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Relationship Between Firearm-Related Deaths and Food Insecurity in Hampton Roads

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Abstract The purpose of this paper was to examine the relationship between gun-related deaths and food insecurity in the Hampton Roads Metropolitan Area of Virginia. We utilized aggregated data from the publicly available Food Access Research Atlas data from the U.S. Department of Agriculture to determine food access levels, and the Virginia Department of Health provided the gun death data. Using a Poisson regression model, we found that there is a statistically significant relationship between food insecurity and gun-related deaths in the Hampton Roads cities of Virginia Beach, Hampton, Chesapeake, Portsmouth, Newport News and Norfolk. The model also revealed a significant relationship for age at death and city of residence with the sum of firearm-related mortalities. When studying the cities independently of each other, the cities with the most pronounced relationship between firearm-related mortalities and food insecurity were Chesapeake, Norfolk, and Portsmouth. We found a notable trend where the younger population, aged 17 to 25, experienced the highest rates of gun deaths in the metropolitan cities studied. Addressing food insecurity, as well as violence prevention for youth and young adults, may help to decrease the number of firearm-related fatalities in Hampton Roads.

Keywords: *food insecurity, gun violence, firearm, social determinants of health, homicide*

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1. Introduction

Gun violence is a major public health issue in the United States and, although preventable, is a leading cause of premature death. Food insecurity has been shown to be associated with gun violence in several major metropolitan cities including Atlanta GA, Philadelphia PA, New Orleans LA, St. Louis MO, and Chicago IL [1,2,3,4]. This association could be due to the same root causes of gun violence and food insecurity; poverty and the additive effects of other social determinants of health which negatively impact urban areas such as unemployment, poor housing, crime, and racial segregation [3]. The purpose of this paper is to examine the relationship between gun-related deaths and food insecurity in Hampton Roads, Virginia.

2. Food Insecurity

The US Department of Agriculture defines food insecurity as "a household-level economic and social condition of limited or uncertain access to adequate food" [5]. Ruth Nicols, President of the Foodbank servicing Hampton Roads states, "although food insecurity does not discriminate by age or race and can become a reality experienced by anyone, African American and Latino individuals are disproportionately impacted in our region and throughout the nation by this complex social issue. These individuals often live in communities with a high concentration of poverty where access is limited to healthy food and other resources – such as health care, affordable housing, employment and workforce development – that can improve one's quality of life and lead to economic self-sufficiency" [6].

According to a 2020 study by the Dragas Center for Economic Analysis and Policy at Old Dominion University, the Hampton Roads area exhibits the highest rates of food insecurity in Virginia. This study went on to indicate that food insecurity in the Hampton Roads cities is highly correlated to median household income, unemployment rate, and consequently poverty rate. Additionally, food insecurity disproportionately affects children, female led households, and households of color [6].

According to Feeding America, in 2021 the food insecurity rate in the following cities in the Hampton Roads area were higher than the average rate of 8.1% for state of Virginia, including City of Hampton (9.1%), City of Portsmouth (10.3%), City of Newport News (10.7%), and City of Norfolk 11.3%) [7] In fact, Newport News and Norfolk were also above the average US food insecurity rate of 10.4%. In addition, blacks are 2.5x more likely to be food insecure than whites. About 23% of Black people in the US experienced food insecurity in 2022 [8]. Discrimination plays a role, as it lowers opportunities for employment and therefore income, which increases food insecurity in black households [8].

2.1. Food Insecurity among Children

The lack of nutritious food is associated with obesity and developmental delays in children, as well as poor academic and psychosocial outcomes [9,10]. Food insecurity has been shown through previous studies to be related to poverty. According to Feeding America, the cities that make up the Hampton Roads area in Virginia had a child food insecurity rate above the Virginia state value of 8.8% and US value of 12.8% (Newport News 19.8%, Norfolk 20.2%, Hampton 20.3%, and Portsmouth 22.4%) [7]. A study revealed a significant association where children residing in food insecure areas were seen to have a sixfold increase in exposure to violence and adverse childhood experiences, which may have enduring detrimental effects on their well-being, including chronic health conditions, mental illness, and substance abuse [11].

3. Gun Violence

According to the Centers for Disease Control and Prevention (CDC), in 2022, there were over 48,000 deaths related to gun violence in the US, and 4 out of every 10 of these deaths were homicides. While not all individuals die from gun related injuries, many suffer from long term medical issues like brain injury, paralysis and chronic mental health problems like PTSD [12]. Injuries related to firearms were among the top 5 leading causes of death for individuals aged 1-44, and for those aged 1-19, gun injuries were the leading cause of death. Black children and teens had a gun violence rate 20 times higher than their white counterparts [12,13]. The majority of gunshot related homicides and injuries also occur in vulnerable minority communities, where the crime and poverty is high [3]. Social determinants of health and structural racism play key roles in this disparity [14].

According to the CDC, gun violence in Hampton Roads is a major public health problem and a leading cause of premature death. Death rates due to firearms from 2018-2020 in Hampton was 16.9 deaths per 100,000, Norfolk was 17.6 deaths per 100,000, Newport News was 18.9 deaths per 100,000, and Portsmouth was 27.1 deaths per 100,000 population, in comparison to the Virginia state value of 12 deaths per 100,000 population [15].

The relationship between food insecurity and gun-related deaths in Hampton Roads is understudied. The aim of this study is to investigate the relationship between food insecurity and the rate of gun-related mortality in Hampton Roads cities with elevated gun violence. We hypothesized that there is a relationship between food insecurity and gun-related deaths in Hampton Roads.

4. Methodology

In this paper, we observed six metropolitan cities in Hampton Roads with high rates of firearm-related incidents to investigate the relationship between food insecurity and firearm-related mortalities. The six cities we studied are Chesapeake, Hampton, Newport News, Norfolk, Portsmouth, and Virginia Beach. The data for this study was gathered from two resources. We utilized the publicly available Food Access Research Atlas (FARA) data from the United States Department of Agriculture (USDA) for the food insecurity variable. The data regarding firearm-related deaths was provided by the Virginia Department of Health (VDH) for the six cities and included variables describing the year of death, age at death, city, census tract, and a specific code describing the type of gun death. The VDH data covered the years from 2018 to 2022.

The FARA data was aggregated from 2014 –2018 and we utilized the variable named “lalowihalfshare” from the dataset, which is a variable that specifies the share of the census tract population that has low income, defined as such that the tract is in a metropolitan area and has a median family income less than or equal to 80 percent of the metropolitan area's median family income [29] and low access at 0.5 miles from a grocery store [16]. The combination of these two factors serves as a robust indicator of food insecurity [30]. Prior to use in analysis, all personal identifiers (names, social security numbers, street addresses, etc.) were removed from the data. Certain census tracts were not included in the study as they were outliers due to the fact that they were not residential areas. These census tracts include organizations such as Norfolk Naval Shipyard, Norfolk International Airport, and Joint Base Langley-Eustis.

There were 1340 total observations in the VDH data for the years from 2018 to 2022. Of this, 1094 (81.64%) were used for the modeling and analysis. Missing or incomplete observations and outlier census tracts were not included. The data included 137 (12.52%) observations from Chesapeake, 118 (10.79%) from Hampton, 155 (14.17%) from Newport News, 280 (25.59%) from Norfolk, 162 (14.82%) from Portsmouth, and 242 (22.12%) from Virginia Beach.

The data from the VDH was aggregated so that modeling could be achieved in order to create a merged dataset between the FARA and the VDH data. This aggregation was accomplished by summing the number of gun deaths within each census tract over the five years of the data. The aggregated data from the USDA and the aggregated data from the VDH was then merged and used to estimate statistical models to describe the relationship between gun deaths and food insecurity. The population data for the census tracts was cross-walked in order to have the most up to date data. Due to limitations in data availability, this study recognizes the temporal difference in datasets. However, this is currently the most up-to-date data on food insecurity that is available. Future research will consider incorporating a more up-to-date dataset.

Finally, a Poisson regression model was used with the count response variable “Sum_of_Deaths”, and explanatory variables “lalowihalfshare”, “AGE_AT_DEATH”, and “City”. The response variable “Sum_of_Deaths” is the aggregated sum of deaths for each included census tract in each city over the five years encompassed by the data set. The explanatory variable "lalowihalfshare" represents the food insecurity of the census tract by describing the share of the census tract population with low access to food and low income. The "AGE_AT_DEATH" is the numerical value of the individual's age at the time of death, and "City" is a qualitative variable describing the individual's city of residence.

4.1. Data Exploration

Firstly, exploratory analysis was completed on the data as well as generating time series graphs on the VDH data for the five years that the data covered. To gain a more comprehensive understanding of the impact of firearm-related deaths on individuals in the studied cities, some of the variables' patterns over time were considered. This analysis aimed to identify emerging patterns based on race, age, and the specific nature of each death. This way an informed decision-making process was ensured, along with a robust framework for the subsequent modeling.

The summary statistics of the variables "Sum_of_Deaths", "AGE_AT_DEATH", and "lalowihalfshare" are shown in Table 1. These statistics include the number of observations, the mean, and the standard deviation for the response variable and the quantitative explanatory variables which were used in the Poisson regression model. It can be seen that "AGE_AT_DEATH" and "lalowihalfshare" have larger standard deviations, indicating more variability in these variables. This is addressed later in the paper.

The histograms showing the distributions for the response and explanatory variables are shown in the following three figures. These histograms describe the distribution for each variable over the entire area of study for the years 2018 to 2022.

Table 1. Observations, Mean, and Standard Deviation of Variables

Variable	N	Mean	Std Dev
Sum_of_Deaths	1094	6.21	3.53
AGE_AT_DEATH	1094	37.60	18.05
lalowihalfshare	1094	22.09	16.67

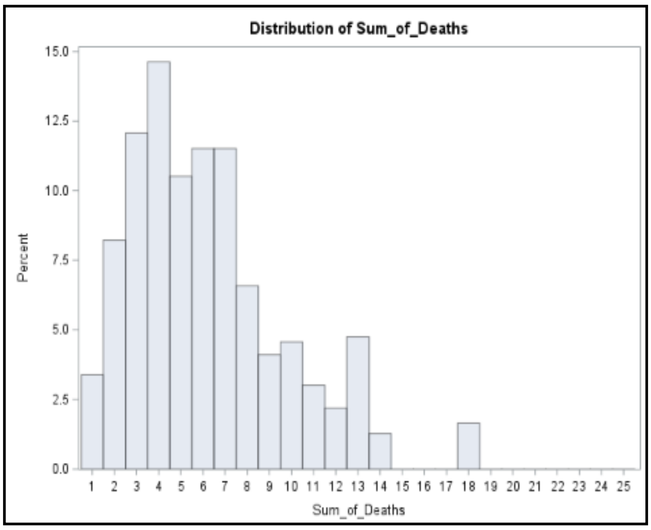

Figure 1. Distribution for "Sum_of_Deaths" for entire study area over 5 years

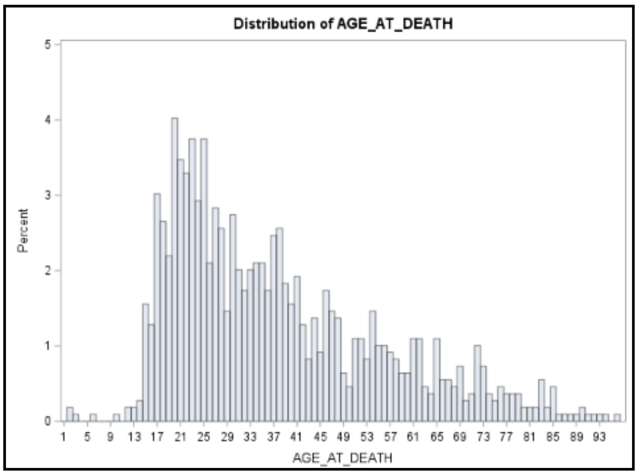

Figure 2. Distribution for "AGE_AT_DEATH' for entire study area over 5 years

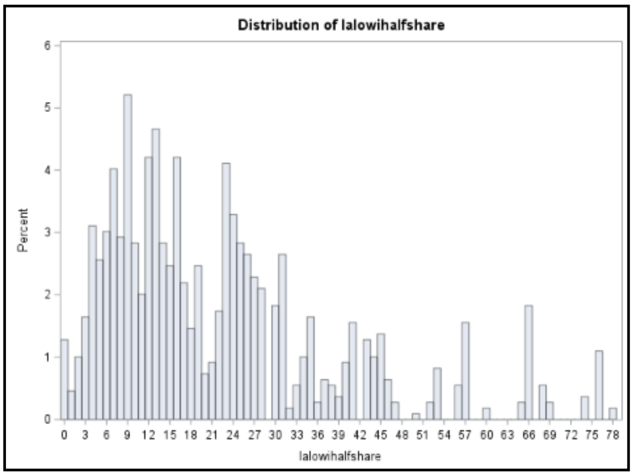

Figure 3. Distribution for "lalowihalfshare" for entire study area over 5 years

Correlation was also checked before proceeding with modeling to rule out multicollinearity between the response and quantitative explanatory variables. Figure 4 shows the correlation matrix and resulting heatmap for the explanatory and response variables used in the model.

The correlation between "Sum_of_Deaths" and "lalowihalfshare is weakly positive, while the correlation between "Sum_of_Deaths" and "AGE_AT_DEATH" as well as between "AGE_AT_DEATH" and "lalowihalfshare" is weakly negative. Thus, the correlation between these model variables exhibits a low strength, suggesting their suitability for inclusion in the Poisson regression model.

Next, we looked at the VDH data to determine if there were any temporal patterns that emerged over the five years that the data comprised. Figure 5 shows the temporal fluctuation in firearm- related mortalities over the years encompassed by the dataset for each city.

There is not a steady upward trend for any of the individual cities. Virginia Beach in pink had less deaths in 2022 than in 2018, but all other cities had more deaths in 2022 than in 2018. Notice the severe increase in the slope on Portsmouth's line in blue from 2021 to 2022, while the other cities increased only slightly, leveled off, or even decreased.

Pearson Correlation Coefficients, N = 1094 Prob > |r| under H0: Rho=0	Sum_of_Deaths	lalowihalfshare	AGE_AT_DEATH
Sum_of_Deaths Sum_of_Deaths	1.00000	0.27532 <.0001	-0.13844 <.0001
lalowihalfshare lalowihalfshare	0.27532 <.0001	1.00000	-0.16534 <.0001
AGE_AT_DEATH AGE_AT_DEATH	-0.13844 <.0001	-0.16534 <.0001	1.00000

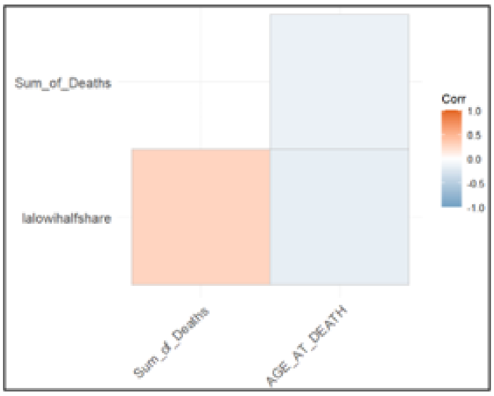

Figure 4. Correlation matrix and heatmap for variables

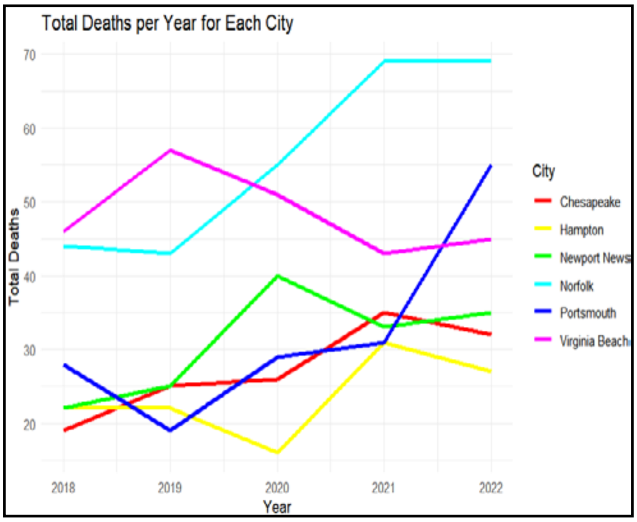

Figure 5. Total deaths for each city from 2018 to 2022

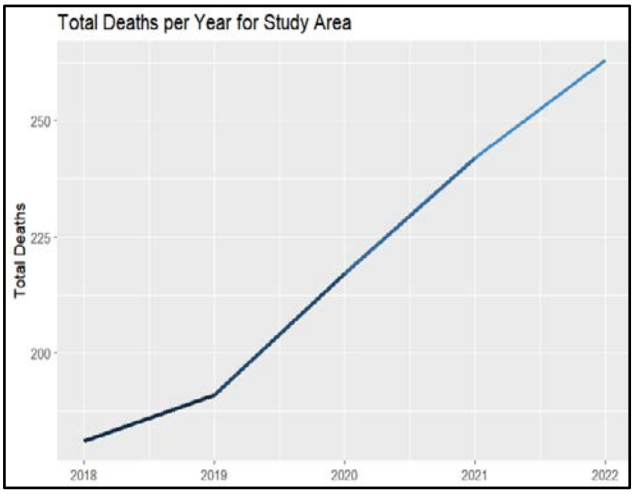

Figure 6. Total deaths per year from 2018 to 2022 for the entire studied area

We then transitioned from examination of the six individual cities to a broader, aggregate analysis of the entire area of study and a discernible trend emerged. Figure 6 shows the total firearm-related deaths of the study area from 2018 to 2022. Specifically, we observed a consistent upward trajectory in the incidence of firearm-related mortalities.

A more in-depth exploration of the firearm-related mortalities in the study area began in order to augment our understanding of the dynamics of the firearm-related mortality patterns emerging in the studied cities. Various demographic and contextual factors were delved into, specifically the complicated interplay between race, type of death, and age distribution. The cities of Hampton, Newport News, and Portsmouth are more heavily populated by black residents, whereas Virginia Beach, Norfolk, and Chesapeake are more heavily populated by white residents. However, in Figure 7 it can be seen that that the majority of the cities lost more blacks to firearms than the other races, even though only three of the cities have a larger white population than black. In fact, a larger percentage of Norfolk's population is white, but it can be seen in Figure 7 that the number of firearm-related mortalities is made up of much more blacks than whites. Out of the six cities, it is clear that more blacks than whites suffer firearm-related deaths in all of the cities except for Chesapeake and Virginia Beach. This led to considering the type of death for the studied cities. The races most heavily affected by firearm-related mortalities are blacks and whites. Blacks apparently died more from homicides, while whites saw more deaths from suicides. Figure 8 shows the distribution of the total number of firearm-related mortalities from 2018 to 2022 in the six cities we studied, separated by race and color-coded by type of death. The second to last column shows the deaths for blacks, and the last column shows the total deaths for whites. As mentioned before, we see that the majority of firearm-related mortalities from 2018 to 2022 for blacks was homicide, while the majority of firearm-related mortalities for whites was suicide. Since homicides and suicides are the most prevalent types of firearm-related deaths in the cities being studied, the distribution of these two types of firearm-related deaths were graphed in Figure 9. In this figure, it can be seen that the homicide distribution is skewed right. This shows that as an individuals' age increases, they are contributing less to the sum of deaths for the studied cities. It can also be seen that the peak of the homicide distribution is above the first peak of the bimodal normally distributed suicide distribution. Homicides seem to be most prevalent among the ages of 17 – 25, which is shown in the distribution in Figure 10. It can be seen in the suicide distribution that the first peak matches with the homicide distribution, but the second peak is around ages 50 to 59. The first peak of suicides underscores the prevalence of firearm-related mortality events, both homicides and suicides, among young individuals transitioning into their early adulthood. Conversely, the resurgence in suicides within the age bracket of 50-59 could underscore the mental health concerns as individuals transition from middle to late adulthood. The prevalence of homicides and suicides among youth and young adults may be indicative of several underlying societal issues, with food insecurity being one of those. Therefore, addressing food insecurity among the younger populations may be an integral part of reducing gun violence in these areas.

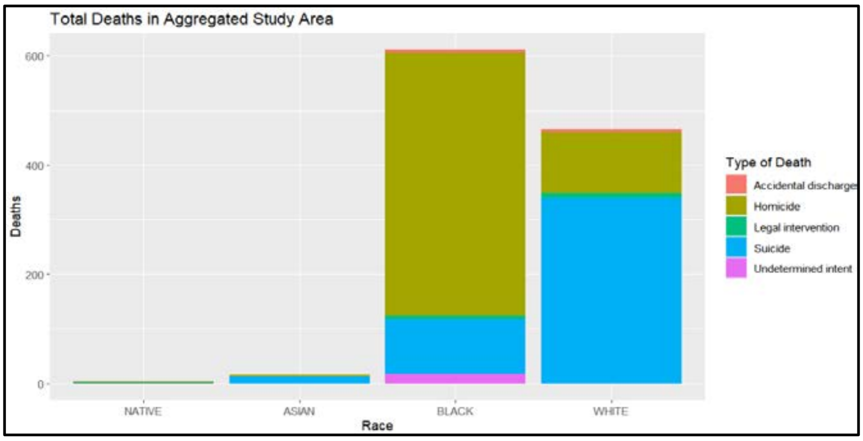

Figure 7. Distributions of death by race in each city

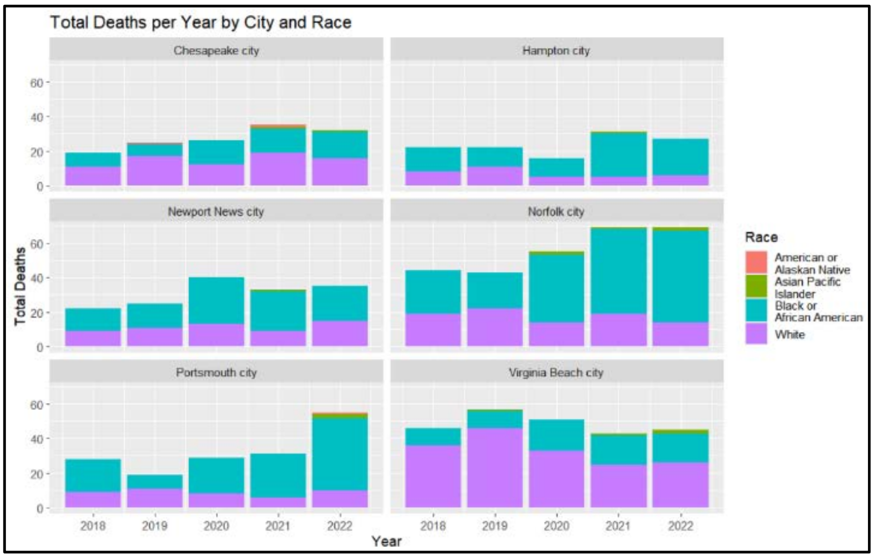

Figure 8. Deaths by race for entire studied area and color-coded by type of death

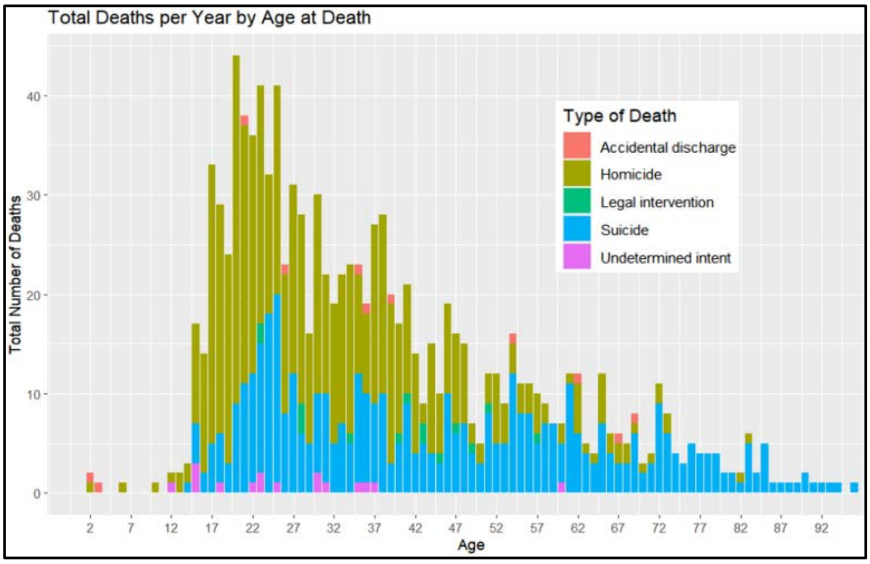

Figure 9. Homicide and suicide distributions for entire study area by age

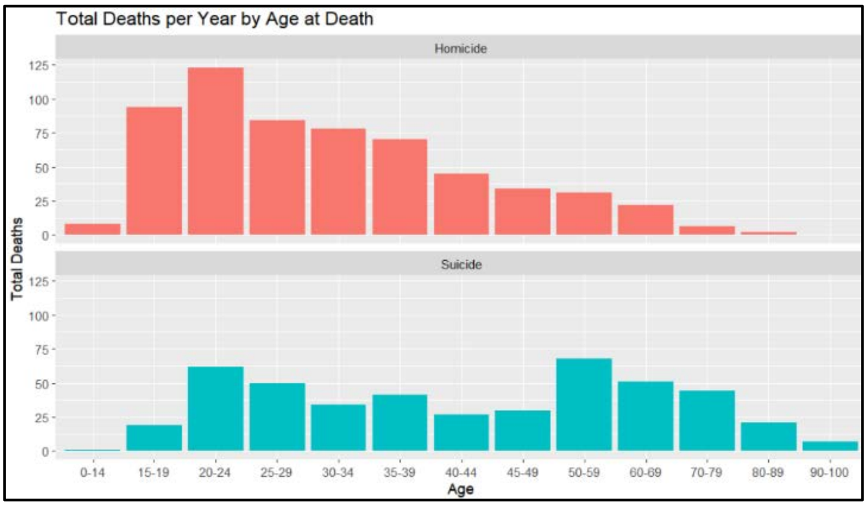

Figure 10. Distribution of deaths by age for entire study area, color-coded by type of death

4.2. Poisson Regression Model

Given the nature of the data, particularly the count-based nature of the sums of firearm-related deaths as the response variable, a Poisson regression model was employed to analyze the relationship between food insecurity and firearm-related deaths. Specifically, the model was utilized to determine if there was a positive relationship between the two variables. It has been seen that there is extensive research indicating that a higher level of food insecurity leads to a higher level of firearm-related incidents and firearm-related mortalities (see Section 1), and we wanted to build upon this body of work. We therefore investigated whether this relationship holds true in the six metropolitan cities in Hampton Roads that experience high levels of firearm-related incidents.

We employed the Poisson regression model for this study and looked at the entire area of the six different metro cities combined as well as each city individually to gain more insight. The response variable is the count of total gun deaths over five years in each census tract. The basic Poisson regression model had the “lalowihalfshare” variable as the predictor variable to determine if the sum of gun deaths from the years 2018 to 2022 in each census tract was positively related to “lalowihalfshare”, indicating a positive relationship between food insecurity and firearm-related mortalities. This Poisson model was described as:

$$log(\lambda) = \beta_0 + \beta_1 x$$

where x is the predictor variable “lalowihalfshare”. After testing this simple Poisson regression model and determining a positive relationship existed, more variables of interest were introduced to this model. Overall, the model included the response variable “Sum_of_Deaths”, and the explanatory variables “lalowihalfshare”, “AGE_AT_DEATH”, and “City”. This Poisson model was described as:

$$log(d) = log(p) + \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_8 x_8,$$

where x_1 and x_2 are the explanatory variables ‘lalowihalfshare’ and ‘AGE_AT_DEATH’, and $x_3, x_4, \ldots, x_8$ represent the factor variables of the six different cities in the study.

The term $log(p)$ is the offset term utilized with the Poisson regression model to account for the varying population sizes across the cities’ census tracts. This offset term accounts for the expected number of firearm-related deaths based on population size, allowing us to better estimate the relationship between food insecurity and firearm-related deaths independent of population size. This model allowed us to describe how the log of the sum of deaths is related to the food insecurity variable ‘lalowihalfshare’, an individual’s age at death using the ‘AGE_AT_DEATH’ variable, and an individual’s city of residence using the ‘City’ variable. The model indicated a statistically significant relationship between food insecurty and firearm-related mortalities in the area of study.

5. Analysis and Results

For this study, a Poisson regression model was used to determine the relationship between food insecurity and firearm-related mortalites in the six selected cities of Hampton Roads, Virginia. In this model, $\lambda = \frac{d}{p}$, where d is the aggregated sum of deaths for each census tract over the 5 years, and p is the total population for each census tract.

The possibility of a geographical relationship to firearm-related mortalities in the study area was considered based on the statistical difference between the six cities. First, a null hypothesis was tested to determine if there was a significant difference in the mean of the total sum of deaths among each of the different cities. This null hypothesis was presented as:

$$H_0 : \mu_1 = \mu_2 = \ldots = \mu_6$$

where $\mu_1, \mu_2, \ldots, \mu_6$ represent the means of the sum of deaths for each city.

An Analysis of Variance (ANOVA) test was used in the statistical software program SAS™ to determine if there was a significant difference between the mean log of the sum of deaths in the six cities being studied. This test returned an F-value of 11.09 with a p-value of less than

0.001, therefore the null hypothesis was rejected, and it was determined that there was indeed a significant difference in the mean log of the sum of deaths between the cities in the study area. Specifically, the cities in Table 2 showed statistically significant pairwise differences.

Table 2. City Significant Pairwise Differences

Cities with Significantly Different Means of the Sum of Deaths
Portsmouth – Hampton
Portsmouth – Newport News
Portsmouth – Virginia Beach
Norfolk – Newport News
Norfolk – Virginia Beach
Chesapeake – Newport News
Chesapeake – Virginia Beach

After pairwise differences between certain cities in the area of study was established, we next utilized a Levene test to determine if the six different cities had equal variances. Some statistical tests assume that variances are equal across groups or samples. The Levene test can be used to verify that assumption. The Levene test was defined as:

$$\mathbf{H}_0 : \boldsymbol{\sigma}_1^2 = \boldsymbol{\sigma}_2^2 = \ldots = \boldsymbol{\sigma}_6^2$$

VS

$$\mathbf{H}_1 : \boldsymbol{\sigma}_1^2 \neq \boldsymbol{\sigma}_2^2 \neq \ldots \neq \boldsymbol{\sigma}_6^2$$

This Levene test was conducted with both the "Sum_of_Deaths" variable and the log transformation of the variable. Both tests concluded that the null hypothesis must be rejected; therefore the conclusion was that the variance among the cities was not equal. Norfolk, Newport News, and Virginia Beach are the cities with the most variance in their minimum and maximum values. Figure 11 displays the output for the Levene test using the log transformed "Sum_of_Deaths" variable, showing the number of observations, mean, and standard deviation for each different city's log sum of deaths. We can see that Virginia Beach had the lowest mean while Hampton had the smallest standard deviation. Norfolk had the highest number of recorded firearm-deaths, which contrasts with its population since it is only the third most populated city out of the six cities that were studied.

Level of County	N	log_sumofdeaths	
		Mean	Std Dev
Chesapeake city	137	1.73583638	0.55613275
Hampton city	118	1.65720425	0.49551620
Newport News city	155	1.55192976	0.51243723
Norfolk city	280	1.68972342	0.70367450
Portsmouth city	162	1.89360924	0.57084398
Virginia Beach city	242	1.47225687	0.62536577

Figure 11. Values for the levels of each city

Finally, to determine geographic significance, a Poisson regression model was tested by employing SAS™ software using "Sum_of_Deaths" as the response variable, "City" as the explanatory variable, and the log of the total population as the offset term. The parameter estimates and corresponding p-values were obtained for each level of the categorical variable "City" concerning the response variable "Sum_of_Deaths". Notably, the SAS™ software automatically designated one level of the categorical variable as the reference (baseline) category for comparison, as indicated by a parameter estimate of 0 and a missing p-value. This reference category served as the baseline against which the effects of other categories were assessed. Such automatic designation facilitates interpretation by highlighting differences in the effects of non-reference categories relative to the chosen reference category. It is important to note that the choice of reference category is arbitrary and does not impact the validity of the analysis. [31]. This analysis indicates that, compared to Virginia Beach (the reference category), residing in Portsmouth is associated with an estimated increase of 0.68 in the log of the response variable. Table 3 shows the data reflecting the significant difference of the 'Sum_of_Deaths' variable of the cities from Virginia Beach. We can see that the other five cities are significantly different from the city of Virginia Beach, and Norfolk and Portsmouth have the highest parameter estimate values, indicating that residing in these two cities would be associated with the greatest increase in the response variable.

Table 3. SAS™ Software Proc Genmod "City" Model Output

Parameter	Estimate	Standard Error	Pr > ChiSq
Intercept	- 6.8683	0.0283	< .0001
Chesapeake	0.2298	0.0439	< .0001
Hampton	0.2249	0.0475	< .0001
Newport News	0.2340	0.0449	< .0001
Norfolk	0.5856	0.0363	< .0001
Portsmouth	0.6795	0.0402	< .0001
Virginia Beach	0.0000	0.0000	.

Since the cities are significantly different from each other, it was determined that including the "City" variable, which is a qualitative variable that labels which city the deceased is from, as a factor would be beneficial to the model and allow for further insight into the relationship between firearm-related mortalities and food-insecurity in the area. These results led to the conclusion that including the qualitative variable "City" in the regression model as a factor would be beneficial to the model and allow for further insight into the relationship between firearm-related mortalities and food-insecurity in the area.

"AGE_AT_DEATH" was tested for use in the Poisson regression model to determine its added benefit in understanding the relationship between firearm-related mortalities and food insecurity, as well. Two different Poisson regression models were tested with "Sum_of_Deaths" as the response variable in both. However, one model tested had "AGE_AT_DEATH" as the only explanatory variable, and the other model had both "lalowihalfshare" and "AGE_AT_DEATH" as the explanatory variables. In both models, "AGE_AT_DEATH" was significant to the model, indicating a statistically significant relationship between the response variable "Sum_of_Deaths" and the age at which a person suffered a firearm-related death. Therefore, "AGE_AT_DEATH" was considered beneficial and added to the final Poisson regression model.

The explanatory variable "lalowihalfshare" was also tested before inclusion in the final Poisson regression model. This variable had a high variance, so a model with a standardized version of the variable was created and tested as well. The variable was standardized by subtracting the mean and then dividing by the standard deviation of the variable. These values can be seen in Table 1. After the standardization of "lalowihalfshare", a Poisson regression model was tested with "Sum_of_Deaths" as the response variable, and "lalowihalfshare" as the only explanatory variable. The parameter estimate for the standardized form of the variable was a positive value, and the p-value was significant. After the standardized form of the variable was tested, the non-standardized form of "lalowihalfshare" was then tested in the same Poisson regression model. Once again, the parameter estimate for the coefficient was positive and the p-value was significant, signifying a statistically significant relationship between "Sum_of_Deaths" and "lalowihalfshare". Since there was such a small difference between the standardized and non-standardized form of "lalowihalfshare", the non-standardized form of the variable was used in the final Poisson Regression model.

The final Poisson regression model is described as:

$$log(d) = log(p) + \beta_0 + \beta_1 x_1 + \beta_2 x_2$$
$$+ \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_8 x_8,$$

where x_1 - x_8 are the explanatory variables "lalowihalfshare", "AGE_AT_DEATH", and the six different cities in the study represented by factor variables. This model was tested using both statistical softwares SAS™ and R Studio and a positive, statistically significant relationship between "Sum_of_Deaths" and "lalowihalfshare" was the result. The parameter estimate for the variable "AGE_AT_DEATH", which describes a person's age at their time of death, was negative. This indicates that as a person ages they are less likely to contribute to the response variable describing firearm-related deaths. This was seen in the exploratory analysis, as well, particularly in Figure 10. The parameter estimates generated for the Poisson regression model, along with the respective p-values, can be seen in Table 4.

Considering the parameter estimates garnered from the Poisson regression model, we can see that all explanatory variables are statistically significant in the model. This means that for each one unit increase in the measure of food insecurity, we expect the log of the expected count of the sum of deaths to increase by 0.0083. This is representative of a positve relationship between firearm-related mortalities and food insecurity in the studied cities. However, for each one unit increase in age, the logarithm of the expected count of the sum of deaths decreases by 0.0026 units. Looking at the cities of residence, we can consider if the individual is from Chesapeake. With a parameter estimate of 0.1515, this indicates that, compared to the reference city of Virginia Beach, living in Chesapeake is associated with approximately a 16% higher expected count of the sum of deaths response variable while holding all other variables constant. On the other hand, we can see that living in Portsmouth is associated with approximately a 72% higher expected count of the sum of deaths variable when compared to living in Virginia Beach; all other variables are held constant. All of these explanatory variables together paint a picture of geographical significance, higher firearm-related deaths among young people, and food insecurity contributing to those deaths.

When testing a similar Poisson regression model on each city, it was seen that "lalowihalfshare" as the explanatory variable had a positive relationship with the response variable "Sum_of_Deaths" (this time describing the total number of deaths from 2018 to 2022 in each specific city) in Chesapeake, Norfolk, and Portsmouth. As shown in Table 4, living in these cities had a higher expected count of the sum of deaths variable when compared to living in Virginia Beach. This suggests that implementing food relief operations in these cities could effectively reduce the upward trend in firearm-related fatalities, making them prime candidates for initiating such interventions.

Table 4. Paramater Estimates for Poisson Regression Model

Parameter	Estimate	Standard Error	P-Value
Intercept	-6.8639	0.0422	< .0001
lalowihalfshare	0.0083	0.0007	< .0001
AGE_AT_DEATH	- 0.0026	0.0007	0.0004
Chesapeake	0.1515	0.0445	0.0007
Hampton	0.1302	0.0481	0.0069
Newport News	0.1239	0.0459	0.0069
Norfolk	0.4201	0.0390	< .0001
Portsmouth	0.5424	0.0420	< .0001
Virginia Beach	0.0000	0.0000	.

6. Discussion

According to the American Public Health Association, preventing death, disability and injury from gun violence requires a public health approach that involves data collection and surveillance, research to understand which programs are effective in decreasing gun violence, initiatives to implement those measures that are shown to work and continued surveillance and evaluation. The Office of Disease Prevention and Health Promotion, Healthy People 2030, has defined social determinants of health (SDOH) as the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks [26].

SDOH have a significant impact on the quality of one's life. Some examples of SDOH described by Healthy People 2030 include health care access and quality, education access and job opportunities, income and economic stability, discrimination and racism, safe neighborhoods and housing, food security and physical activity, to name a few. Those individuals that live in poverty often find themselves in an environment that contributes to poor health and disadvantage, with few resources to make improvements to their plight so that they can reach their full potential for health wellness.

Oftentimes poor families are restricted to living in poor housing, where the neighborhood is filled with violence and crime, as options for affordable housing in safer neighborhoods are not available. Exposure to violence and crime day after day takes its toll on the physical body. Stress and mental health issues often arise, along with other chronic health conditions like diabetes, obesity, high blood pressure, and cancer to name a few health conditions that are disproportionately high in Black communities. These communities mostly provide low wage employment to the residents like fast food work or jobs as cashiers in stores, or no employment opportunities at all, especially for those that are uneducated and unskilled. The lack of transportation is another barrier which prevents urban residents from reaching better employment opportunities. The lack of healthy food choices just exacerbates the previously mentioned health conditions and contributes to more mental stress. When communities do not have the basic necessities of food, safe housing, and a decent living wage, this is a human rights violation, and an example of structural violence.

Structural violence was first described by Norwegian sociologist Johan Galtung, as “a form of violence where social structures or institutions harm people by preventing them from meeting their basic needs” [27]. Racism is a form of structural violence, and some urban communities have been systematically deprived of opportunities that will improve their health and quality of life. According to Christie, when economic deprivation occurs, the need for well-being is not satisfied, resulting in deficits in human growth and development which is a human rights violation [28].

In order to correct the violation of human rights, more needs to be done to address SDOH that contribute to one’s overall wellbeing, including educational and job opportunities, affordable housing, enhanced community safety, educational advancement, and trauma care. More after school and violence prevention and intervention programs are needed not only for at-risk youth, but for all youth that are exposed to childhood trauma and poverty.

In addition, doctors and teachers should ask questions related to food insecurity, so that those in need can be connected to the appropriate resources that can provide aid in this area, such as non-profits and places of worship. To assist non-profits and places of worship with helping to feed those in need, more grants and partnerships with foodbanks and government agencies are necessary.

Finally, reducing food insecurity in the community may be a good start to helping to improve health inequities and overall well-being for those in need, as well as decreasing community gun violence.

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