and Gini also experienced higher pedestrian injury rates. These implications are further discussed in the next section. The pedestrian injury rate has decreased over time in both models ($\beta = -0.05, p < 0.01\ for\ Model\ 1;\ \beta = -0.01, p < 0.01\ for\ Model\ 2$). In terms of healthcare access, the number of primary care physicians ($\beta = 0.01, p < 0.05\ for\ Model\ 1;\ \beta = 0.02, p < 0.01\ for\ Model\ 2$) was found to be significant.

Table 25. Detailed and Significant Results of the Pedestrian Injury Rate at the County Level

Response Variable: Pedestrian Injury Rate							
Detailed Results					Significant Results		
		Model 1	Model 2			Model 1	Model 2
SES	Education	0.08**			Education	0.08**	
	Income	0.00	0.05**		Income		0.05**
	Poverty	0.02	0.03**		Poverty		0.03**
	SNAP	0.03**	0.02*		SNAP	0.03**	0.02*
	Gini	0.01	0.02**		Gini		0.02**
Time	Wave	-0.01**	-0.01**		Wave	-0.01**	-0.01**
Access to Healthcare	Uninsured	-0.01	-0.02		Uninsured		
	PCP	0.01*	0.02**		PCP	0.01*	0.02**
	PHS	0.01	0.00		PHS		
VMT	DVMT_S	0.01	0.00				
	DVMT_P	-0.03**	-0.03**				
	DVMT_I	0.00	-0.01				
Locality – Fixed Effects		Y	Y				
Model Fit	AIC	-1808.18	-1782.56				
	BIC	-1733.63	-1712.99				
Panel Information	Panel	133	133				
	Observations	1,064	1,064				

Green indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Pedestrian Injury Rate at the Census-Tract Level

In a similar fashion, the census-tract analysis provided another perspective on the pedestrian injury rate, as demonstrated in Tables 26 and 27. This analysis confirms the findings of the county-level analysis that both affluent areas and poor areas had a higher pedestrian injury rate. For example, education ($\beta = 0.04, p < 0.01$) and poverty ($\beta = 0.04, p < 0.01$) on secondary roads were statistically positive and significant. These results remained consistent across all non-interstate roads and urban roads. In terms of automobile ownership, the results aligned with other traffic crash metrics, indicating that areas with a higher proportion of residents lacking automobile access experienced higher pedestrian injury rates and areas with a higher proportion of households owning two or more vehicles had a lower pedestrian injury rate. No consistent patterns were found in the relationship between race and pedestrian injury rates, although areas with a higher Asian population tended to exhibit lower rates. Additionally, densely populated areas on all non-interstate roads were found to have a lower pedestrian injury rate.

Table 26. Detailed Results of the Pedestrian Injury Rate at the Census-Tract Level

Response Variable: Pedestrian Injury Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	0.07**	0.04**	-0.01	0.07**
	Income	0.02	0.01	0.01	-0.01
	Poverty	0.07**	0.04**	0.00	0.08**
	SNAP	-0.03*	0.00	0.00	-0.02
	Gini	-0.01	-0.01	0.00	-0.01
Time	Wave	-0.01	-0.004	0.00	-0.01*
COVID-19	Covid Dummy	-0.04**	-0.03**	-0.01	-0.04**
Automobile Ownership	ZeroVeh	0.05**	0.03**	0.00	0.04**
	TwoMoreVeh	-0.13**	-0.06**	0.00	-0.10**
Race	Black	0.01	0.01	0.00	0.01
	Asian	-0.03**	0.00	0.00	-0.01
	Hispanic/Latino	0.01	0.00	0.00	0.00
Population Density	PopDensity	-0.04**	0.00	-0.01	-0.02
Model Fit	AIC	6720.51	1916.97	-1168.73	7167.18
	BIC	6832.44	2028.70	-1095.57	7278.62
Panel Information	Panel	1,425	1,413	154	1,381
	Observations	8,068	7,699	715	7,827

* p < 0.05; ** p < 0.01.

Table 27. Significant Results of the Pedestrian Injury Rate at the Census-Tract Level

RV: Pedestrian Injury Rate					
		All Non-Interstate Roads	Secondary Roads Only	Rural Roads Only	Urban Roads Only
SES	Education	0.07**	0.04**		0.07**
	Income				
	Poverty	0.07**	0.04**		0.08**
	SNAP	-0.03*			
	Gini				
Time	Wave				-0.01*
COVID-19	COVID-19	-0.04**	-0.03**		-0.04**
Automobile Ownership	ZeroVeh	0.05**	0.03**		0.04**
	TwoMoreVeh	-0.13**	-0.06**		-0.10**
Race	Black				
	Asian	-0.03**			
	Hispanic				
Population Density	PopDensity	-0.04**			

indicates supporting results while orange implies conflicting results. * p < 0.05; ** p < 0.01.

Generally, both the county and census-tract analyses indicated that highly educated areas have higher pedestrian injury rates. While the overall pedestrian injury rate has decreased at the county level, only urban roads at the census-tract level demonstrated a decrease in this specific target variable.

DISCUSSION

This study has highlighted stark differences in traffic crash measures across socioeconomic groups. In other words, this study has shown traffic safety disparities with regard to Virginia roads, suggesting that individuals with lower SES may face increased road safety risks as compared to their higher SES counterparts. This section discusses implications for the impact of SES and examines the findings, shedding light on potential avenues for addressing these disparities and promoting equitable road safety outcomes. In fact, disparities extend beyond lower SES areas to broader societal implications, hindering social mobility, deterring long-term economic growth, and perpetuating inequalities. This section is useful in understanding the underlying factors that contribute to disparities, enabling the formulation of effective interventions and policies.

It should be noted that all coefficients presented in the tables of this Discussion section are results derived from the full research models, particularly Equations (3) and (4), explained in the previous section. When a coefficient is insignificant, it is left blank to improve readability. Additionally, the colors are used to pinpoint implications regarding socioeconomic inequality and traffic crashes on Virginia roads. Green indicates supporting results, while orange implies conflicting results in the context of this study.

Road Safety and Socioeconomic Inequality

This study has examined socioeconomic inequality with regard to Virginia roads in three ways: (1) analyzing SES indicators, (2) examining crash trends in DACs, and (3) assessing households' vehicle access. The findings of this study may illuminate the pressing need for targeted policies and interventions to address the socioeconomic inequalities with regard to Virginia roads.

SES Indicators

Table 28 integrates empirical results pertaining to SES indicators across different roads. As depicted, the findings of this study demonstrate the presence of socioeconomic inequality with regard to Virginia roads. Education emerges as a significant contributing factor in decreasing four crash measures (i.e., total crash rate, fatal crash rate, serious injury crash rate, and people injury rate). Additionally, median household income plays a major role in explaining the decrease in total crash rate and people injury rate. This suggests that higher education and income levels may enable individuals to afford safer and more reliable vehicles equipped with advanced safety features. Conversely, census tracts with lower levels of education and income may see more traffic crashes. The magnitude of coefficients provides insights into the impact of SES indicators on a specific road type.

Table 28. Overview of SES Indicators Across Different Roads at the Census-Tract Level

		Education	Income	Poverty	SNAP	Gini
Total Crash Rate	All with no Interstates		-1.28**			-0.42*
	Secondary Roads		-1.00**	-0.31**	-0.70*	
	Rural Roads	-1.23**				
	Urban Roads		-1.86**	-0.39**		
Fatal Crash Rate	All with no Interstates	-0.03*				
	Secondary Roads	-0.01**		-0.006*		
	Rural Roads	-0.03*				
	Urban Roads	-0.02**		-0.01*		
Serious Injury Crash Rate	All with no Interstates	-0.23**				
	Secondary Roads	-0.09**				
	Rural Roads	-0.30**				
	Urban Roads	-0.12**				
People Injury Rate	All with no Interstates					
	Secondary Roads		-0.43**			
	Rural Roads	-0.71**				
	Urban Roads		-0.80**			

Green indicates supporting results in terms of socioeconomic inequality, while orange implies conflicting results. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * p < 0.05; ** p < 0.01.

Comparison of Traffic Crash Trends between Disadvantaged and Advantaged Communities

To ensure a comprehensive examination of socioeconomic disparities with regard to Virginia roads, this study has delved deeper into area-specific data. As previously mentioned, the study's cluster analysis at the census-tract level generated three distinct areas: disadvantaged, intermediate, and advantaged census tracts. These areas were determined based on five SES variables, namely, education, income, SNAP, poverty, and Gini. Panel data for each cluster were reconstructed using Virginia crash data, and traffic crash measures were tested using a fixed effects model. Equation (4) was explored in the previous section. It should be noted that the analysis did not include the five SES variables, as the three areas were derived from the cluster analysis utilizing those variables. The analysis was conducted with all non-interstate roads and secondary roads.

While all traffic crash measures were analyzed, Table 29 focuses on total crash rates, serious injury crash rates, and people injury rates, as they exhibited notable differences among the three areas. As depicted, DACs (i.e., Area 1) demonstrated higher crash rates compared to advantaged communities (i.e., Area 3), such as the coefficient of Wave in Area 1 $(\beta = 0.64, p < 0.05)$ and Area 3 $(\beta = -0.21, p < 0.05)$ on all non-interstate roads. This means that from 2015 to 2021, the total crash rate increased in DACs, while advantaged communities experienced a decrease in the rate. These findings reinforce the existence of socioeconomic inequality.

Table 29. Area-Specific Analysis at the Census-Tract Level

Response Variable: Total Crash Rate							
		All Non-Interstate Roads			Secondary Roads		
		Disadv.	Inter.	Adv.	Disadv.	Inter.	Adv.
Time	Wave	0.64*		-0.21*	0.38*	-0.07*	-0.22*
COVID-19	Covid Dummy	-1.97*	-1.93*	-2.17*	-1.03*	-0.92*	-1.03*
Automobile Ownership	ZeroVeh				-0.39*	0.31*	
	TwoMoreVeh	-3.87*	-2.32*	-1.80*	-1.45*		-0.35*
Race	Black						
	Asian						
	Hispanic/Latino			-0.94*			
Pop. Density	PopDensity	-5.24*	-3.17*	-1.80*	-4.06*	-1.5*	-0.75*

Response Variable: Serious Injury Crash Rate							
		All Non-Interstate Roads			Secondary Roads		
		Disadv.	Inter.	Adv.	Disadv.	Inter.	Adv.
Time	Wave		-0.02*	-0.03*			-0.02*
COVID-19	Covid Dummy						
Automobile Ownership	ZeroVeh			0.1*			0.06*
	TwoMoreVeh						
Race	Black		0.07*				
	Asian		-0.14*				
	Hispanic/Latino		-0.06*			-0.03*	
Pop. Density	PopDensity	-0.41*	-0.21*	-0.10*	-0.22*	-0.08*	-0.05*

Response Variable: People Injury Crash Rate							
		All Non-Interstate Roads			Secondary Roads		
		Disadv.	Inter.	Adv.	Disadv.	Inter.	Adv.
Time	Wave	0.46*		-0.2*	0.30*	-0.04*	-0.15*
COVID-19	Covid Dummy	-0.97*	-1.01*	-0.8*		-0.54*	-0.4*
Automobile Ownership	ZeroVeh	-1.1*			-0.58*		0.27*
	TwoMoreVeh	-4.31*	-1.25*	-0.82*	-1.43*	-0.27*	-0.23*
Race	Black		0.73*		0.98*	0.46*	
	Asian						
	Hispanic/Latino						0.26*
Pop. Density	PopDensity	-3.89*	-2.04*	-0.95*	-1.81*	-0.87*	-0.42*

Disadv. = Disadvantaged Cluster, Inter. = Intermediated Cluster, Adv. = Advantaged Cluster. Green indicates supporting results in terms of socioeconomic inequality. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * $p < 0.05$; ** $p < 0.01$.

Household Vehicle Access

The results presented in Table 30 demonstrate the impact of automobile ownership on traffic crash metrics. The analysis reveals that census tracts characterized by a significant proportion of households without a vehicle tend to have higher rates of traffic crashes. In contrast, areas with a high proportion of households possessing two or more vehicles exhibit lower traffic crash rates. It is worth noting that regions with a substantial number of households lacking access to a vehicle are often linked to poverty. This finding underscores a prevalent correlation between limited vehicle accessibility and economic disadvantage. It is another aspect of socioeconomic disparity that may result in road safety challenges. Understanding these relationships can contribute to addressing the issue of traffic crashes and promoting equitable road safety measures.

Table 30. Impact of Automobile Ownership on Crash Measures at the Census-Tract Level

Crash Measure	Road Type	Zero Vehicle	Two or More Vehicles
Total Crash Rate	All Non-Interstate Roads		-2.46**
	Secondary Roads		-0.39**
	Rural Roads		
	Urban Roads	0.49**	-0.76**
Fatal Crash Rate	All Non- Interstate Roads		
	Secondary Roads	0.005**	
	Rural Roads	-0.03**	
	Urban Roads		-0.01**
Serious Injury Crash Rate	All Non- Interstate Roads		-0.04**
	Secondary Roads		-0.05**
	Rural Roads		
	Urban Roads		-0.15**
People Injury Rate	All Non- Interstate Roads		-1.58**
	Secondary Roads		-0.39**
	Rural Roads		0.33*
	Urban Roads		-0.99**
Pedestrian Fatality Rate	All Non- Interstate Roads		-0.006**
	Secondary Roads	0.002*	
	Rural Roads		
	Urban Roads		-0.005**
Pedestrian Injury Rate	All Non-Interstate Roads	0.005**	-0.13**
	Secondary Roads	0.03**	-0.06**
	Rural Roads		
	Urban Roads	0.04**	-0.10**

Green indicates supporting results, while orange implies conflicting results. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * $p < 0.05$; ** $p < 0.01$.

Taken together, through the analysis of education and income levels, DACs, and the prevalence of limited vehicle access, this study has explored the intricate web of socioeconomic inequality that exists with regard to Virginia roads. Research shows that road investments are related to reduction in poverty and economic growth (Hine et al. 2019). Although changes in social mobility, such as education and income, may not happen overnight, increasing investments in road infrastructure, maintenance, and enhancement, particularly for disadvantaged areas, will lead to better opportunities for education attainment and economic growth in these communities. Justice40 is a commendable initiative for improving transportation infrastructure in such communities. This systematic research may provide insights into where to begin and how to enhance the effectiveness of the Justice40 program in Virginia. This equity-driven approach helps bridge the gap between privileged and disadvantaged areas, promoting inclusivity and social cohesion within society.

Road Safety from the Perspective of Vulnerable Road Users

Table 31 displays the estimates derived from the longitudinal analysis, focusing specifically on vulnerable road users such as pedestrians. Although certain SES variables are deemed insignificant and produce conflicting results, the variables of education and poverty yield intriguing findings. Census tracts with higher levels of education exhibit higher pedestrian injury rates, and similarly, census tracts with higher poverty levels also display elevated rates of pedestrian injuries. While the presence of socioeconomic inequality is observed in relation to other crash metrics, the pedestrian injury rate, in particular, stands out and exhibits distinct patterns.

This uniqueness prompted the study to explore possible explanations. One plausible reason is that affluent neighborhoods tend to engage in more jogging, walking, and other outdoor activities, which encourages a healthier lifestyle. However, this increased activity level might also lead to a higher number of road crashes, as residents are more exposed to potential risks. On the other hand, in poor neighborhoods, people are often compelled to walk more out of necessity, as they may lack access to private transportation options. Unfortunately, this higher dependence on walking might expose them to greater risks, as they are more vulnerable to crashes in areas that may not be adequately designed for pedestrian safety.

Table 31. Impact of SES on Pedestrian Fatality/Injury Rates at the Census-Tract Level

		Education	Income	Poverty	SNAP	Gini
Pedestrian Fatality Rate	All Non-Interstate Roads					
	Secondary Roads					
	Rural Roads					
	Urban Roads					
Pedestrian Injury Rate	All Non-Interstate Roads	0.07**		0.07**	-0.03*	
	Secondary Roads	0.04**		0.04**		
	Rural Roads					
	Urban Roads	0.07**		0.08**		

Green indicates supporting results, while orange implies conflicting results. Although this table displays only necessary impacts in terms of socioeconomic inequality, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * $p < 0.05$; ** $p < 0.01$.

Road Safety from the Perspective of Race

This study also examined road safety across different road types, with a specific focus on race. It should be noted that the race category of White was not included due to concerns about multicollinearity. Table 32 summarizes excerpts from the longitudinal analysis derived from the full model, Equation (3). Neighborhoods with a higher Black population show higher rates of serious injury crashes and people injuries. It is necessary to comprehend the implications of these findings, especially considering that certain roads show a decrease in these rates. Additionally, neighborhoods with a larger Hispanic population exhibit elevated rates of pedestrian fatalities. Going a step further, this study explored the intricate impacts of race within DACs, as illustrated in Table 33, which contains excerpts from Equation (4). Specifically, in combined areas such as secondary roads, DACs, and the Black community, the rate of people injury is particularly high ($\beta = 0.98, p < 0.01$). These results can be understood by considering SES, environmental and infrastructural factors, and access to healthcare. These findings are consistent with existing literature that suggests higher traffic fatalities per miles traveled in Black and Hispanic communities compared to areas with a higher proportion of White population (Raifman and Choma 2022). It is also critical to recognize that traffic fatalities and injuries are a preventable public health challenge and demand urgent attention to address these disproportionate situations (Raifman and Choma 2022).

Table 32. Impact of Race on Traffic Crash Measures at the Census-Tract Level

		Black	Asian	Hispanic/Latino
Serious Injury Crash Rate	All Non-Interstate Roads		-0.04*	-0.11**
	Secondary Roads	0.04**		-0.04**
	Rural Roads	-0.11**		-0.08**
	Urban Roads	0.12**		-0.04**
People Injury Rate	All Non-Interstate Roads	0.81**		
	Secondary Roads	0.56**		
	Rural Roads	-0.39*		
	Urban Roads	0.65**		
Pedestrian Fatality Rate	All Non-Interstate Roads			0.003*
	Secondary Roads			
	Rural Roads			
	Urban Roads			0.002*

Green indicates supporting results, while orange implies conflicting results. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * p < 0.05; ** p < 0.01.

Table 33. Combined Impacts of Race at the Census-Tract Level

Response Variable: People Injury Crash Rate							
		All Non-Interstate Roads			Secondary Roads		
		Disadv.	Inter.	Adv.	Disadv.	Inter.	Adv.
Time	Wave	0.46*		-0.2*	0.30*	-0.04*	-0.15*
COVID-19	Covid Dummy	-0.97*	-1.01*	-0.8*		-0.54*	-0.4*
Automobile Ownership	ZeroVeh	-1.1*			-0.58*		0.27*
	TwoMoreVeh	-4.31*	-1.25*	-0.82*	-1.43*	-0.27*	-0.23*
Race	Black		0.73*		0.98*	0.46*	
	Asian						
	Hispanic/Latino						0.26*
Pop. Density	PopDensity	-3.89*	-2.04*	-0.95*	-1.81*	-0.87*	-0.42*

Disadv. = Disadvantaged Cluster, Inter. = Intermediated Cluster, Adv. = Advantaged Cluster. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * p < 0.05; ** p < 0.01.

Road Safety and Crash Trends

The longitudinal analysis at the census-tract level has indicated an increasing trend in some traffic crash rates in Virginia between 2015 and 2021, as shown in Table 34. The analysis specifically identifies the following traffic crash measures and road types that exhibit the increasing trend in Virginia:

- The total crash rate on rural roads

- The fatal crash rate on all non-interstate roads
- The fatal crash rate on secondary roads
- The fatal crash rate on urban roads
- The pedestrian fatality rate on all non-interstate roads
- The pedestrian fatality rate on urban roads.

In particular, the fixed effects regressions provide evidence of Virginia's rising road fatality rates. Given the serious consequences associated with fatalities, their impact extends beyond individuals to families and communities. Therefore, there is a need for public awareness and education campaigns tailored to these specific road types. Furthermore, enhancing traffic law enforcement and improving infrastructure are vital strategies to effectively reduce traffic fatalities. In addition to these measures, fostering collaboration among government agencies, communities, and healthcare providers can yield positive outcomes. By working together, these stakeholders can develop strategies to tackle the increasing trend in traffic crash rates. This study employed data-driven approaches, which provide valuable insights for addressing this issue.

It is worth noting that between 2015 and 2021, the serious injury crash rate in Virginia decreased, as illustrated in Table 34. This decline in serious injury crashes is consistently observed across all types of roads, including all non-interstate roads, secondary roads, and urban roads. This positive trend is indeed encouraging, emphasizing that crashes represent more than just numbers.

Table 34. Traffic Crash Trends at the Census-Tract Level

Crash Measure	Road Type	Time	Crash Measure	Road Type	Time
Total Crash Rate	All Non-Interstate Roads		People Injury Rate	All Non-Interstate Roads	
	Secondary Roads			Secondary Roads	
	Rural Roads	0.17**		Rural Roads	
	Urban Roads			Urban Roads	
Fatal Crash Rate	All Non-Interstate Roads	0.004**	Pedestrian Fatality Rate	All Non-Interstate Roads	0.002**
	Secondary Roads	0.002**		Secondary Roads	
	Rural Roads			Rural Roads	
	Urban Roads	0.004**		Urban Roads	0.002**
Serious Injury Crash Rate	All Non-Interstate Roads	-0.02**	Pedestrian Injury Rate	All Non-Interstate Roads	
	Secondary Roads	-0.01**		Secondary Roads	
	Rural Roads			Rural Roads	
	Urban Roads	-0.02**		Urban Roads	-0.01*

Green indicates supporting results, while orange implies conflicting results. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * $p < 0.05$; ** $p < 0.01$.

Road Safety and Population Density

Table 35 clearly indicates that dense neighborhoods have lower rates of collisions, injuries, and fatalities. It is possible that slower speeds can reduce the severity of collisions and the likelihood of fatal outcomes when crashes do occur. Dense neighborhoods may implement traffic calming measures such as speed bumps, traffic circles, narrower streets, and enhanced crosswalks. These measures contribute to creating a safer environment for pedestrians and drivers alike. Furthermore, dense neighborhoods may have better-developed infrastructure as compared to less populated areas. They may have lower speed limits, sidewalks, designated bike lanes, and street lighting, all of which play crucial roles in enhancing safety. These factors provide possible reasons why dense neighborhoods tend to experience lower collision rates, fewer injuries, and reduced fatalities.

Table 35. Impact of Population Density at the Census-Tract Level

		PopDensity
Total Crash Rate	All Non-Interstate Roads	-2.82**
	Secondary Roads	-1.21**
	Rural Roads	-1.55**
	Urban Roads	-2.55**
Fatal Crash Rate	All Non-Interstate Roads	-0.01**
	Secondary Roads	
	Rural Roads	
	Urban Roads	-0.01**
Serious Injury Crash Rate	All Non-Interstate Roads	-0.14**
	Secondary Roads	-0.06**
	Rural Roads	-0.12**
	Urban Roads	-0.15**
People Injury Rate	All Non-Interstate Roads	-1.64**
	Secondary Roads	-0.65**
	Rural Roads	-0.79**
	Urban Roads	-1.54**
Pedestrian Fatality Rate	All Non-Interstate Roads	-0.004**
	Secondary Roads	
	Rural Roads	
	Urban Roads	-0.004**
Pedestrian Injury Rate	All Non-Interstate Roads	-0.04**
	Secondary Roads	
	Rural Roads	
	Urban Roads	

Green indicates supporting results, while orange implies conflicting results. Although this table displays only necessary impacts, all empirical results were excerpted from the full research model at the census-tract level. When the coefficients are insignificant, they are left blank to improve readability. * $p < 0.05$; ** $p < 0.01$.

Limitations and Suggestions for Future Research

This study has focused on 133 counties/cities in Virginia, providing a comprehensive overview of the socioeconomic disparities with regard to the state's roads. However, it is important to recognize that counties can encompass a wide spectrum of socioeconomic status, leading to significant discrepancies within their boundaries. To gain a more sophisticated understanding of the topic, obtaining more detailed data on SES is essential. As a next step, this study has investigated road safety at the census-tract level. Census tracts, averaging about 4,000 residents and ranging from 1,200 to 8,000 people, offer more nuanced results. Nevertheless, it is crucial to acknowledge the limitations of this approach when interpreting the findings.

First, the ACS employs a sample-based approach, where a selected sample of households and individuals represents the entire population within each census tract. In smaller census tracts with fewer residents, the sample size may be limited, leading to increased variability and uncertainty in the estimates. Researchers should exercise caution when drawing conclusions from such data. For future studies, exploring data at the block group level could be beneficial, as it provides finer granularity than census tracts, potentially revealing more detailed patterns of socioeconomic inequality with regard to Virginia roads. Such a study would require consideration of the margin of error as reported by the Census, since these margin of errors (MOEs) can tend to be a larger portion of the estimate for smaller geographic units, such as block groups, than for larger geographic units, such as tracts.

Second, the variables used to examine socioeconomic inequality with regard to Virginia's roads may involve complex interactions, including income, education, SNAP, poverty, and Gini. While this study conducted tests for multicollinearity using the VIF, it is important to exercise caution when extrapolating the findings to the empirical results of this study. These intricate relationships among socioeconomic factors should be considered.

Third, this study has focused on specific regions, including Northern Virginia District, Hampton Roads Areas, Richmond Areas, and Salem District. While these regions account for the majority of crashes in Virginia, other areas might contribute to the overall picture. Conducting studies that include all crash data from the entire state would offer a more comprehensive understanding of the socioeconomic disparities and their impact on road safety. By addressing these considerations and enhancing data collection methodologies, future research endeavors can build upon the insights from this study, contributing to a deeper understanding of socioeconomic inequality with regard Virginia roads and paving the way for more effective policy interventions and equitable transportation planning.

Fourth, while the models have been thoroughly developed, it is crucial to comprehend them and interpret the results within the context of this research domain. This understanding can provide valuable guidance for future studies. Applying these models should be carried out in accordance with the specific research context. Furthermore, the applicability and generalizability of these models may vary depending on variables unique to each research setting. Therefore, researchers should exercise caution and tailor the use of these models to align with the specific needs and conditions of their own studies.

CONCLUSIONS

- *Several SES metrics were correlated with differences in the rates of crashes per 1,000 people.* Increasing proportions of college graduates and above and higher median income emerged as significant contributing factors in deceasing traffic crash rate measures. The cluster analysis also showed that communities in the disadvantaged cluster experience higher traffic crash rates than those communities in the advantaged cluster. Census tracts with a high proportion of households with no vehicle access generally exhibited higher rates of traffic crashes.

- *Several trends in road safety were also observed with respect to the racial composition of the census tract.* Tracts with a higher Black population showed higher rates of serious injury crashes and people injuries. Tracts with a larger Hispanic population exhibited elevated rates of pedestrian fatalities.

- *Pedestrian crashes occurred at a higher rate under two distinct scenarios.* Census tracts with higher levels of education exhibited higher pedestrian injury rates. Conversely, census tracts with higher poverty levels also demonstrated higher pedestrian injury rates.

- *Census tracts with a higher population density had lower rates of collisions, injuries, and fatalities.*

- *The road fatality rate in Virginia increased at both the census-tract and county levels of analysis during the study period.* Empirical results showed that the increasing crash trends between 2015 and 2021 in Virginia pertained to the total crash rate on rural roads, fatal crash rate on all non-interstate roads, fatal crash rate on secondary and urban roads, and pedestrian fatality rate on all non-interstate roads and urban roads.

- *The manner in which crash risk was assessed might alter the interpreted impact of certain socioeconomic parameters.* In several instances in this study, revised models led to a reversal of initial inferences. For instance, the first version of the model for Table 19 suggested that higher education was associated, significantly, with a higher people injury rate. However, another model suggested that education was a statistical artifact: it ran contrary to the impact of income (where higher income reduced this injury crash rate). Further, the magnitude when both variables were included showed that income had a substantially greater impact than education: a change of 1 percentage point in persons with a bachelor's degree was roughly equivalent to a change in $1 dollar of income.

RECOMMENDATION

1. *VDOT's Traffic Operations Division (TOD) should share the results of this study with key internal and external stakeholders that could incorporate these findings into investment decisions.* In particular, this report should be presented to VDOT's district planning and safety staff, planners with Virginia's Planning District Commissions (PDCs) and the Virginia Association of Metropolitan Planning Organizations (VAMPO), and the Office of Intermodal Planning and Investment (OIPI). In these presentations, emphasis should be placed on how this information can inform regional and statewide planning and engineering practice. The information in this report could provide useful information for project selection, VTrans, and SMART SCALE.

IMPLEMENTATION AND BENEFITS

The researcher and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

With regard to the recommendation, VDOT's TOD will share the report with VDOT district planners and associated engineering staff, planners within Virginia's PDCs, and OIPI within 1 year of the publication of this report. Afterward, as suggested in Virginia's Strategic Highway Safety Plan (SHSP), these groups can determine how to incorporate this study's methodology or results into various safety-related programs. A possible avenue for this information sharing is the OIPI MPO Quarterly Coordination Meeting, but other opportunities for information share can be explored.

This presentation should emphasize the importance of socioeconomic data in Virginia's SHSP. The plan points out that such information, along with transportation and health data, comprises "fundamental information components to performance-based highway safety planning" (Virginia Department of Transportation 2021) in terms of supporting countermeasures in the areas of education, engineering, enforcement, and emergency medical services (EMS).

As just one example, the SHSP observes that "the socioeconomic and demographic community composition contributes to the level of bicyclist and pedestrian activity" (Virginia Department of Transportation 2021). Table 31 of this report provides additional insights to complement the SHSP: higher injury rates for pedestrians were observed in two different types of areas: (1) those that have much higher income levels, and (2) those where rates of poverty were higher. Thus, the presentation may articulate how to identify these different locations within a given region and as well as possible countermeasures. Examples of such countermeasures given in the SHSP include, but are not limited to, identification of high risk facilities for engineering treatment, educational initiatives for children, education initiatives for seniors regarding certain types of engineering improvements for nonmotorized users (such as pedestrian hybrid beacon signals), signal retiming to account for slower walking speeds for some pedestrians, and recruiting "new and effective partners to ensure the pedestrian . . . programs are reaching diverse and underserved communities" (Virginia Department of Transportation 2021).

Additionally, there are several ways in which this information may be used by an audience composed of VDOT staff, staff from PDCs and MPOs, and OIPI. Examples include, but are not limited to, the following:

- PDCs and MPOs could use this report to choose among candidate projects for submissions to SMART SCALE. PDCs and MPOs may also examine ways that the transportation element for comprehensive plans could support nonmotorized transportation needs.

- VDOT planning staff, in conjunction with engineering staff, may identify engineering improvements as part of other highway projects. Examples of such treatments are provided by VDOT in Virginia Department of Transportation (2020).

- OIPI may use this report in its establishment of mid-term transportation needs as part of Virginia's Statewide Multimodal Transportation Plan. Appendix E of the SHSP points out that such needs “feed the investment program through the SMART SCALE prioritization process” (Virginia Department of Transportation 2021).

Benefits

Implementation of the recommendation with a broad base of stakeholders will heighten awareness of the relationships between SES and safety. Depending on how those groups incorporate these findings, a number of possible benefits could be realized.

As VTrans constitutes the transportation plan for the Commonwealth of Virginia, managed by OIPI, the information gathered from this analysis can be of great value in aligning VTrans with the overarching visions and goals for transportation in the state. For example, the communities identified during this study’s analysis might receive more thorough consideration under the SMART SCALE framework. The insights obtained in this study can significantly contribute to shaping VTrans’ Mid-Term Needs and Priorities, making it a vital component of transportation planning in Virginia.

This study’s analysis delved into the varying impacts of SES on Virginia roads, considering both county and census-tract data. The results obtained in this study will provide valuable guidance for making informed decisions in urban/rural planning and selecting projects that reflect the specific needs of different communities. Sharing these insights with VAMPO can foster collaborative efforts in improving transportation infrastructure and addressing socioeconomic disparities across the state.

PDCs play a vital role in conducting a diverse range of transportation studies, addressing various aspects such as transportation deficiencies, access management, safety hazards, and multimodal studies by encompassing all forms of transit and pedestrian concerns. The analysis undertaken in this study specifically focused on examining the impact of SES on Virginia roads, considering different road types and vulnerable road users. The valuable insights derived from this study could enhance the effectiveness of PDCs’ transportation planning processes. By sharing the findings of this study with PDCs, VDOT can contribute to their endeavors in ensuring safer, more accessible, and equitable transportation infrastructure for all members of the community.

VDOT’s district planners can use the findings of this study to make informed decisions while formulating and implementing transportation plans within their respective regions. This data-driven approach will allow VDOT to be at the forefront of efforts to create more equitable and inclusive transportation systems, thus promoting better accessibility and opportunities for all residents of the Commonwealth.

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APPENDIX A

SES EXAMPLES OF COUNTIES/CITIES

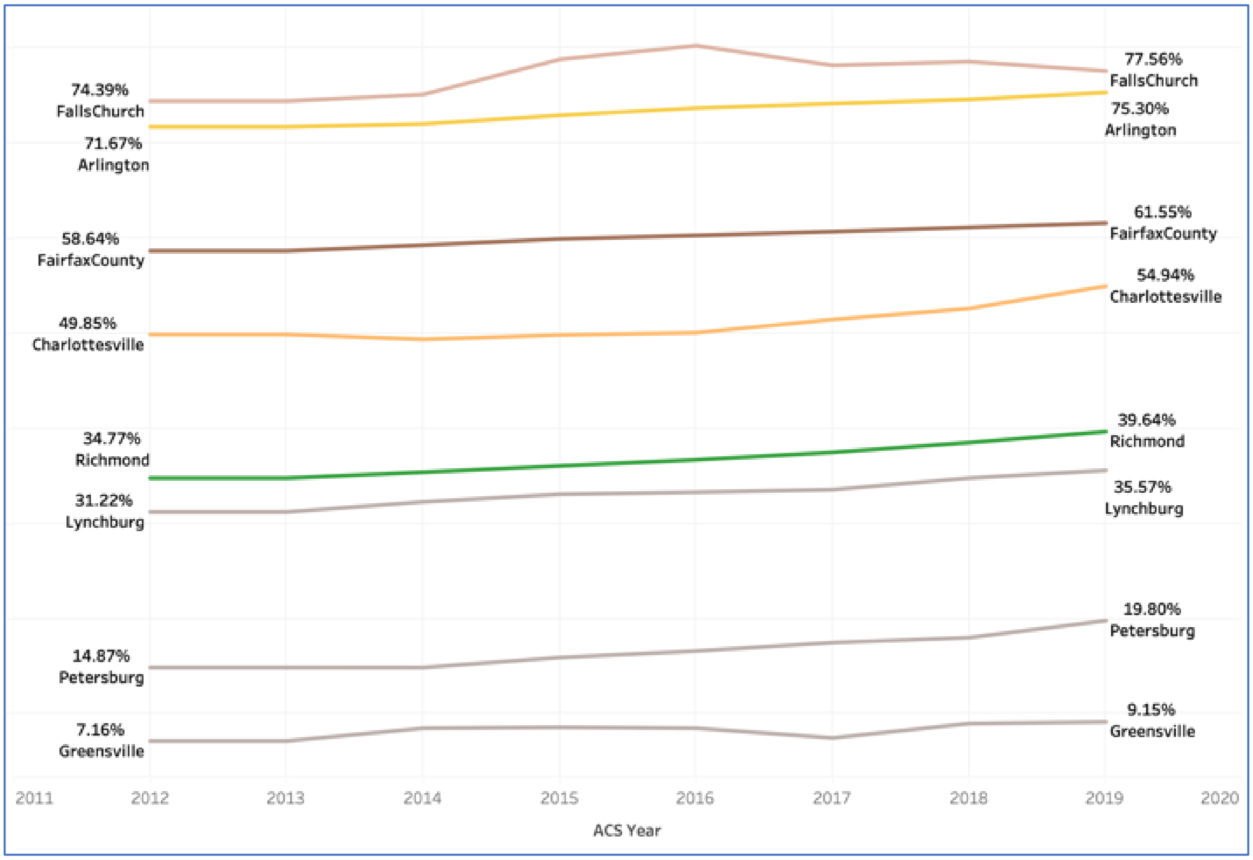

Figure A-1: Education (Bachelor's Degree or Higher)

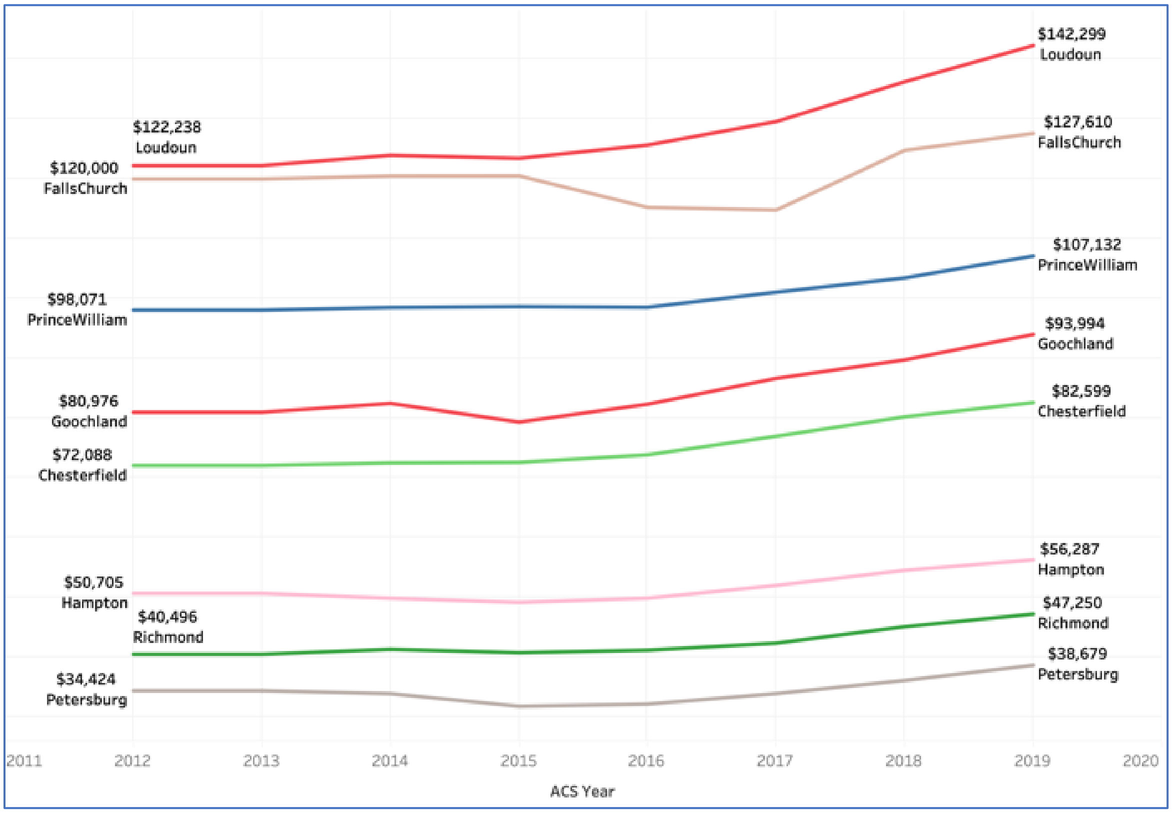

Figure A-2: Median Household Income

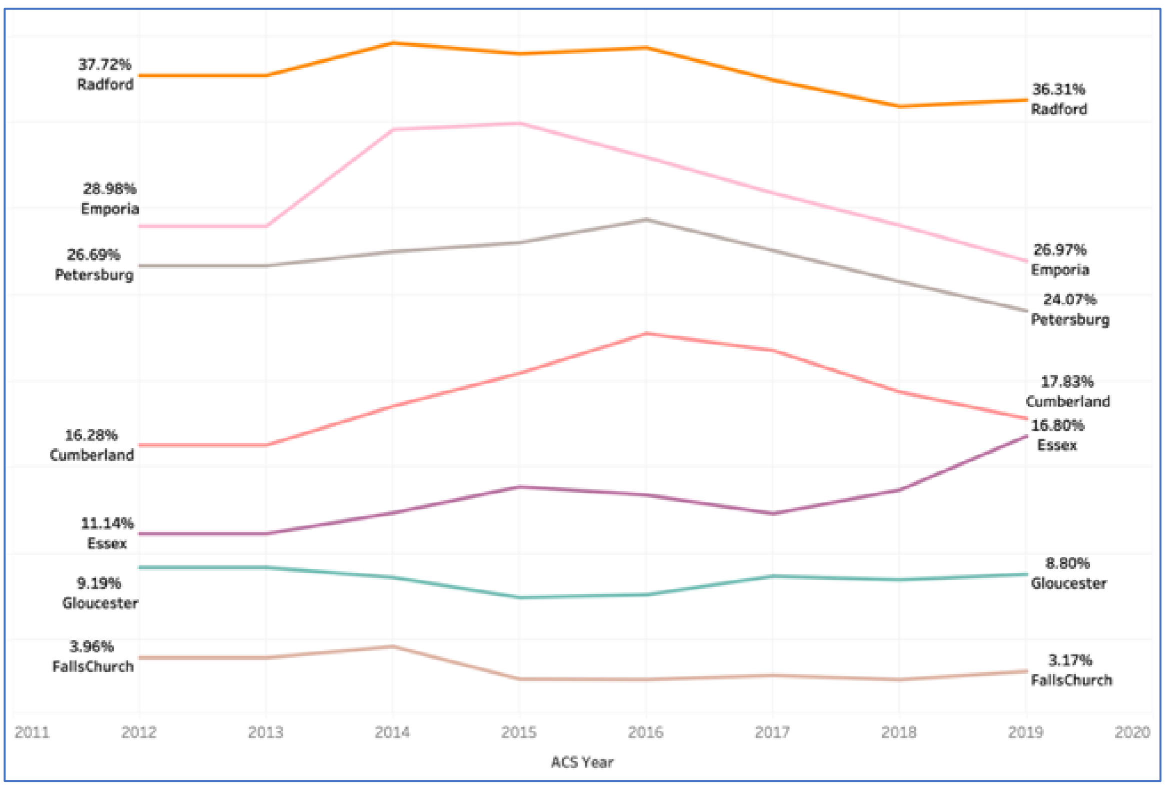

Figure A-3: Poverty Level

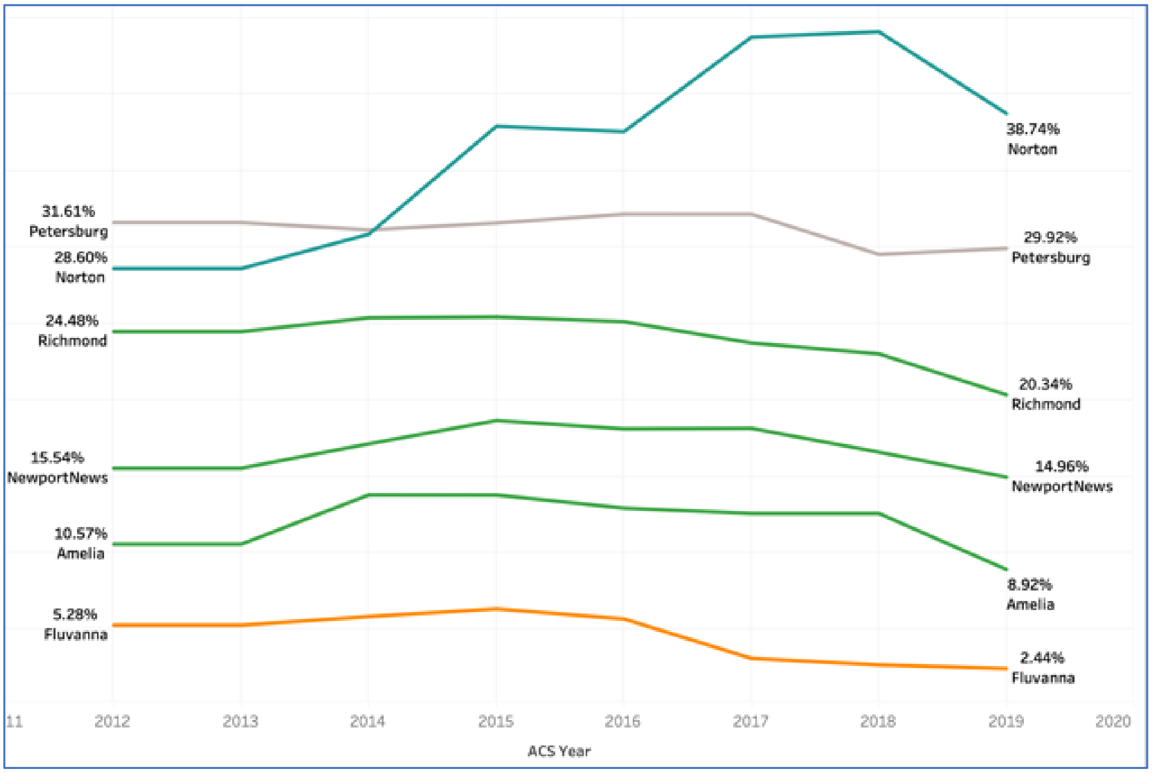

Figure A-4: SNAP Participation Rate

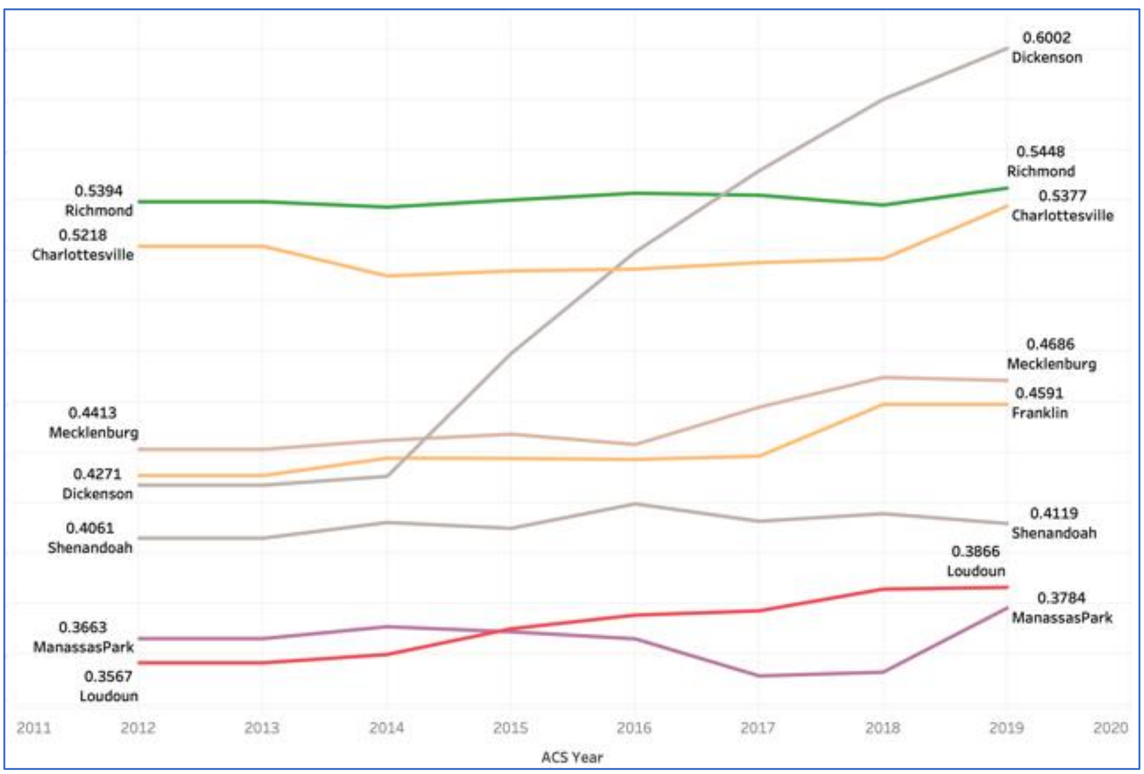

Figure A-5: Gini Index

APPENDIX B

DESCRIPTIVE STATISTICS FOR PREDICTORS USED IN PHASE 1

Table B-1: Descriptive Statistics for Phase 1 Predictors

Predictors		Year							
		2013	2014	2015	2016	2017	2018	2019	2020
Education	Minimum	7.16	7.16	8.49	8.6	8.5	7.48	8.99	9.15
	Maximum	74.39	74.39	75.09	78.77	80.21	78.13	78.53	77.56
	Average	24.05	24.05	24.5	25.08	25.53	26.05	26.45	27
	SD	12.82	12.82	12.94	12.99	13.21	13.13	13.4	13.48
	N	133	133	133	133	133	133	133	133
Income	Minimum	28116	28116	27746	27731	26000	26971	28071	27063
	Maximum	122238	122238	123966	123453	125672	129588	136268	142299
	Average	52596	52596	53051	53083	54078	56270	58501	60757
	SD	19236	19236	19622	19692	19724	20056	21136	22068
	N	133	133	133	133	133	133	133	133
Poverty	Minimum	3.63	3.63	3.84	2.72	2.69	2.93	2.69	3.17
	Maximum	37.72	37.72	39.61	38.97	39.33	37.45	35.93	36.31
	Average	14.68	14.68	14.94	14.98	14.79	14.37	14.2	13.86
	SD	6.85	6.85	6.85	6.98	6.82	6.48	6.6	6.64
	N	133	133	133	133	133	133	133	133
SNAP	Minimum	0.74	0.74	0.73	0.98	0.31	1.3	1.16	0.75
	Maximum	38.03	38.03	41.91	37.91	37.55	43.74	44.08	38.74
	Average	13.09	13.09	13.56	13.62	13.32	12.84	12.34	11.74
	SD	0.74	0.74	0.73	0.98	0.31	1.3	1.16	0.75
	N	133	133	133	133	133	133	133	133
Gini	Minimum	0.35	0.35	0.36	0.36	0.37	0.35	0.35	0.37
	Maximum	0.54	0.54	0.54	0.54	0.56	0.55	0.58	0.6
	Average	0.43	0.43	0.43	0.44	0.44	0.44	0.44	0.44
	SD	0.35	0.35	0.36	0.36	0.37	0.35	0.35	0.37
	N	133	133	133	133	133	133	133	133
DVMT_S	Minimum	2626	2587	2597	2602	2609	2517	2512	1925
	Maximum	18451	18851	18869	18950	18778	19097	18801	18100
	Average	7229	7267	7324	7289	7330	7333	7335	6838
	SD	2236	2322	2365	2369	2381	2443	2456	2578
	N	133	133	133	133	133	133	133	133
DVMT_P	Minimum	1966	1953	1995	1829	1841	1893	1865	2588
	Maximum	50654	49654	48978	50201	51064	50641	52002	46215
	Average	14567	14624	14541	14637	14874	14850	14892	13612
	SD	8369	8323	8064	8288	8604	8646	8735	7540
	N	133	133	133	133	133	133	133	133
DVMT_I	Minimum	0	0	0	0	0	0	0	0
	Maximum	83256	84711	89489	95876	96195	95854	96048	84830
	Average	8218	8343	8669	9046	9194	9069	9107	7956
	SD	14411	14654	15345	16163	16446	16179	16302	14197
	N	133	133	133	133	133	133	133	133
Uninsured	Minimum	8.2	7.52	7.13	6.67	4.62	4.83	3.74	3.7
	Maximum	24.8	25.31	25.78	26.68	24.54	19.87	17.86	17.79
	Average	16.64	16.07	16.05	15.54	14.03	11.78	11.11	11.3
	SD	3.06	3.02	3	2.92	2.88	2.54	2.29	2.3
	N	133	133	133	133	133	133	133	133

PCP	Minimum	0.06	0.05	0.05	0.05	0.05	0.06	0.06	0.07
	Maximum	4.27	3.95	3.44	3.26	3.16	3.31	3.21	2.88
	Average	0.73	0.67	0.66	0.65	0.65	0.64	0.63	0.61
	SD	0.7	0.55	0.54	0.54	0.52	0.53	0.52	0.47
	N	133	133	133	133	133	133	133	133
PHS	Minimum	24.61	31.75	32.91	20.98	21.22	21.06	21.1	25.31
	Maximum	182.45	183.8	182.47	134.6	148.29	109.82	105.21	103.29
	Average	67.94	70.26	64.69	57.16	49.71	48.33	47.36	48.08
	SD	67.94	70.26	64.69	57.16	49.71	48.33	47.36	48.08
	N	133	133	133	133	133	133	133	133

SD = standard deviation, DVMT_S = daily vehicle miles traveled per 1,000 people on secondary roads, DVMT_P = daily vehicle miles traveled per 1,000 people on primary roads, DVMT_I = daily vehicle miles traveled per 1,000 people on interstates, Uninsured = percentage of the population under age 65 without health insurance, PCP = rate of primary care physicals per 1,000 people, PHS = rate of hopisital stays for ambulatory-care sensitive conditions per 1,000 Medicare enrollees.

APPENDIX C

DESCRIPTIVE STATISTICS FOR PREDICTORS USED IN PHASE 2

Table C-1: Descriptive Statistics for Phase 2 Predictors

Predictors		Year						
		2015	2016	2017	2018	2019	2020	2021
Education	Minimum	1.55	1.89	1.91	0.21	0.79	2.49	1.71
	Maximum	97.68	95.54	95.32	93.83	93.46	92.29	96.59
	Average	41.63	42.17	42.54	43.17	43.72	44.27	45.34
	SD	22.48	22.5	22.58	22.52	22.6	22.52	22.75
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Income	Minimum	3984	9357	3250	10878	3894	2744	2650
	Maximum	250001	250001	250001	250001	250001	250001	250001
	Average	83411.53	83717.09	84787.39	87436.84	90416.62	93477.49	95568.14
	SD	44043.32	44164.54	44713.62	45505.05	46778.53	48240.17	49112.61
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Poverty	Minimum	0	0	0	0	0	0	0
	Maximum	88.73	82.92	77.18	76.73	82.81	80.1	88.94
	Average	11.09	11.04	11.13	10.94	10.65	10.27	9.72
	SD	11.26	11.02	11.07	10.81	10.74	10.41	10.28
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
SNAP	Minimum	0	0	0	0	0	0	0
	Maximum	90.34	88.91	91.1	89.56	87.35	93.08	86.09
	Average	10.26	10.57	10.28	9.97	9.39	9.02	8.58
	SD	12.35	12.36	12.2	11.9	11.5	11.18	11.44
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Gini	Minimum	0.22	0.06	0.06	0.24	0.21	0.22	0.18
	Maximum	0.72	0.7	0.67	0.67	0.74	0.79	0.82
	Average	0.39	0.39	0.39	0.39	0.39	0.4	0.39
	SD	0.07	0.07	0.07	0.07	0.07	0.07	0.07
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
ZeroVeh	Minimum	0	0	0	0	0	0	0
	Maximum	72.71	68.6	72.93	78.52	79.96	73.84	79.3
	Average	6.76	6.8	6.81	6.68	6.75	6.6	6.66
	SD	8.43	8.4	8.48	8.36	8.34	8.19	8.29
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
TwoMoreVeh	Minimum	1.76	1.64	1.68	1.92	1.02	3.53	3.01
	Maximum	96.33	100	100	100	100	96.71	100
	Average	61.19	61.27	61.23	61.46	61.62	61.96	61.67
	SD	18.61	18.48	18.68	18.57	18.58	18.54	19.35
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Black	Minimum	0	0	0	0	0	0	0
	Maximum	97.84	98.03	97.06	96.64	97.32	96.87	98.31
	Average	21.75	21.67	21.8	21.73	21.72	21.68	21.49
	SD	23.56	23.25	23.28	22.99	22.96	22.79	22.77
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Asian	Minimum	0	0	0	0	0	0	0
	Maximum	60.44	61.72	59.7	61.28	58.79	56.5	61.82
	Average	7.71	7.83	7.87	8.07	8.12	8.17	8.68
	SD	8.57	8.77	8.77	8.96	8.96	8.95	9.89
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485

Hispanic	Minimum	0	0	0	0	0	0	0
	Maximum	82.85	79.94	78.19	76.57	76.09	76.95	83.03
	Average	10.04	10.16	10.27	10.44	10.64	10.86	10.86
	SD	10.63	10.63	10.65	10.84	10.94	11.09	11.38
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Population Density	Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Maximum	0.0251	0.0265	0.0249	0.0248	0.0248	0.0262	0.0366
	Average	0.0018	0.0018	0.0018	0.0019	0.0019	0.0019	0.0020
	SD	0.0022	0.0022	0.0022	0.0023	0.0023	0.0024	0.0027
	N	1,485	1,485	1,485	1,485	1,485	1,485	1,485

SD = standard deviation, ZeroVeh = Percenage of households without a vehicle, TwoMoreVeh = Percentage of households with two or more vehicles.

APPENDIX C

DETAILED RESULTS OF CLUSTER ANALYSIS AT THE COUNTY LEVEL

Table D-1: Cluster Analysis Results at the County Level

County	Mean of College+ Graduates	Mean of Income	Mean of Poverty	Mean of SNAP	Mean of Gini	Cluster	FIPS
Accomack	18.42%	$40937.88	19.92%	14.59%	0.46	1	51001
Albemarle	52.57	71217.25	9.83	5.1	0.48	2	51003
Alexandria	61.85	91013.38	9.38	6.96	0.44	2	51510
Alleghany	16	45863.88	16.75	11.59	0.43	1	51005
Amelia	14.98	56470.75	10.81	11.97	0.4	2	51007
Amherst	18.58	47618.75	12.8	11.51	0.41	2	51009
Appomattox	17.99	52370.62	16.22	16.24	0.42	1	51011
Arlington	73.23	109448.5	8.08	4.61	0.44	2	51013
Augusta	21.99	56624	9.23	7.97	0.42	2	51015
Bath	18	47234	11.2	6.16	0.45	2	51017
Bedford	27.14	58677.62	9.06	7.37	0.42	2	51019
Bland	14.96	45856.12	11.78	12.72	0.4	2	51021
Botetourt	26.76	65132.25	7.66	4.21	0.43	2	51023
Bristol	22.35	35309.38	21.14	24.13	0.46	1	51520
Brunswick	13.03	39077.88	22.29	23.94	0.44	1	51025
Buchanan	9.76	30372.25	26.05	22.63	0.46	1	51027
Buckingham	11.55	42690.12	19.3	19.52	0.41	1	51029
Buena Vista	15.57	33072.12	23.31	19.04	0.43	1	51530
Campbell	19.89	48103.5	13.06	11.24	0.43	1	51031
Caroline	18.73	60014.62	11.64	13.76	0.4	2	51033
Carroll	13.57	37595.12	16.45	13.15	0.44	1	51035
Charles City	13.27	52516.62	13.06	10.67	0.48	1	51036
Charlotte	13.33	35987.62	21.45	16.15	0.45	1	51037
Charlottesville	50.98	51258.12	25.94	13.67	0.52	1	51540
Chesapeake	30.62	71863	9.06	8.53	0.4	2	51550
Chesterfield	37.81	75368.75	7.07	7.3	0.41	2	51041
Clarke	31.44	75509.25	9.15	5.55	0.44	2	51043
Colonial Heights	22.05	51670	11.53	11.4	0.41	2	51570
Covington	11.45	36487	19.95	19.36	0.44	1	51580
Craig	16.39	48977.25	9.9	11.21	0.39	2	51045
Culpeper	23.1	68460.25	8.91	9.89	0.4	2	51047
Cumberland	15.39	42012.25	19.16	20.04	0.44	1	51049
Danville	17.81	33529.5	24.1	27.62	0.49	1	51590
Dickenson	10.38	31708.25	22.25	18.67	0.5	1	51051
Dinwiddie	15.48	53778	13.81	15.49	0.42	1	51053
Emporia	15.37	29458.25	30.92	33.12	0.51	1	51595
Essex	15.95	47183	13.09	11.36	0.42	1	51057
Fairfax City	55.4	104981.62	7.77	2.79	0.41	2	51600
Fairfax County	60	115380.75	6.02	4.5	0.42	2	51059
Falls Church	77.14	120433.38	3.34	0.84	0.44	2	51610
Fauquier	34.43	93094.12	5.82	5	0.42	2	51061

Floyd	18.55	47714.75	11.44	10.43	0.4	2	51063
Fluvanna	31.31	68918.5	6.32	4.58	0.42	2	51065
Franklin	20.28	48970.75	14.69	11.52	0.44	1	51067
Franklin City	21.89	35909.12	19.65	31.69	0.46	1	51620
Frederick	28.14	70735.38	6.31	4.92	0.39	2	51069
Fredericksburg	39.18	54431.12	16.93	19.07	0.47	1	51630
Galax	12.51	31202.25	24.83	21.13	0.52	1	51640
Giles	16.9	48374.75	11.98	7.69	0.41	2	51071
Gloucester	22.55	63392	8.5	7.03	0.4	2	51073
Goochland	38.45	84556.88	5.49	5.9	0.5	2	51075
Grayson	11.54	31727.12	20.19	16.59	0.46	1	51077
Greene	25.52	62618.62	9.74	9.08	0.39	2	51079
Greensville	8.19	41731.62	18.73	21.54	0.44	1	51081
Halifax	15.45	37605.38	18.57	17.27	0.45	1	51083
Hampton	24.34	51653.38	15.24	14.67	0.42	1	51650
Hanover	37.07	81312.75	5.57	4.13	0.39	2	51085
Harrisonburg	35.64	40966	31.32	17.62	0.47	1	51660
Henrico	41.16	64311.62	10.37	9.93	0.45	2	51087
Henry	12.05	35751.38	18.36	18.89	0.44	1	51089
Highland	22	46500.12	11.37	3.39	0.42	2	51091
Hopewell	12.67	39392.38	20.4	24.87	0.44	1	51670
Isle of Wight	26.69	67438	11.09	10.75	0.42	2	51093
James City	47.55	79757.38	8.04	4.46	0.44	2	51095
King and Queen	18.08	51460.62	12.74	9.44	0.38	2	51097
King George	33.2	84871.5	5.96	8.46	0.37	2	51099
King William	19.37	64794.75	10.52	7.71	0.37	2	51101
Lancaster	29.65	50548.62	10.69	7.87	0.46	2	51103
Lee	11.48	31842.38	25.83	23.45	0.46	1	51105
Lexington	42.69	36842.25	22.33	7.75	0.51	1	51678
Loudoun	59.09	128215.25	3.73	2.93	0.37	2	51107
Louisa	21.24	56989.62	11.02	10.08	0.43	2	51109
Lunenburg	11.57	39185	19.87	19.84	0.41	1	51111
Lynchburg	33.12	40967.25	23.35	18.28	0.48	1	51680
Madison	23.74	52368.12	11.15	10.82	0.45	2	51113
Manassas	29.32	74756.75	9.92	9.03	0.4	2	51683
Manassas Park	28.17	76539.12	8.29	9.04	0.37	2	51685
Martinsville	18.66	30803	25.15	28.37	0.51	1	51690
Mathews	27.73	62037.88	9.84	8.96	0.42	2	51115
Mecklenburg	16.52	39254	18.93	13.59	0.45	1	51117
Middlesex	24.51	53581.88	9.7	9.67	0.45	2	51119
Montgomery	44.78	49789.12	24.39	8.29	0.49	1	51121
Nelson	29.22	53301.75	14.01	11.94	0.46	1	51125
New Kent	25.47	76080.12	5.75	6.18	0.38	2	51127
Newport News	24.65	51175.12	15.57	16.84	0.43	1	51700
Norfolk	26.65	46408.12	20.06	19.74	0.48	1	51710
Northampton	21.28	38280	21.84	15.39	0.5	1	51131
Northumberland	25.49	54721.12	12.3	7.64	0.43	2	51133
Norton	19.38	31594.12	23.1	36.26	0.5	1	51720
Nottoway	13.49	38634	19.99	26.62	0.46	1	51135
Orange	24.3	65436.62	10.57	9.3	0.4	2	51137

Page	12.71	45460.38	16.28	14.43	0.42	1	51139
Patrick	12.79	36972.25	18.85	14.81	0.42	1	51141
Petersburg	16.55	34436.88	26.96	31.21	0.47	1	51730
Pittsylvania	14.1	43617	15.14	14.18	0.42	1	51143
Poquoson	39.2	87237.38	5.16	2.72	0.4	2	51735
Portsmouth	20.67	47802.88	17.87	18.85	0.42	1	51740
Powhatan	28.26	79696	5.37	5.03	0.39	2	51145
Prince Edward	24.21	41703.5	20.1	17.49	0.45	1	51147
Prince George	21.05	65156.88	9.46	8.91	0.38	2	51149
Prince William	39.21	100436.88	6.66	6.25	0.38	2	51153
Pulaski	17.86	48427.25	13.81	13.08	0.42	1	51155
Radford	35.03	32775.38	37.88	15.86	0.53	1	51750
Rappahannock	33.33	61641	9.75	7.67	0.47	2	51157
Richmond City	36.66	42373.88	25.08	24	0.54	1	51760
Richmond County	13.82	47532.62	14.34	11.91	0.44	1	51159
Roanoke City	23.54	40461.5	21.62	21.99	0.47	1	51770
Roanoke County	34.18	62498.5	7.46	6.43	0.42	2	51161
Rockbridge	24.93	51234.75	13.82	10.25	0.45	1	51163
Rockingham	24.49	55777.88	10.39	6.2	0.44	2	51165
Russell	12.22	36906.25	19.15	16.25	0.46	1	51167
Salem	29.05	52351.88	10.33	9.59	0.44	2	51775
Scott	12.34	38279.38	18.47	15.62	0.45	1	51169
Shenandoah	19.72	51643.62	11.46	10.32	0.41	2	51171
Smyth	14.77	38893.5	18.5	16.87	0.45	1	51173
Southampton	16.04	51453	13.48	15.87	0.42	1	51175
Spotsylvania	29.65	81056.75	7.87	8.28	0.39	2	51177
Stafford	37.75	101062.38	4.96	5.02	0.37	2	51179
Staunton	31.7	43483.62	15.72	9.93	0.46	1	51790
Suffolk	27.05	67945.38	11.16	13.31	0.42	2	51800
Surry	19.19	52984.75	12.69	16.86	0.38	2	51181
Sussex	10.93	41656.12	17.57	17.16	0.42	1	51183
Tazewell	14.02	38365.25	17.62	16.49	0.47	1	51185
Virginia Beach	34.18	69136	7.94	7.34	0.41	2	51810
Warren	20.64	63953.25	9.87	9.4	0.41	2	51187
Washington	23.11	44124.75	13.47	11.64	0.46	1	51191
Waynesboro	21.59	44849.25	18.3	16.49	0.42	1	51820
Westmoreland	18.33	51293.75	12.42	13.36	0.44	1	51193
Williamsburg	53.24	51531.38	21.16	8.57	0.51	1	51830
Winchester	30.78	48363.12	16.28	12.8	0.46	1	51840
Wise	13.85	37380	21.76	20.82	0.47	1	51195
Wythe	16.7	43813.62	15.11	12.66	0.45	1	51197
York	43.44	84927.75	5.62	4.31	0.39	2	51199

Note that “1” in the cluster column indicates the disadvantaged areas, while “2” implies the advantaged areas. The results are also provided in an Excel file in the supplemental material for this report.