Identifying Disproportionate Burden Through the Spatial Covariance of Two Acute Deaths of Despair: Firearm Suicide and Opioid Overdose

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Abstract

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Objectives: To evaluate the spatial covariance in two acute deaths of despair outcomes, firearm suicides and opioid overdoses, to better understand how these two public health crises intersect across US counties. The identification of communities which share similar risk for both outcomes as well as those with a disproportionate burden of one outcome compared to the other will allow for more effective resource allocation and targeted intervention strategies.

Methods: CDC NVSS county-level detailed mortality data from 2013-2017 was used to classify deaths due to firearm suicide and opioid overdose. Local county standardized mortality ratios were smoothed using a Bayesian BYM model to reduce the influence of extreme, variable rates due to small numbers. The smoothed standardized mortality ratios for these two acute deaths of despair within each county were intersected to classify counties by their shared and distinct cause-specific burden of death compared to the US average risk.

Results: There is significant heterogeneity in the incidence of firearm suicide and opioid overdose deaths at the county-level compared to the US average risk of death (3.48 firearm suicide deaths per 10,000 people and 7.66 opioid overdose deaths per 10,000 people). The burden of mortality from these preventable causes reveals a distinct spatial pattern of intersection and avoidance, creating a uneven landscape of risk across the United States.

Conclusions: Spatial Bayesian smoothing techniques are crucial tools for making valid inferences regarding risk in small areas. Recognizing the shared or disproportionate burden of these two acute deaths of despair in a community can guide the development and refinement of programs designed to prevent them. To intervene to reduce deaths, a welfare geography approach should be used to equitably allocate shared resources to address the specific mediating pathways from despair to firearm suicide or opioid overdose deaths.

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Chapter 1: Introduction

General Overview

This study evaluates the spatial heterogeneity in two acute deaths of despair outcomes, firearm suicides and opioid overdoses, to better understand how these two public health epidemics covary across counties in the contiguous United States (US). A deaths of despair approach is used to identify disparities observed in these self-inflicted fatal injuries, and a welfare geography conceptual framework is considered for how these disparities should be addressed. Ultimately the rates of these two deaths of despair outcomes are driven by the composition and the context of each county, creating an emergent social environment that exists beyond the sum of its parts, reminiscent of Durkheim's social facts[1]. While there are individual risk or protective factors that may individually be associated with mortality at the county level, the specific collection of these factors in a single area creates a new latent context that can promote or protect against poor outcomes such as self-inflicted injury. In this way, county context can be considered an exposure beyond simply the composition of its individual risk factors. While deaths by either opioid overdose or firearm suicide may be driven by cause-specific factors, such as the availability of opioids or access to firearms, the "deaths of despair" narrative claims there is an underlying economic and sociological condition that can facilitate the pathways from means to outcome.[2]

Adopting this deaths of despair theory, counties with similar socioeconomic characteristics and a comparable level of economic stagnation or stability can be expected to have similar burdens of firearm suicide and opioid overdose. Areas where these two ratios are drastically out of balance can reveal divergent influences affecting the causal pathways from county context to either cause-specific death outcome. Similarly, counties found to have high rates of both outcomes may share common risk factors on a shared pathway to these deaths of despair, and counties that have consistently low rates of death from both outcomes may contain clues to promoting resilience in other communities. As was first espoused by British Geographer David Smith in his call for a welfare geography[3], recognizing that there are differential mechanisms at work is the first step in equitably allocating resources to reduce the identified disparities. This targeted provision of funds and human capital can better identify appropriate interventions to reduce excessive burden of mortality in specific communities. Areas that experience a high burden of both outcomes may be suffering from a number of structural issues that have given rise to "despair" and should be targeted for interventions that address upstream social determinants at the core of many enduring health disparities that exist throughout the US, including firearm suicide and opioid overdose.

Background

Although suicide is a relatively rare event when measured at the county-level, in total each year in the US it steals years of potential life from individuals of all age groups and is highly preventable making it a major public health concern. Suicide rates in the US have been increasing steadily since 2000 and the rate of this change seems to have increased since 2006[4,5]. In terms of overall burden, suicide is the tenth leading cause of death for all Americans and has risen to become the fourth leading cause among those in midlife aged 35-54.[6] There are also clear geographic patterns of suicide death, with almost one and a half times the number of suicide deaths in rural areas compared to urban areas,[7,8] a reality that is recognized in the deaths of despair narrative.

While the despair hypothesis includes all types of suicide, firearm suicide is the most common method accounting for half of the suicide deaths in the US and is by far the most lethal method of suicide.[9] Though only about 4% of suicide attempts are attempted using a firearm, approximately 90% of these attempts result in death.[6] For comparison, other suicidal means are far less lethal with case-fatality rates of below 60 percent for hanging and only three percent for poisoning and cutting.[6] Furthermore, a systematic review of suicide research in high income countries found that among those who attempt suicide, fewer than ten percent ultimately die by suicide within a decade,[10] but this favorable survival statistic is conditional on surviving a first attempt which is much less likely if a firearm is used. This suggests that firearm suicide may be one of the most intervenable methods to reduce the overall burden of deaths by suicide.

The trajectory of drug poisoning in the US has been well documented in recent years given the meteoric rise of deaths by opioid overdose resulting in the declaration of a national public health emergency in 2017.[11] Between 1999 and 2018, the rate of death from opioid overdose, whether accidental or intentional, has risen increasingly with each year and in total about 446,032 people died of an opioid overdose in the US during this period.[12] However, Centers for Disease Control and Prevention (CDC) Vital Statistics data from 2018 suggest that the overall rate of drug overdoses may have decreased by about 4% from the previous year, driven primarily by a decrease in prescription opioid deaths even as the death rate from synthetic opioids continues to climb.[12] This divergent pattern of deaths by opioid type – type meaning prescription opioids, illicit street opioids such as heroin, or synthetic opioids – reveals the multifaceted nature of the opioid epidemic and hints at the differences in risk associated with drug supply and geography.

In fact, the opioid epidemic can be better understood as three separate but overlapping epidemics which shape the modern landscape of opioid overdose today.[13] Overprescribing of prescription opioids in communities across the US, and particularly in rural communities, catalyzed the rapid rise of opioid overdoses in this country. These rural communities, particularly those with a higher proportion of manual labor employment, higher work disability, and poor socioeconomic conditions still bear the brunt of prescription opioid overdose.[13] Conversely, heroin is more common in urban communities because their populations are large enough to sustain a high demand and they are conveniently located closer to interstate highways, granting them easier access to the illicit supply chain.[14] The third wave of the opioid epidemic is characterized by the rise of fentanyl and other synthetic opioids, which can be tens or even thousands of times more lethal than heroin or prescription opioids.[15] These synthetic opioids are more common in the Eastern US, and may be the cause of the rapid increase in overdose deaths east of the Mississippi River.[16] However, it is clear that the supply of these synthetic opioids is also moving West as the rate of deaths from synthetic opioids in the past few years continue to rise there.[15]

While both firearm suicide and opioid overdose are each public health epidemics individually, the fact that they are occurring concurrently across the US has doubly taxed local public health infrastructure responsible for addressing such crises. A coordinated, national response is needed to adequately respond to the specific needs of diverse local communities. Welfare geography seems particularly appropriate as a conceptual framework for considering the equitable allocation of resources in this case. First championed by David Smith in 1974 during the quantitative revolution in the social sciences, welfare geography is entirely dedicated to the question of, “who gets what, how, and where?”[3] It attempts to leverage new quantitative techniques for identifying disparities in order to understand how to optimally allocate social goods to produce the most collective benefit. The theory is intimately tied to the idea of "spatial injustice" – that inequality exists not just between individuals or groups, but also structurally across space. Finally, welfare geography emphasizes that redistribution of resources should not be equal, but rather it needs to be equitable, fair, and measured by need.

Welfare geography has been more popular in European and Scandinavian counties, perhaps because these counties have more extensive safety net systems in place to be able to assess what equitable reallocation should look like. At its core, welfare geography has been engaged in assessing the effects of social policies aimed at the redistribution of primarily monetary resources and services.[17] Consideration of welfare landscapes prompted the understanding that local space should provide an individual with the ability to satisfy their needs, not only in terms of essential goods such as housing and food, but also the ability to live well in a more holistic wellbeing sense.[18] Norwegian geographer Nina Berg traces the legacy of a welfare geography approach in this way through development and planning research and migration studies.[18] Recent studies of urban and rural places has benefited from this way of conceptualizing welfare as it questions whether an individual is able to provide for their physical as well as emotional wellbeing in their local environment.[18] Economic opportunity and social cohesion feature prominently in in a welfare landscape, aligning very well the hypothesized drivers of the observed mortality disparities in deprived areas. Indeed, in the title of Case and Deaton's new book, "Deaths of Despair and the Future of Capitalism," the emphasis on political economy is unmistakable.[19]

The identification of health disparities has been a main tenant of modern Health Geography. In fact, it has been identified as one of the five broad areas of study that quantitatively minded Health Geographers tend to address.[20] The use of small geographies is also a common feature of this type of geographical work, and as such has become increasingly technical which has caused a slight division from qualitative geographers studying health inequity. While both groups focus on vulnerable populations, they each confront the subject differently. Quantitative work has mainly been focused on identification, a goal of this analysis, while a qualitative approach has spent much time exploring specific elements of the environment that promote health and well-being such as therapeutic landscapes, or probing for common experiences and causes of inequality[20–22]. Both approaches are necessary to fully understand how to recognize and address inequity.

In Geography the role of context is highly relevant because it is ecological in nature. One favorable outcome of this focus on contextual factors is that researchers are more strongly promoting the structural influences faced by individuals and this has resulted in a move away from victim-blaming[22]. However, many important advances in health geography have come from multi-level modelling which can concurrently examine both ecological as well as individual level variables at a number of different geographical scales. [23] Multi-level models have been particularly helpful in studying neighborhood effects of social determinants of health, which can operate both at an individual and community level[24]. Future studies with the funding and capability to do so should test the deaths of despair theory using multi-level models to test the concept of individual despair within areas of differing economic opportunity.

While health inequities research maintains a large foothold in health geography, it seems that health geography has not adopted a deaths of despair framework for assessing these inequalities, preferring its own rigorous theories concerning health inequality. Unlike the nebulous concept of despair, many geographers ascribe to either the material deprivation or psychosocial framework for how social determinants of health lead to health inequality.[25] The former hypothesizes that it is the lack of basic needs such as the inability to pay for necessary goods and services that produce the observed health disparities, while the latter considers the personal experience of lesser means, including social comparisons or stress leading to unhealthy behaviors as the causal pathway. However, the prominent epidemiologist Ichiro Kawachi claims that this is a false dichotomy because material possessions are inherently imbibed with psychosocial meaning so these two risk contributions cannot be dissentagled.[25] Understanding how and where the pathways between deprivation and poor health outcomes are intervenable is the first step in addressing health inequities.

When the underlying cause of disparity is recognized and yet allowed to perpetuate, health inequalities can be thought of as a type of structural violence, as Geoffrey DeVerteuil makes a strong case for in his article, "Conceptualizing violence for health and medical geography."[26] The concept of structural violence was first introduced by Johan Galtung in 1969, which he equated with social injustice. Galtung cites the uneven distribution in resources as an example of structural violence, particularly if those with less access also bear other inequalities such as income, education, or power as so often occur together.[27] Even though there may not be individual actors committing inter-personal violence, if a system maintains an unequal allocation of social goods then structural violence is present. DeVerteuil cites Paul Farmer's influential work in structural barriers to health, particularly his discourses on poverty and stigma, to emphasize the importance of overarching social, economic and political landscapes. Farmer is well-known for highlighting the economic, political, and social systems that prevent health, as evidenced by his books, "Infections and Inequalities: The Modern Plagues,"[28] "Pathologies of Power: Health, Human Rights, and the New War on the Poor,"[29] and "AIDS and Accusation:

Haiti and the Geography of Blame."[30] This type of structural violence does not just affect how illness can occur but also the ways in which certain illnesses, particularly those with stigma such as mental health or HIV, are perceived, managed, and acknowledged in society.[26]

DeVerteuil reflects on the spillover between structural and personal violence through a lens of embodiment, suggesting that the experience of structural violence may lead to the perpetration of violence against other or one's self.[26] Interestingly, excessive alcohol and drug use are implicated in this framework of the spillover of structural violence into personal violence, which aligns nicely with some of the tenets of the deaths of despair theory. Lack of economic opportunity clustered within areas with higher proportions of socioeconomically disadvantages individuals can be considered a form of structural violence and the outcomes of opioid overdose and firearm suicide may be its interpersonal embodiment.

Following in the vein of quantitative geographers engaged in health equity research, it is necessary to accurately measure health disparities before any allocation calculation can be made, which is where the deaths of despair hypothesis becomes applicable. Case and Deaton were the primary researchers to recognize the declining life expectancy for middle-aged non-Hispanic White Americans, a phenomenon that Case and Deaton coined as "deaths of despair."[31] Case and Deaton found that increases in deaths from accidental or intentional causes such as poisonings, suicide, and alcohol related diseases were driving a marked increase in premature mortality in this group, reversing the long-running trajectory of increasing life expectancy in the US. Additionally, those with the lowest educational attainment seemed to experience the highest burden of these deaths of despair.[32] Case and Deaton hypothesized that the cumulative effect of stagnant economic conditions and a lack of economic mobility over time leading to greater social fragmentation and loss of family structure might be the underlying structural cause of the despair they believed was producing the increase in premature mortality.[2]

While Case and Deaton do not explicitly mention rurality in their original 2015 article,[31] the differential economic opportunities they implicate in the pathway to premature death necessitate that urban or rural context be considered. Disparities in urban and rural health have been persistent in America, with socioeconomic disadvantage, poor access to healthcare, lack of economic opportunity, lack of healthy foods or safe spaces for exercise, or lack of social cohesion being just a few of the primary proposed drivers of the observed inequalities.[33,34] For these reasons, rural areas in the US structurally tend to have higher proportions of socioeconomically disadvantaged individuals including by measures such as unemployment, poverty, and low educational attainment that are highlighted by Case and Deaton.[35] Economically, rural areas may also be able to adapt to macroeconomic changes because they tend to be less diversified than urban areas, potentially leading to the type of cumulative economic stagnation at the core of the deaths of despair hypothesis.[14] In fact, the deaths of despair theoretical framework cites the these very same pathways from economic risk factors to the breakdown of family life, social isolation, and a lack of satisfaction or fulfillment in life that might predispose a community to self-injurious behavior.[32] Even though rurality as a purely spatial concept may not be a strong individual risk factor for deaths of despair, because it is associated with this constellation of variables, rurality it is reflexively implicated in the conceptualization of the deaths of despair risk.

Since the initial publication of this theory in 2015, it has received considerable media attention – some say it went viral – which has spurred many scholars to corroborate[36] or critique the findings. For example, one critique claims that the striking reversal in life expectancy in non-

Hispanic White Americans may actually be the result of age-group aggregation bias and can be partially explained away by age-standardizing the mortality rates.[37] However, although standardization is common in health research to compare risk across dissimilar groups where age is a strong risk factor, it is also an abstraction of reality by imposing a population structure to groups that do not follow that structure and can impose bias if there are other causal risk factors associated with age. While controlling for age is very necessary in some cases, in the case of deaths of despair as well as for this analysis age-standardization is not appropriate for the scientific question being asked.

Many studies have similarly found an increase in the number of deaths from these causes but question whether the causal pathway through despair highlighted in the deaths of despair narrative explains the phenomenon. Specific to overdoses, it has been found that counties with poorer economic health and family distress, including current economic factors such as unemployment, poverty, disability, low education, rental stress, divorce, and single parent families, do experience higher rates of fatal drug overdoses.[38] However in another analysis, economic variables only explain a fraction of the increase in overdose deaths, suggesting there were other more important drivers behind the rise in rates.[39] In fact, the supply of drugs, both the type and geographically where they are available, seems to be a more significant individual predictor of overdose death than economic factors.[40] This suggests that the economic measures implicated in the deaths of despair narrative may not be the predominant risk factors for opioid drug deaths. Since opioid overdose deaths are one of the main contributors to the decrease in life expectancy, whether they fit neatly into the deaths of despair narrative has been a main point of investigation in verifying Case and Deaton's findings.

While the role of opioid overdoses in the reduction of life expectancy observed is not in question, some studies have suggested other morbidity and mortality causes are also to blame for the rise in premature mortality which are inconsistent with the deaths of despair narrative.[41] Specifically, cancer and heart disease are common among the same less-educated, rural individuals who are highlighted by Case and Deaton, and may be contributing to early deaths among the middle-aged.[42] Although the relationship is multifaceted and extremely complex, high stress has been found in some studies to be a risk factor for certain cancers as well as heart disease – despair has not.[43] An opposing hypothesis suggests that life expectancy disparities among those with lower levels of educational attainment may actually be due to such a stress response leading to epigenetic aging, or a weathering effect, among those who employ active coping mechanisms in the face of adversity.[43] This type of intentional, functional coping is the exact opposite of despair. Interestingly, this theory does not negate the hypothesis that the root cause of these outcomes is economic in nature, but it excludes despair from the causal pathway.

These findings draw into question the role of despair in the increases of crude rates of premature mortality that are being seen. Moreover, the "despair" in deaths of despair has been largely assumed as the logical node on the pathway from the proposed exposure of economic stagnation and social fragmentation to the self-injurious outcomes, but not well measured nor operationalized.[44] Case and Deaton simply assume that individuals faced with the economic and family experiences they outline would feel despair, but they do not define the concept nor do they quantify it. When measures of poor mental health were assessed in the context of deaths of despair, a study by Goldman et al. found that while there were indeed significant declines in self-reported mental health since the 1990's among individuals with low socioeconomic status (SES), this phenomenon was not restricted to those in middle-age. Moreover, those with high SES did not see the same declines.[45] Similarly, O'Connor et al. found there was a positive association between longer life expectancy and higher levels of optimism, measured by the question, "have you usually felt pretty sure your life would work out the way you want it to…," and longer lives.[46] This study also found that Black Americans were more optimistic than Whites, but not as happy.[46]

The question still remains as to why despair has led to rising premature mortality among middle-aged non-Hispanic Whites and not Black Americans even though economic risk factors are present for both groups and may even be more severe for Blacks. One hypothesis known as the reference group theory claims this could be due to a perceived, though unfounded, loss of status among lower SES non-Hispanic White Americans.[35,47] In this theory, despair may be parameterized as the unfavorable comparison between the life someone is living and the life they expected for themselves. This differential effect by race is a main sticking point as to why the hypothesized causal pathway from poor economic health to premature death does not seem to operate in the same way for everyone. Is it resilience, or that those who are already structurally disadvantaged have been living with these realities for some time and thus do not experience the same gradual decline?

Opioid overdose deaths have historically been lower among Black Americans compared to non-Hispanic White Americans, characteristic of the first wave of the opioid epidemic. White Americans were consistently more likely to be treated for their pain, despite the fact that Black Americans with chronic pain experience more severe pain, have greater disability due to their pain, and more frequently experience pain-related psychosocial symptoms[48]. As a result, White Americans have historically been prescribed more prescription opioids than Black Americans.[35,49,50] However, with rise of the second and third waves of the opioid epidemic characterized by heroin and synthetic opioids, this gap in overdose mortality has begun to shrink as opioid overdose rates among Black Americans have increased considerably in the past few years.[15] Additionally and regrettably, there has also been an increase in all-cause mortality among other race and ethnic groups, including a significant rise among American Indian and Alaskan Native populations.[49] deaths of despair may not be just a White phenomenon.

Race is unignorable in the deaths of despair discussion, as much for the race-specific findings of the original analysis as for the subsequent media attention. The original deaths of despair findings were swiftly met by an outcry and call to action, positioning them in stark contrast to the War on Drugs response to the crack epidemic in the 1980's whose victims were predominantly Black.[51] Case and Deaton have addressed these concerns outright by stating that their focus on inequalities in cumulative economic opportunity generally and the recognition that certain groups may be more or less resilient to these economic risk factors will have wide-reaching benefits beyond just lower educated non-Hispanic Whites.[52] However, the concern persists that such a focus on non-Hispanic White mortality overshadows the persistent disparity in Black life expectancy in the US compared to non-Hispanic Whites.[53] Indeed, this analysis does not address race-specific mortality and may be complicit in the involuntary shift in focus away from racial inequalities to other types of disparity.

Although the deaths of despair hypothesis has been previously associated with premature mortality among middle aged non-Hispanic Whites, the underlying hypothesis that structural inequalities in cumulative economic opportunity can result in a higher risk of premature mortality can be expanded to be more inclusive. The deaths of despair revelation of the increased mortality risk for certain groups can be seen as one step in understanding the whole health of a community. Using a welfare geography conceptual framework, the most benefit to the collective can be weighed in balance with the benefit for the most disadvantaged within each community. The goal of redistribution is not efficiency, but rather to shrink inequality. This requires that health risks be considered holistically or jointly so as to maximize the potential benefit of resource attribution. Given that opioid overdose and firearm suicide are two of the leading public health crises facing the US today, and they are preventable causes of premature mortality, it is paramount that the larger discussion of health disparities begin to assess how these two epidemics covary at a local level.

The ability to identify local, sub-state patterns in mortality is often hindered by the fact that there is less reliability that the observed data represent a true underlying phenomenon and not simply random chance when they arise from a smaller sample. Many disciplines refer to this concern as a small area estimation (SAE) problem. It is well known in statistics that there is better power to detect a true signal in a larger sample size. This issue is exacerbated when the outcome being examined is rare as this limits the number of events that can be observed over time on top of the constraints of using small geographical units. Nonetheless, the ability to measure outcomes locally and reliably is essential for targeting resources and interventions directly to those who can most benefit from them.

The goal of small area estimation is to supplement sparse raw data that has been collected with complementary information in order to gain confidence in the estimates for these areas, or to predict estimates or areas where there is incomplete data. Often this is done by creating prediction models using correlated data and mixed effects to account for space in order to estimate the prevalence of outcomes in areas where data is available for only a subset of individuals, like a survey sample.[54] When using survey sample data there is inherent uncertainty in the weighted survey estimates. In order to get estimates that are more precise often the first thought is that the sample size needs to be increased substantially, which is often not feasible. Instead, SAE techniques such as Bayesian smoothing allow for the calculation of estimates with more narrow confidence intervals by utilizing all the available data for the outcome, including adjacent areas or time periods, as well as correlated covariates.[55,56] It has been used extensively to look at the relatively rare outcome of under-five mortality,[57] or for estimating the prevalence of stigma-related diseases or behaviors such as HIV[58] or opioid use.[59]

Bayesian spatial smoothing techniques using INLA are a particularly useful method of SAE because the conditional autoregressive nature of the approach is able to maximize the information contained in the outcome of interest itself in order to increase confidence in the results without the need for additional covariates, though relevant covariates may be included. The article by Khana et al. using a similar Bayesian INLA approach for estimating suicide death rates both at the county-level and also annually over time serves as an excellent methodological introduction to the benefits and limitations of small area inference using INLA adjusted rates as opposed to raw rates.[60] These authors are affiliated with the Division of Research Methodology at the CDC National Center for Health Statistics and are thus situated to influence what the best practices are for analyzing the NVSS death data that is used in this research. The Bayesian spatial smoothing method using INLA was most appropriate for the following analysis because unlike survey data, the death data used here is a complete tally of all deaths that occurred in the contiguous United States during the study period. The goal of using the smoothing methods is not to predict unknown information, but rather to calculate estimates with more confidence for the raw mortality ratios with high variance, high variance being more common in small areas.

Specific Aims

There are two specific aims of this research:

1) To identify landscapes of firearm suicide and opioid overdose death risk at the county-level across the US using a Bayesian spatial smoothing technique to reduce the variability of high rates due to small numbers and to estimate the true underlying risk of death for each outcome locally.

2) To classify counties by the magnitude and degree of their joint firearm suicide and opioid overdose death risk in order to distinguish counties that may share similar contexts. Given that these two causes are both outcomes resulting in self-injurious behavior and are implicated in the deaths of despair narrative, they may both be driven in part by underlying factors of economic stagnation. Therefore, investigating the outcomes themselves may reveal common constellations of risk factors that lead to early injury death. Areas with divergent patterns of firearm suicide and opioid overdose deaths will reveal areas in which other causal pathways are operating to produce each outcome.

    i. As a supplementary analysis, the classifications developed in aim two will be stratified by urban/rural status in order to assess whether the hypothesis of rurality as a risk factor for deaths of despair is corroborated when looking at the joint experience of two different but related self-injurious outcomes. Rurality in this case is used both as a risk factor itself as well as a proxy for the numerous economic risk factors highlighted by Case, Deaton, and others that tend to be found in higher proportions in rural counties.

Chapter 2: Data Analysis

Data Sources

Mortality data are from the Centers for Disease Control and Prevention (CDC) National Vital Statistics System (NVSS) restricted Detailed Mortality file for the years 2013-2017.[61] Population data for the same time period were obtained from the CDC Race-Bridged population files. The mortality and population data were aggregated over the five years of data at the county-level and filtered to include only deaths that occurred in the contiguous United States. The NVSS Detailed Mortality file contains the primary cause of death as well as five additional variables to record additional cause of death ICD-10 codes if they are reported on the death certificate. The two outcomes of firearm suicide and opioid overdose death were defined using ICD-10 external cause of injury codes (Table 1) and classified as a firearm suicide or opioid overdose (including both accidental or intentional) if any of the six cause of death variables contained a matching code. The CDC National Center for Health Statistics (NCHS) urban-rural classification from 2013 was used to identify rural counties.[62] For reference, county population counts were obtained from the US Census Bureau using the 2010 US Decennial Census.[63] Lastly, County Health Rankings and Roadmap reports, developed by the University of Wisconsin Population Health Institute as a part of the Robert Wood Johnson Foundation, were gathered for a subset of five US counties.[64]

Methods

Standardized mortality ratios (SMRs) were calculated for both outcomes for each county in the contiguous US as the proportion of observed events over the number of events that would be expected for that county population. The expected number of events for each county was estimated using internal standardization: the total sum of deaths from each outcome was divided by the total population of the lower 48 US states and the resulting cause-specific rate of death was then multiplied by each county's average 5-year population (3.48 firearm suicide deaths per 10,000 people and 7.66 opioid overdose deaths per 10,000 people). Therefore, the expected number of deaths represent the deaths for each population as if the overall number of deaths from each cause was shared equally throughout the country. SMRs allow firearm suicide and opioid overdose deaths to be compared on the same scale even though the absolute number of deaths from these two causes might differ, and they provide a simple quantification of local risk on a multiplicative scale compared to the national average.

Since deaths from firearm suicide and opioid overdose are rare at the county level, mortality ratios were calculated for each county using the observed deaths and expected number of deaths by each cause aggregated over the five-year study period. Average population was used rather than the sum of the total population over five years to better estimate the population at risk over the study period without double counting individuals who remained in a county for the entire study period. The mid-point population is also commonly used in multi-year studies, but the average was used in this analysis to attempt to account for the possibility of rapid, non-linear population growth or decline in county areas. These ratios can be interpreted as the risk of death by opioid overdose or firearm suicide over five years in each county compared to what would be expected from the national average in that population over the same five-year period. For example, an SMR value greater than one would suggest the county experienced a higher burden of death compared to the US average, and vice versa for SMRs lower than one.

Because rates of rare outcomes can be unstable when they are based on small numbers of observed or expected events, a spatial Bayesian approach was used to smooth variable mortality ratios using the observed and expected events. For areas where the observed number of deaths was zero, a value of 0.5 was added to both the observed and expected number of deaths, which corresponds to the default model precision gamma prior values of (0.5, 0.0005), since the model cannot accommodate zero values[65]. A conditional auto-regressive model was fit utilizing Integrated Nested Laplace Approximations (INLA) to estimate the locally smoothed cause-specific SMRs in each area by supplementing the observed data with information from each area's contiguous neighbors. The influence of a county's neighbors is weighted by the variability of the estimate in that county, defined by the number of observed and expected events for the area. Therefore, the SMRs in counties with small numbers of events and thus more uncertainty would be pulled in the direction of their neighbor's values more so than would a county that experienced more events. This approach assumes Tobler's first law of Geography – that everything is related, but closer things are more related than things that are farther apart. In this way, counties with variable rates from small numbers can gain power from their adjacent neighboring counties, which are assumed to be somewhat similar to the county in question in composition and context.

In Bayesian statistics, as opposed to frequentist statistics, the observed data is considered known or fixed and the parameters being estimated, in this case SMRs and represented as θ below, are random unknowns representing a latent true risk for that population:

$$\log(\theta i) = \alpha + Si + ei$$

where for each county i, ei are the error terms centered around the true mean and do not have spatial structure, and Si are the spatial random effects conditional on the neighbors. To estimate the unknown parameter theta, a posterior distribution of possible parameter values is estimated based on the observed data and then the median of the resulting distribution is taken as the resulting SMR value. A prior distribution which penalizes values that are highly unlikely needs to be specified ahead of time in order to guide estimation. This analysis uses the BYM (Besag, York and Mollié) model, reparametrized as BYM2, and the default penalized complexity prior as it is considered to have the most robust spatial structure[66]. The resulting SMR values from this model represent the relative risk of death for a hypothetical infinite population living in area i, or rather the true underlying risk of death compared to what would be expected for area i.[67]

To estimate the covariance of firearm suicide and opioid overdose at the county level across the contiguous US the smoothed outcomes from the INLA model were plotted on two axes that crossed at the median of the SMR values for each cause. This allowed counties to be classified as having a risk of death that was higher than average or lower than average for both outcomes. Given the truncation of SMR values as ratios from 0 to infinity, the log of the smoothed SMR values were used in the plot so that outcomes above and below the median were more symmetrical. This allowed for the identification of counties with a higher or lower than expected burden of deaths from both firearm suicide and opioid overdose, as well as counties that exhibited an asymmetrical burden of death from one cause and not the other.

The 50 percent of counties that were closest to the median values of both outcomes were considered to have average risk of death for both outcomes. This distance was calculated by centering the median of the log SMR values at (0,0), and then using the Pythagorean theorem to calculate the Euclidean distance from this (0,0) point. A threshold of 50 percent was chosen so that the counties with the most extreme burden of deaths from the two causes would be detected. Counties were classified by their quadrant membership as high firearm suicide (FS)-high opioid overdose (OD), low FS-low OD, high FS-low OD, low FS-high OD, or average risk of both FS and OD outcomes, and mapped to identify the landscape of fatalities across the US for the intersection of these two acute deaths of despair outcomes.

Each county was assigned a metropolitan or non-metropolitan status (hereon referred to as urban and rural respectively) using the NCHS classification scheme from 2013.[62] Quadrant membership groups were then stratified to show the proportion of counties in each group that were classified as urban vs. rural as rurality is identified in the deaths of despair narrative as a predominant risk factor.

In order to compare the utility of using smoothed SMRs, these methods were repeated using the raw SMRs calculated from the original data before smoothing was performed. The raw SMR values were calculated using the observed count of deaths divided by the same expected count of deaths as above. These unadjusted SMRs were then used as the input data for quadrant identification, which were graphed and mapped as well. Results of this analysis can be found in figures 6 and 7 for the cause specific SMR maps and the Appendix for the quadrant classifications.

Lastly, as a supplementary exploration five counties were selected for further study, one from each of the classifications developed above: median 50 percent of counties, high FS-high OD, high FS-low OD, low FS-high OD, and finally low FS-low OD. These counties had smoothed firearm suicide and opioid overdose SMRs that seemed to be illustrative examples of the five mortality risk categories. These five counties were assessed by their economic, demographic, and social characteristics to determine whether they fit a deaths of despair narrative or not. The results of this investigation can be found in Chapter 5.

All analyses were performed in R version 3.6.2[68] using the INLA[69,70], dplyr[71], rgdal[72], sp[73,74], and spdep[75,74] packages. This analysis is considered non-human subjects research and as such did not require IRB review.

Chapter 3: Results

During the five-year study period from 2013-2017, a total of 355,085 deaths from these two acute deaths of despair were experienced in the contiguous US states. 110,836 (31.2%) of these deaths were attributable to firearm suicide and 244,249 (68.8%) were due to opioid overdose (including both accidental and intentional). There were 149 deaths (0.04%) with ICD-10 codes related to both firearm suicide and opioid overdose and these deaths were thus counted towards both outcomes. After smoothing the cause-specific, county-level SMRs, mortality from firearm suicide in each county ranged from 0.08 to 5.34 times what would be expected in the county population and from 0.11 to 7.06 times what would be expected for opioid overdoses over this five-year period. The median SMR for firearm suicide deaths within counties was 1.42 and the median SMR for opioid overdose deaths was 0.67. These numbers suggest that for more counties the firearm suicide risk is greater than what would be expected if deaths were shared proportionally across the whole US population, suggesting perhaps that the majority of firearm suicide deaths occur primarily in small population counties, whereas the opposite is found for opioid overdoses.

The maps of the INLA smoothed SMRs for firearm suicide and opioid overdose deaths are shown in Figures 1 and 2 respectively. Recall that SMRs are ratios of the observed deaths compared to what would be expected in that county if all deaths in the United States were evenly distributed across the population. Counties were divided into five equal groups by SMR value with the middle 20% of counties classified as the median group. Counties with the highest 20 percent of smoothed SMRs are categorized as having the greatest excess deaths compared to what would be expected for the county, and the 20 percent of counties with the lowest SMRs have the fewest deaths compared to what would be expected in the county. It is clear from these figures that these two death outcomes exhibit distinct geographical patterns of excess and reduced risk. Firearm suicide burden is high in most of the Mountain West and Appalachia, and low in most of California, parts of the Midwest and all of the Eastern Mid-Atlantic. Conversely, opioid overdose burden is low in much of the Central Plains states and parts of the South, but high in New England, Appalachia, and the Southwest.

When firearm suicide and opioid overdose outcomes are compared to each other, counties are approximately evenly divided into the four quadrants representing high FS-high OD, low FS-low OD, high FS-low OD, and low FS-high OD (Figure 3). After the 50 percent of counties that are closest to both median SMR values for the two outcomes are removed (1,554 counties), there are 464 counties with high FS-high OD, 446 counties with low FS-low OD, 257 counties with high FS-low OD, and lastly 387 counties with low FS-high OD. Similar to what was seen in the separate cause-specific mortality maps, much of the Southwest and Appalachia are being detected as areas of high burden in both firearm suicide and opioid overdoes (Figure 4). Parts of California, South Texas, and a cluster of counties in the Central Plains seem to have the lowest joint burden of these two outcomes. While the Northern West of the US seems to be composed of high firearm suicide but low opioid overdose risk, much of New England and parts of the Midwest exhibit the opposite pattern.

The NCHS rural-urban classification defines 1,160 urban counties and 1,948 rural counties. When the outcome risk quadrant classifications are stratified by rurality, 88% of the high FS-low OD counties are rural, 70% of the high FS-high OD counties are rural, while only 27% of the low FS-high OD counties are rural (Figure 4). The counties with low FS-low OD risk and the 50% of counties classified as average share a similar proportion of rural counties with 61% and 66% respectively.

When the raw SMR values are used to identify areas of high and low firearm suicide and opioid overdose death occurrence, the results are more difficult to interpret and can misrepresent the true occurrence of death in certain small population counties. Compared with figures 1 and 2 showing the INLA smoothed SMRs of firearm suicide and opioid overdose deaths, figures 6 and 7 of the raw SMRs appear more scattered. While there appear to be some spatial patterns emerging, such as low firearm suicide rates around the New York City metro area and California, and high opioid overdose rates in New England and the Midwest, more rural areas are highly variable. Directly adjacent counties can exhibit drastically different observed death rates. While this representation seems promising at first for comparing similar counties with such different experiences of opioid overdose or firearm suicide deaths, it is impossible to detect a true signal from among the random Poisson noise characteristic of raw rates from small numbers. Small counties are more likely to exhibit drastically high death rates because the occurrence of just a few deaths has a more substantial effect in a small population than it would if the same number of additional deaths were to occur in a county with a larger denominator. In the raw data of calculated SMR values, the highest opioid overdose SMR in the contiguous US at almost 12 times higher than what would be expected for the county was based on the occurrence of a single overdose death. Similarly, the highest firearm suicide SMR in the raw data was approximately 8 times higher than what would be expected in the county but was based on only 3 deaths. After smoothing, the SMR values for these counties became 1.25 times higher opioid overdose deaths and 3.33 times higher firearm suicide deaths respectively. Both values convey a higher than expected risk of death in these counties, but the magnitude of the excess risk is shrunk in accordance with the level of confidence in the estimate.

Chapter 4: Discussion

The spatial configuration of excess opioid overdose deaths found here aligns with previous investigations of the spatial patterns of risk. Evidence of the third wave of the opioid epidemic can be seen in the high risk of opioid overdose death in areas of New England, mid-Atlantic coast, and Appalachia where synthetic opioids are more common (Figure 1). Drug potency and supply certainly drive who dies and who survives an opioid overdose, but these factors can also be mitigated by local investment in naloxone programs, substance abuse treatment resources, and proximity to healthcare, including rapid Emergency Medical Services who can provide naloxone and respiratory support. These programs can vary more locally on a smaller scale and thus may not be seen in larger landscape patterns of death risk.

The landscape of firearm suicide deaths also follows a recognizable pattern with states that have laxer firearm laws exhibiting higher rates of firearm suicide than states with more comprehensive firearm legislation. For example, Montana, Idaho, Wyoming, South Dakota, and Nevada have among the fewest firearm provisions in the US and are also found here to high the highest firearm suicide rates in the contiguous US (Figure 2). California, Massachusetts, Illinois, New Jersey, and New York have some of the strictest firearm laws and patterns of low firearm suicide risk cluster within these states.[76] This is a crucial finding because state legislation affects the risk within every single county within the state and thus has an enormous impact on overall death rates from firearm suicide. However, since firearm policy is notoriously difficult to pass, in the meantime it is the sub-state and county-level variation in risk that may provide opportunities to investigate factors that prevent or promote risk. Likely areas for further research include access to mental health care, trauma center capability, proximity to a state with fewer firearm restrictions (see the CA counties that border NV[77]), or specific differences in firearm accessibility such as density of gun shops. These factors should be compared between counties that exhibit high vs. low firearm suicide risk, accounting for state.

It is particularly thought-provoking to compare swaths of the county that share similar risk for one outcome, but divergent risk of the other. For example, the coral and yellow areas of the map both indicate low opioid overdose risk while the light blue and turquoise areas represent high opioid overdose risk (Figure 4). As noted above and consistent with previous literature, New England and Appalachia are clustered with blue and turquoise – high OD – while the North Central Plains are yellow and coral – low OD. More interestingly, there are deviations at the individual county level where a county with high firearm suicide risk falls directly next to a county with low firearm suicide risk, even though they both share the same high risk of opioid overdose. Windham, Vermont and Cheshire, New Hampshire, or Lincoln and Wayne, West Virginia are counties that exhibit such a pattern. Similarly, in the Central Plains at the center of the wider swath of low opioid overdose risk there looks to be a dividing line between areas of low firearm suicide and high firearm suicide risk. Comparing the individual counties that fall along this seam, such as the South Dakota counties of Tripp, Lyman, Buffalo, Brule, and Jerauld may provide more explicit information about why neighbors that are similar in one outcome are so different in another. In this same vein, there are only three local areas that display completely opposite patterns of risk: yellow counties of high FS-low OD next to light blue counties of low FS-high OD. These areas, which include 1. Bates, Johnson, and St. Clair, Missouri; 2. Shelby and Fayette, Tennessee; and 3. Randolph, Alabama and Carroll, Georgia, should be examined specifically in future research. Another interesting local arrangement that should be investigated is the island of high opioid overdose risk in Hennepin and Ramsey, Minnesota completely surrounded by counties with low overdose risk. Further perusal of this map by individuals with local knowledge of different county geographies will yield additional insight into powerful comparisons.

While other causes of death exist within the deaths of despair narrative, notably alcohol related liver disease or obesity related morbidity and mortality,[2,31] firearm suicide and opioid overdose were selected because they are acute outcomes in which the context of the county at the time of death is more relevant in the pathway from despair to death compared to outcomes with a longer incubation period. Since the individual county context is considered to be the exposure in this analysis, these deaths can be viewed as arising from the specific social and economic environment that existed at the time of the study period because the death onset is sudden. Including these specific causes of death allow public health officials to more clearly understand the pathway from county context to death, and more importantly, how those pathways may be intervened upon to prevent further death.

When stratified by rurality, it becomes clear that firearm suicide exhibits a higher relative burden in rural counties as opposed to urban ones as the vast majority of high FS counties were classified as non-metropolitan, consistent with the suicide literature. Conversely it seems that high opioid overdose risk is more common in urban counties. This may be a result of the more recent years of data included in the study period as the early prescription opioid epidemic largely affected more rural communities, but the influx of heroin and particularly synthetic opioids has changed the opioid death landscape. Furthermore, this pattern marks the counties that are highlighted as high FS-high OD as even more singular. However, although the patterns of firearm suicide and opioid overdose tend to collect in rural and urban areas respectively, from Figures 1, 2, and 5 it is clear that there are deviations from this rule. Further attention should be paid to urban counties with high firearm suicide burdens and also rural counties with high opioid overdose burden to identify differing risk factors, particularly since rural counties are more likely to exhibit the economic risk factors highlighted in the deaths of despair narrative.

The results of the supplementary analysis assessing the impact of rurality on these death outcomes highlights concerns about the level of inference at which the deaths of despair hypothesis is being applied. Rurality can be considered a contextual risk factor, meaning that it does not have an individual correlate; it is an emergent property of an area rather than the sum of its individual parts. Rurality is therefore an appropriate measure to for inference at the county level because it is itself an ecological measure. However, using rurality as a proxy measure of other risk factors that are more explicitly named in the deaths of despair literature, such as percent unemployed, percent with low education, or percent below the poverty line must the interpreted with caution because these are compositional measurers. Similarly for studies corroborating the county-level associations of economic risk factors with greater levels of deaths of despair,[38,78] it is impossible to know whether the same association is true at the individual level; even if counties with higher rates of unemployment are associated with higher rates of despair deaths, it does not follow that individuals who are unemployed are more likely to die of a despair death. This is the ecological fallacy whereby results found at one level of analysis is used to make inference at another.

The deaths of despair hypothesis in general suffers from this type of fallacy. It states that areas that are more economically stagnant will experience more deaths from self-injurious behaviors because individuals will feel despair. However, despair is not measured in a meaningful way at the individual level to determine whether people who despair are more likely to die from drugs or suicide. In fact, there is an ecological framework for how economic instability can lead to higher rates of death through some of the very pathways that Case and

Deaton highlight, such as family dysfunction, social fragmentation, and lack of opportunity even for individuals who are currently employed with stable incomes. These things can function at the community level by altering the fabric of society, or the networks that bring people together, as "no man is an island."[79] However, in such an ecological analysis there is no direct implication of individual despair. Therefore, the moniker of deaths of despair is misleading and the assumptions it summons of dejected, pessimistic individuals who have simply given up is likely unjust.

Additionally, this conceptualization of despair may not actually fit well with the outcomes of opioid overdose or firearm suicide death. Suicide research suggests that the time from an individual's first thought of suicide to an actual suicide attempt is often quite short.[80] Deisenhammer et al. found that half of their studied attempts were made within ten minutes.[81] This is not necessarily consistent with the idea of consistent personal despair but rather could be catalyzed by other more acute stimuli. Similarly, a 2019 research letter in JAMA found that ninety percent of opioid overdose deaths are unintentional and just four percent are documented as intentional.[82] While illicit drug use is certainly self-injurious, addiction does not equate to despair. Ultimately this study finds the label of despair to be counterproductive, but the underlying theory of community level economic risk and mortality offered by Case and Deaton remains suitable.

Recently with improvements made to data storage and computation, the ability to assess mortality trends in a local context on a wide scale has increased, and the demand for small area estimates has grown. Smaller areas have less potential for ecological bias because there is less within-area heterogeneity,[83] but the reliability of these local estimates is a concern when they are based on small numbers. A Bayesian approach that leverages the inherent spatial structure of adjacent outcomes in modeling these estimates can help to better identify the true underlying risk of death in small geographies so that genuine disparities can be recognized. Smoothed rates can be interpreted as the true or latent risk of death in an area for a hypothetical infinite population residing there. However, it is important to note that these estimated relative risks are simply the first step in understanding the burden of death in counties. The decision to smooth rates is an example of the well-known statistical trade-off between variance and bias – the resulting SMRs may smooth over some real local heterogeneity in order to account for the high variability in small areas and thus should be supplemented with local knowledge in order to develop culturally appropriate and locally pragmatic interventions.

Given that firearm suicide and opioid overdose are relatively rare when broken into such small geographies, particularly in rural and sparsely populated areas, variability and potential identifiability due to small numbers are concerns. The CDC recommends that any rate calculated from NVSS data that is based on fewer than ten deaths be suppressed due to the instability of the rate due to small numbers as well as a concern for privacy and identification.[84] In the NVSS data from 2013-2017, there were 1,190 out of 3,108 study counties with fewer than ten firearm suicide deaths (38%) and 1,330 counties with fewer than 10 opioid overdose deaths (43%), and these deaths are aggregated over five years. Given that it is often the rural counties that are disproportionately burdened by poor health outcomes and particularly the hypothesized deaths of despair, being able to estimate reliable rates in small counties is crucial to understanding the health disparities faced by rural communities. Spatial Bayesian smoothing methods such as INLA are essential tools for geographers and epidemiologists working with relatively rare outcomes because they help to overcome issues of highly variable rates due to small numbers so that valid inference can be made for small, sub-state areas.

Figure 8 shows the 2010 Decennial Census total population count for counties in the United States[63]. The coasts have consistently high population areas and there are pockets of high population areas displayed in darker greys in cities across the United States, but most of the central US is made up of counties with very low population. It is clear in the comparison of the INLA smoothed SMR values in figures 1 and 2, and the raw SMRs in figures 6 and 7 that the more sparsely populated counties are the ones that display the most difference from the raw to the smoothed SMR values. This is because smaller population counties have fewer expected deaths and often fewer observed deaths, so the variability associated with their SMR estimates is higher. Highly variable rates are more likely to be influenced by the values of the counties directly adjacent to them and thus more likely to have their values shrunk towards the mean of the neighbors. In this way, the observed death counts for a county can be viewed as a single manifestation of the true underlying risk of death as estimated by the smoothed rates, but subject to random Poisson noise which can have a greater impact in small populations. For comparison, figures 1 and 2 in the Appendix show the effects of using raw rather than smoothed SMRs on the final classification of counties in to high and low FS and OD quadrants, including the influence of zero incidence counties (which were adjusted to 0.001 as the natural log of zero cannot be quantified as negative infinity). Because the unstable, highly variable SMRs in the raw data can be unusually high, these values determine the classification of risk for the individual county but also shift where the median value falls which has cascading influence on how all other counties are identified in each of the risk categories.

Given the scope of the concurrent opioid overdose and firearm suicide epidemics in the US today, understanding the singular geographical patterns of each outcome is just the first step. It is clear that the risk of deaths from these two outcomes vary substantially across the country and reveal considerable heterogeneity even within states from county to county. Counties, particularly small and sparsely populated communities, do not have the economic resources, infrastructure, or capacity to address these two epidemics locally.[14] In order to reduce the incidence of death by firearm suicide and opioid overdose in the US, state and federal resources must be leveraged to allocate resources to address these overt health disparities in mortality where they are occurring. Whether counties with similar rates of death from these two outcomes are really plagued by "despair" or rather they are connected by other common risk or protective factors, investigation of the joint occurrence of firearm suicide and opioid overdose may reveal structural factors that have an overarching influence on self-injurious behavior. Areas that are highlighted in Figure 4 as experiencing high FS and high OD may benefit the most from interventions designed to address the underlying disparity in economic opportunity at the core of the deaths of despair narrative. However, areas that are high is one outcome and low in the other may benefit most from cause-specific interventions that can interrupt the precise pathway that results in death from either firearm suicide or opioid overdose. Areas that have both low FS and low OD risk should be studied further to see if protective factors may be identified beyond what is already known. With a scarcity of resources, investment must be tailored to best address the specific risk landscapes that arise from the joint experience of these two predominant causes of preventable death to produce the most social good.

Lastly, it is important to recognize that while the SMRs calculated here represent the risk of death from each outcome compared to what would be expected if each county shared equally in the burden of death, this does not speak to the absolute risk of death in each of these local areas. The average rate of death in the US during the five-year period from 2013-2017 of firearm suicide is 3.48 deaths per 10,000 people and for opioid overdose it is 7.66 deaths per 10,000 people. Already far too many people are dying from these preventable causes. This analysis identifies areas that have a higher or lower risk compared to the US average, but areas highlighted as low risk are not spared from these causes of premature mortality. Similarly, while 50 percent of US counties are classified as suffering an average risk of death, it should be stated that average risk does not imply acceptable risk.

Limitations

The use of the NVSS Detailed Mortality file allowed for deaths to be classified as either a firearm suicide or an opioid overdose if any of the six cause of death ICD-10 codes in the data matched the classification scheme. This is an improvement over using just the primary cause of death field as opioid overdose are rarely classified as the primary cause of death on a death certificate – typically the immediate cause of death such as cardiac or respiratory arrest is used in this field instead.[85] Yet, an analysis of all drug poisoning deaths from 1999-2015 estimated that a substantial proportion of opioid overdose deaths may be misclassified on death certificates as unspecified drug deaths,[86] and that certain states are more likely to record a non-specific drug overdose on death certificates than others. In the states with the most prevalent under reporting more than 35 percent of their opioid overdoses were misrepresented as unspecified drug poisonings.[87] To address this potential misspecification with spatial structure, the non-specific drug overdose ICD-10 code T50.9 was included in the opioid overdose classification. The opioid overdose events reported here may contain some overdoses from other drugs as well and thus overestimate the true number of opioid specific deaths. However, opioid-related overdoses were the most common drug death during the study period and accounted for almost 70 percent of the drug overdose deaths in the US in 2018.[88] While including these unspecified drug deaths may introduce some measurement error, it also addresses the concern over the spatial structure of the missing opioid deaths which is particularly damning for an autoregressive spatial analysis.

Secondly, it is important to note that this analysis uses a single strategy for identifying county neighbors, but there are other ways in which to define adjacency. This analysis uses perhaps the most straightforward method of identifying neighbors by classifying a county as a neighbor if it shares an administrative boundary with the county in question. The resulting sparse, symmetrical, zero/one matrix of neighbors also allows for faster computation[60], but the implication of this simple structure is that only directly adjacent counties will share information with each other. However, other ways of defining neighbors may be more appropriate in terms of the true interactions and similarities between counties. For example, some analyses choose to use a distance threshold from the center of each area, either in terms of Euclidian distance or in road networks traveled to assign neighbors that may have more contact with each other. Another approach is to systematically assign neighbors using one of the aforementioned techniques, and then add a central metropolitan hub as a neighbor to all counties in the surrounding region to account for the disproportionate economic or social influence of regional cores. Lastly, some researchers choose to manually and painstakingly assign neighbors using multiple criteria such as distance, contiguity, landscape features that can obstruct or facilitate contact, known economic or social networks, or other measures relevant to the analysis at hand. Without local knowledge of the social or economic interdependence of different counties, the continuity approach is the simplest and is what is most commonly used but may not fit well for all counties, particularly adjacent counties that have very dissimilar contexts.

Lastly, while this study uses a binary method of classifying counties by either urban or rural status, it should be noted that rurality can be conceptualized more as a continuum rather than a dichotomy. Additionally, while rural areas are typically considered to have higher rates of poor health outcomes when compared to urban areas, some studies using a continuum of rurality and urbanicity have found that in fact suburban areas show consistently better health outcomes compared to both rural and urban core areas.[34] This is because rurality is more than just a spatial concept. While geography is a key contributor in identifying areas along the urban-rural spectrum, the reality of rural and urban spaces are inherently intertwined with sociological, cultural, economic, and social ways of being that more directly affect the lived experience of rurality. Thus, a more nuanced consideration of rurality may lead to findings contradictory to those found using a less sensitive approach since truly distinct communities collapsed, masking their unique differences.

Chapter 5: County Profiles

The following paragraphs introduce five different US counties, each categorized as a different classification identified in the above analysis, either the median 50 percent for both firearm suicide and opioid overdose deaths, high FS-high OD deaths, high FS-low OD deaths, low FS-high OD deaths, or low FS-low OD deaths. Because of HIPAA privacy and potential identification concerns, illustrative counties were selected only if they had experienced ten or more deaths from each cause of death. For this reason, the following examples may underrepresent very rural areas. The counties that were chosen as demonstrative examples of the intersecting risk categories include: Cole County, Missouri; McDowell County, West Virginia; Coos County, Oregon; Baltimore City, Maryland; and Hidalgo, Texas.

Median 50 Percent: Cole County, Missouri

Cole County, Missouri is situated on the south banks of the Missouri river and is approximately equidistant to both Kansas City and St. Louis. The 2010 Decennial Census population of the county was 75,990[63] and it is classified by the CDC as a small metro.[62] It has a smoothed firearm suicide SMR of 1.44 and a smoothed opioid overdose SMR of 0.66. Recall that the median SMR values for US county firearm suicide and opioid overdose deaths are 1.42 and 0.67 respectively. These smoothed SMR values do not differ from the raw values of 1.42 for firearm suicide and 0.66 for opioid overdose deaths.

Using the 2020 County Health Rankings reports, which collect data from a variety of data sources from preceding years, it is possible to gain an understanding of the county context near the end of the study period.[64] Cole County, MO seems to be inhabited by a predominantly non-Hispanic White, fairly educated population (Table 2). The median household income is higher than what is seen for the other counties presented here and correspondingly there are few children living in poverty. The most different measure for Cole compared to the other counties was the very high rate of social associations in the county at 23.7 per 10,000 people. Indeed, it seems that Cole County has certain economic and social advantages that may protect its residents from the type of despair that Case and Deaton propose in the deaths of despair narrative. However, the county does exhibit a higher percentage of individuals who drink excessively than the other counties profiled (Table 2), a behavior that has been linked to poor mental health and economic hardship mostly in studies investigating the 2008 recession.[89] Even though this may suggest a trend of self-injurious behavior among a portion of the residents, the county does not suffer from the same economic instability outlined in the deaths of despair framework. Yet, it still experiences moderate rates of firearm suicide and opioid overdose deaths.

<u>High FS-High OD: McDowell County, West Virginia</u>

McDowell County, West Virginia, located in the Appalachian region of the United States, is recognized as one of the poorest counties in the United States.[90] It gained some notoriety after the 2016 election as the face of a mining community that voted overwhelmingly for Donald Trump. Historically, the county had a large coal mining industry but the past few decades have seen declining economic opportunities and a diminishing population that is less than half the size it was in the 1970's.[91] The population of the county from the 2010 Decennial Census was 22,113 people[63] and it is categorized as a non-core area by the CDC urban-rural classification.[62]

McDowell has a smoothed firearm suicide SMR of 3.39 and a smoothed opioid overdose SMR of 4.05. This means that McDowell County was at risk for 3.39 times more deaths from firearm suicide and 4.05 times more deaths from opioid overdose than would have been expected for a county of that size if all deaths from these two outcomes were shared equally across the entire US population. In this county, the smoothed SMR values were slightly lower than what was seen in the raw values, consistent with the fact that this rural county has a smaller population than the others presented here and thus may have been more influenced by its neighbors. The raw firearm suicide SMR was 3.80 and the raw opioid overdose SMR was 4.24.

The County Health Rankings data in Table 2 paint a consistent picture of the deprivation of the county. Only a quarter of the population has some secondary education and the median household income is the lowest of the five counties presented here by over $10,000. The unemployment rate is high at 9.4%, and 43% of children are living in poverty. Unlike the other counties profiled here, McDowell actually displays elevated values of measures that could be associated with individual despair, including frequent mental distress and the average number of poor mental health days in the past month. There are also few social organizations in the county, which is often used to measure a lack of social cohesion. McDowell seems to fit the image that the deaths of despair narrative paints of cumulative economic stagnation leading to social fragmentation and despair, and this analysis also finds that it has among the highest SMRs for both firearm suicide and opioid overdose. Nonetheless, McDowell County also exhibits shockingly high ratios of people to primary care and mental health care providers, and thus lack of access to care cannot be overlooked as a contributor to the increased risk of death – it is not just “despair.”

High FS-Low OD: Coos County, Oregon

Coos County, Oregon is located on the West Coast directly on the Pacific Ocean with miles of beach coastline. The 2010 Decennial Census population estimate for the county was 63,043 people[63] and it is considered a micropolitan area by the CDC.[62] The County has a smoothed firearm suicide SMR of 2.58 and a smoothed opioid overdose SMR of 0.56. As such, the county was at risk for 2.58 times more deaths from firearm suicide than what would be expected from the US death rate, but also experienced about 44% lower risk of death from opioid overdose than expected. These smoothed SMR values are quite similar to the raw SMR values of 2.56 and 0.54 for firearm suicide and opioid overdose respectively. However, if the raw SMR values had been used to classify counties rather than the smoothed SMRs, Coos County would have been classified among the median 50 percent of counties. This is most likely due to the fact that raw SMR values can have exceedingly high rates arising from small denominators, and these high rates could have shifted where Coos County ranked relative to the median in the raw data. However, it makes Coos County an interesting locale to focus on since in the smoothed rate classification map it sits adjacent to a high FS-high OD county but still maintains its protective low OD status (Figure 4).

In terms of the county's economic characteristics, it does not seem to stand out in terms of the typical measures that are characteristic of economic health such as education, median household income, unemployment, or children in poverty (Table 2). It also has a high rate of social associations at 9.8 associations per 10,000 people in the county, suggesting that a framework potentially exists for fostering social cohesion. None of this aligns with the hypothesized pathway from economic instability, through despair, to suicide. For Coos County it may be that there are other drivers leading to high levels of firearm suicide.

Low FS-High OD: Baltimore City, Maryland

Baltimore City, Maryland has a smoothed firearm suicide SMR of 0.75 and a smoothed opioid overdose SMR of 5.03. Baltimore City thus had 25% reduced risk of firearm suicide deaths compared to what was expected, but 5.03 times more opioid overdose deaths compared to what was expected for this population. As anticipated, Baltimore City is classified by the CDC as a large central metro[62] and in the 2010 Decennial Census had a population of 620,961 people.[63] As this county has such a large population and thus high confidence in the death rates observed, it is the case that the smoothed SMR values are almost identical to the raw values of 0.76 and 5.04 for firearm suicide and opioid overdose deaths after rounding.

Baltimore City, MD is located on the Eastern Seaboard just about an hour from the nation's capital in Washington, DC. As an urban area on the East Coast close to a number of major interstates that can bring in illicit opioids such as heroin and fentanyl, the city seems to fit a few of the risk factors for high opioid overdose. Conversely, it does not seem to exhibit the typical deaths of despair economic risk factors. The unemployment rate may be higher than the national average in 2017[64], but a large proportion of the residents have at least some college and median household incomes are high (Table 2). As other researchers have noted, it is possible that the deaths of despair framework is less appropriate for assessing drugs deaths compared to actual drug availability and lethality considerations.[40] Or, it is possible that the ecological nature of the data is masking patterns of risk that may be evident at an individual level.

The deaths of despair narrative highlights the increase in premature mortality among non-Hispanic Whites, but the city of Baltimore's population is predominantly Black. While it is impossible to tell who within the community is dying of opioid overdoses, and attempting to generalize based on the composition would be to commit the sin of ecological fallacy, this example may suggest that we need to stop focusing on non-Hispanic Whites alone and consider that economic instability, addiction, and poor mental health are not just a White problem.[49] In fact, Black Americans face greater economic disparity on average and continue to experience a lower life expectancy at birth than do non-Hispanic White Americans,[92] although they have consistently lower rates of suicide overall which may be a contributor to the low rates of firearm suicide seen in Baltimore.[35] This is particularly striking given that gun violence is not uncommon in Baltimore city.[93] While the deaths of despair narrative may be helpful in drawing attention to a growing rate of deaths by self-injurious behavior, it is also harmful to the more productive discussion of how and why health disparities in the United States affect individuals differently, which should be kept in mind when considering Hidalgo County, TX.

<u>Low FS-Low OD: Hidalgo, Texas</u>

Hidalgo County, Texas is located directly along the southern border with Mexico. The population is almost entirely Hispanic at 92.4% (Table 2). According to the 2010 US Decennial Census, the county had a population of 774,769 in the preceding year[63] and is classified by the CDC as a medium metro area.[62] It has a smoothed firearm suicide SMR of 0.37 and a smoothed opioid overdose SMR of 0.11. As such, Hidalgo county was at lower risk than what would be expected for firearm suicide death by 63% less risk, and by 89% less risk for opioid overdose deaths. Again, with such a large population contributing data, the smoothed SMR values are incredibly similar to the raw values of 0.36 for firearm suicide and 0.11 for opioid overdose.

Although Hidalgo County, TX does exhibit some of the lowest observed rates of both firearm suicide and opioid overdose versus what would be expected for a population of that size in the contiguous US, it does not seem to exemplify an absence of the risk factors promoted in the deaths of despair framework to accompany that low risk (Table 2). The median household income is among the lowest of the five profiled counties, it has the lowest rate of social organizations of the group and also the highest proportion of uninsured. Additionally, just about half of the county population had some secondary education, and the county's unemployment rate is higher than the national average in 2017.[64] While the county exhibits some of the economic risk factors consistent with the deaths of despair narrative and also may have poor access to healthcare, the county does not have the accompanying expected increased mortality. This suggests that this community is somehow resilient to the harmful effects of relative deprivation that is so often associated with poor health outcomes, a phenomenon that has been identified before among Hispanics and known as the Latino Health Paradox.[94] While the deaths of despair theoretical framework focuses on the harmful effects of poor economic health, it is not able to diagnose factors associated with resiliency which are more helpful for considering how to prevent deaths.

Chapter 6: Conclusions

This analysis highlights the need to identify health disparities not simply in a single outcome, but rather to assess leading causes of death jointly in order to get a more holistic picture of the lived experience of local communities. When there are scarce resources to respond to the collection of issues that face a society, it is more advantageous to quantify the shared and individual burden of particular hazards in order to better understand where intervention is most needed. A welfare geography approach will be exceptionally useful as it is considers, “who should get what, how and where.”[3] It is a valuable and fair conceptual framework for translating the identification of health disparities into the next step of mitigation and action plans to reduce mortality risks and promote change. Generally, systems of public funding and redistribution should embrace the social justice tenets of Geography, and health geographers should consider Smith’s proposed welfare geography agenda, which surprisingly has failed to find a solid footing in contemporary human geography despite its dedication to thoughtful quantitative analysis, resource allocation, and spatial injustice.

Many of the patterns of firearm suicide and opioid overdose risk individually have already been identified and the landscapes of risks identified in this analysis support those findings. However, this is the first analysis to classify counties by their joint mortality risk with the goal of identifying the combined burden of these two preventable causes of death. Since firearm suicide and opioid overdose are two of the most severe public health epidemics to face the US today, it is necessary to understand how the risk of death from these two preventable causes covary across local geographies to better target our scare resources to address the health disparities that have come to light in the deaths of despair narrative.

It is clear from the results of this analysis that certain areas of the US are doubly impacted by both public health crises of opioid overdose and firearm suicide while other communities have been largely spared. Using these patterns of shared risk to identify the specific causal pathways between economic stagnation and firearm suicide or opioid overdose may lead to intervention strategies specific to addressing the shared and individual mortality burdens. Conversely, the results of this joint analysis may be able to detect areas that share common latent risk factors other than economic variables that warrant further study. The next step for such disparities research is to engage with public health practice to address the root causes of mortality locally, whether upstream economic factors or interventions to promote social cohesion. Recognizing which communities may be suffering from these specific pathways will allow for targeted local interventions that interrupt the specific mediating pathways from despair to firearm suicide or opioid overdose.

There is great disparity in the rates of firearm suicide and opioid overdose across counties in the US. However, some of the most outstanding high rates are based on unstable estimates due to small numbers. These unstable estimates are more likely to occur in rural or sparsely populated areas which have specifically been implicated in the deaths of despair narrative. A Bayesian approach can help to smooth over the uncertainty implicit in raw rates calculated from small numbers to identify areas truly burdened by these two causes of death. The results of such an analysis can be understood as the latent or underlying risk for a community, which has very favorable implications for interpretability. Geographers, epidemiologists, and public health scientists involved in spatial disparities research should add these methodologies to their toolkit, particularly when they are interested in rare outcomes.

Lastly, it is important to recognize that the results found in this analysis are based on rates of death rather than attempts or occurrences. For example, opioid overdose deaths can be averted in the event of an overdose with the swift administration of naloxone. Similarly, firearm suicide is the most lethal method of suicide and thus more likely to result in death compared to attempts with other means.[6] Therefore, the patterns of risk identified in this study may be influenced by the existence or lack of programs that reduce lethality, masking the true burden of non-lethal overdoses and survived suicide attempts in each local area. Investment in healthcare access including emergency medical services and trauma center capability may help to reduce the proportion of suicide or overdose events that result in death in the short term while the underlying causes prompting these events is addressed.

Next Steps

Brilliant research has already been done to understand the dynamics of opioid overdose and firearm suicide risks in general in the US, such as the identification of the three waves of the opioid epidemic, and recognition of the astonishingly high case fatality rate of firearm suicide. This study adds vital understanding of the true landscape of risk of these two outcomes at a local level, as well as their covariance, accounting for the variability of unstable rates due to small numbers. Future research should investigate how county-level economic, social, and civic factors differ between the four identified joint risk groups. Identifying qualities that are shared by counties classified as low FS-low OD may illuminate characteristics that are jointly protective of mortality from either outcome. This evidence of resiliency can then be operationalized to create tailored interventions in counties that were highlighted as high FS-high OD.

Finally, though the availability of data currently precludes this type of analysis, further research should be dedicated to measuring suicide attempts and overdoes events that do not result in death in order to get a more complete picture of the burden of these outcomes locally. Firearm suicide is an incredibly lethal means of suicide suggesting that there are only a few attempts that would not be represented in this data. However, an opioid overdose can be reversed with the swift administration of the drug naloxone in hospital or by Emergency Medical Services, and it can even be obtained by the public from a local pharmacy. For this reason, the data presented here are almost certainly an underestimation of the toll of opioid overdose in the US. Using deaths alone allows for the assessment of lethality but gives an incomplete depiction of the lived experience of these self-injurious behaviors.

Figures and Tables

ICD-10 Codes	Definition	Classification
X72	Intentional self-harm by handgun discharge	Firearm Suicide
X73	Intentional self-harm by rifle, shotgun and larger firearm discharge	Firearm Suicide
X74	Intentional self-harm by other and unspecified firearm and gun discharge	Firearm Suicide
T40.0	Poisoning by, adverse effect of and underdosing of opium*	Opioid Overdose
T40.1	Poisoning by and adverse effect of heroin	Opioid Overdose
T40.2	Poisoning by, adverse effect of and underdosing of other opioids	Opioid Overdose
T40.3	Poisoning by, adverse effect of and underdosing of methadone	Opioid Overdose
T40.4	Poisoning by, adverse effect of and underdosing of other synthetic narcotics	Opioid Overdose
T40.6	Poisoning by, adverse effect of and underdosing of other and unspecified narcotics	Opioid Overdose
T50.9	Poisoning by, adverse effect of and underdosing of other and unspecified drugs, medicaments and biological substances	Opioid Overdose

Table 1: ICD-10 codes for death outcome classification

*While the ICD-10 codes included in the outcome classification contain underdosing of the specified opioid in their definition, deaths due to underdosing of an opioid are rare. Additionally, deaths due to underdosing are still overdose related deaths and thus may share some of the same risk factors as overdosing deaths.

Table 2: Comparison of County Health Rankings Data for Selected County Profiles

	Cole, MO	**McDowell, WV**	**Coos, OR**	**Baltimore City, MD**	**Hidalgo, TX**
Non-Hispanic White	81.4%	88.7%	85.0%	27.8%	6.0%
Non-Hispanic Black	12.2%	8.2%	0.5%	61.9%	0.4%
Hispanic	2.9%	1.4%	6.7%	5.5%	92.4%
Life-expectancy	79.2	68.6	76.7	72.8	82.1
Frequent mental distress*	13%	21%	15%	15%	15%
Poor mental health days**	4.0	6.3	4.6	4.9	4.5
Excessive Drinking***	20%	10%	17%	19%	16%
Uninsured adults	10%	10%	9%	9%	42%
Primary care physicians^	1,430:1	3,690:1	1,230:1	1,030:1	2,220:1
Mental health providers^	510:1	3,040:1	250:1	220:1	1,690:1
Unemployment	2.5%	9.4%	5.4%	5.7%	6.6%
Some College^^	66%	24%	56%	64%	48%
Children in poverty	12%	43%	24%	26%	40%
Median Household Income	$62,800	$27,300	$48,400	$50,500	$38,800
Social Associations`	23.7	5.4	12.5	9.8	3.6

* Defined as the percentage of adults reporting 14 or more days of poor mental health per month.

** Defined as the average number of mentally unhealthy days reported in past 30 days. This value is age-adjusted.

*** Defined as the percentage of adults reporting binge or heavy drinking

^ Expressed as a ratio of population to provider in the county

^^ Defined as the percentage of adults ages 25-44 with some post-secondary education

` Measures the number of membership associations per 10,000 population

Figure 1: Quintiles of INLA Smoothed Opioid Overdose Death SMRs by US County

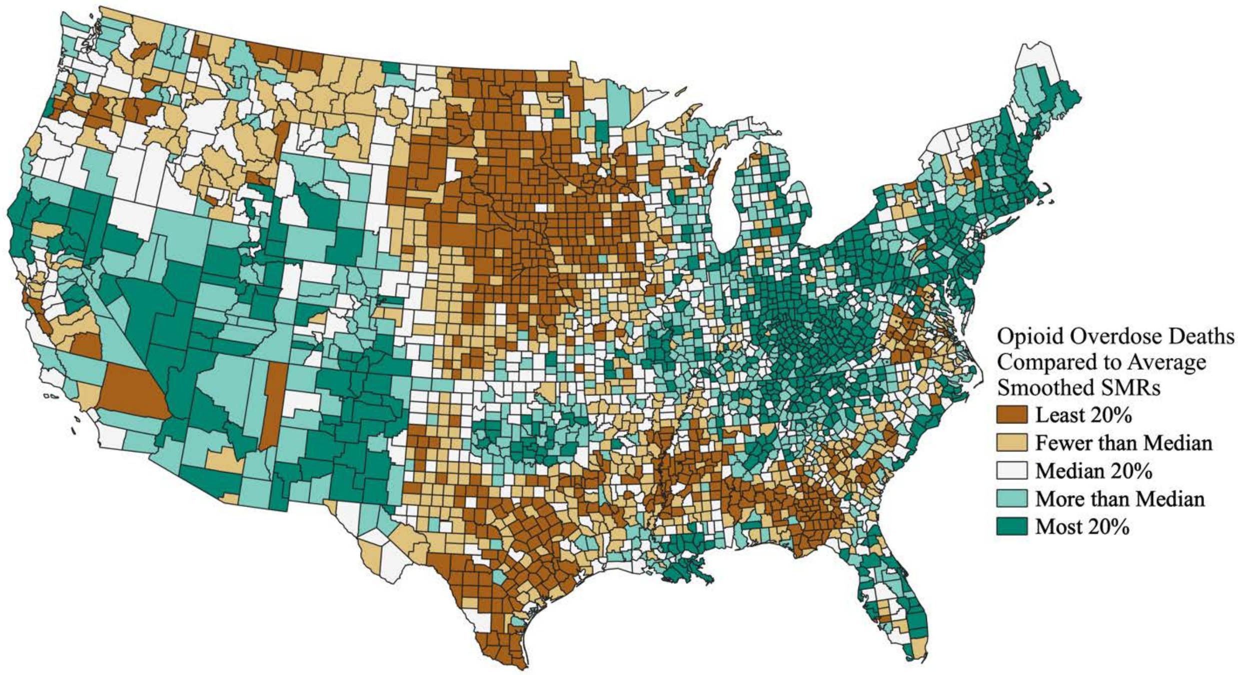


Figure 2: Quintiles of INLA Smoothed Firearm Suicide Death SMRs by US County

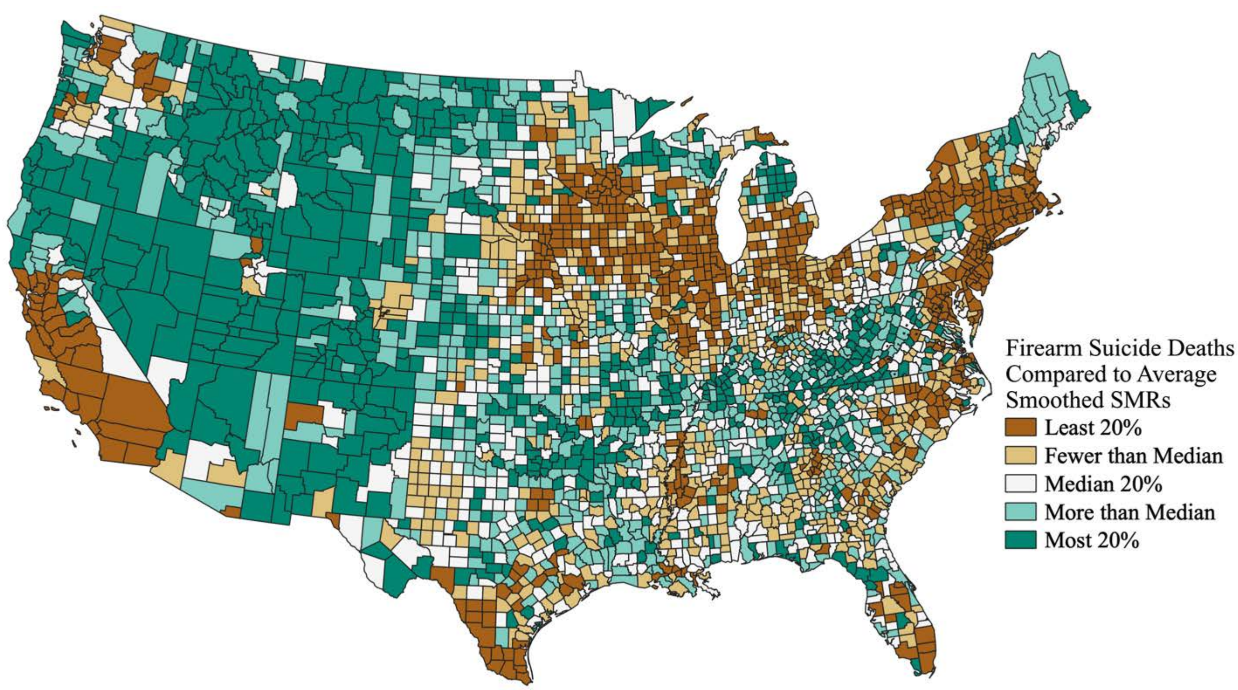


Figure 3: County Firearm Suicide and Opioid Overdose Death SMRs Compared to the Median SMR for Each Outcome

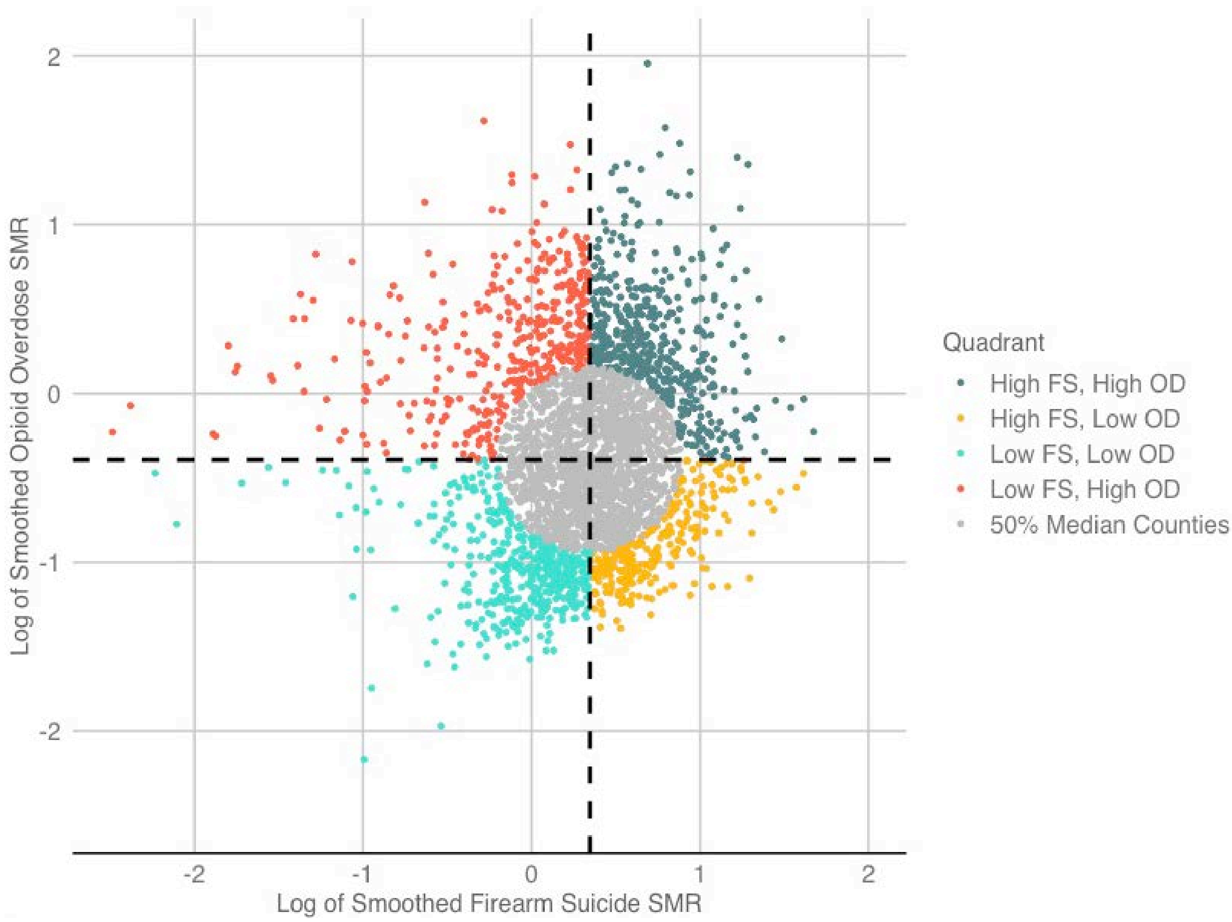


Figure 4: 50 Percent Most and Least Burdened Counties in the United States by Firearm Suicide and Opioid Overdose Death SMRs

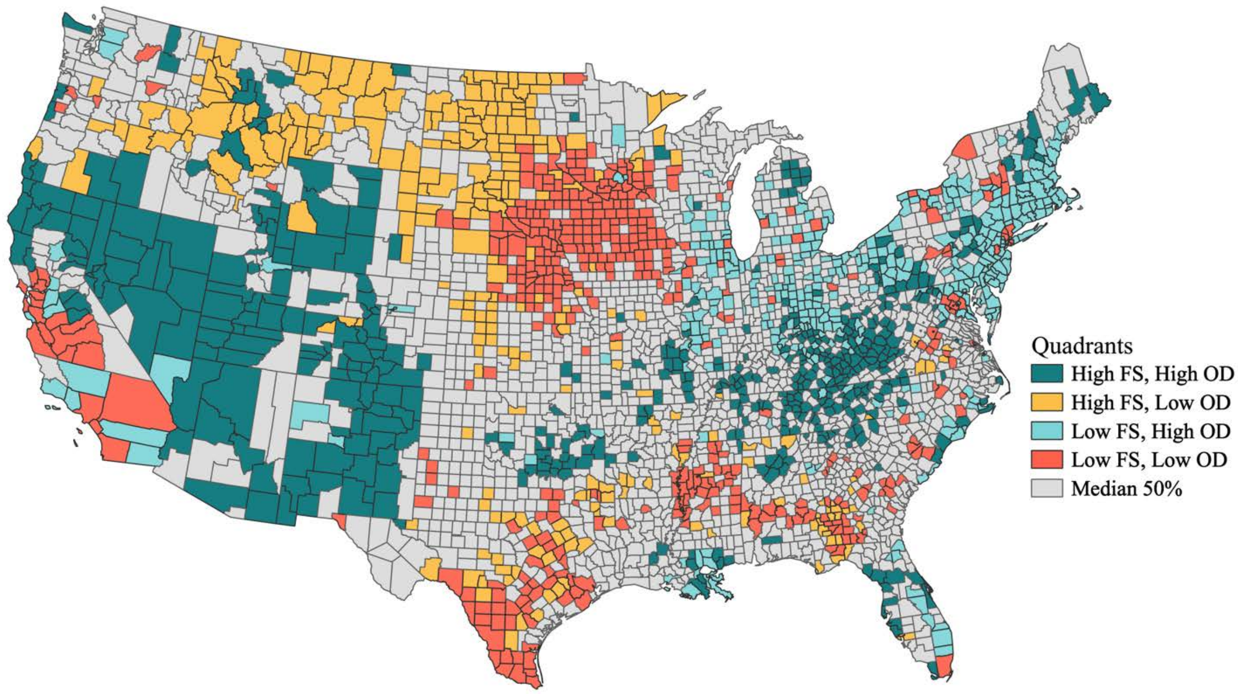


Figure 5: Proportion of Counties that are Urban or Rural for Each Risk Category

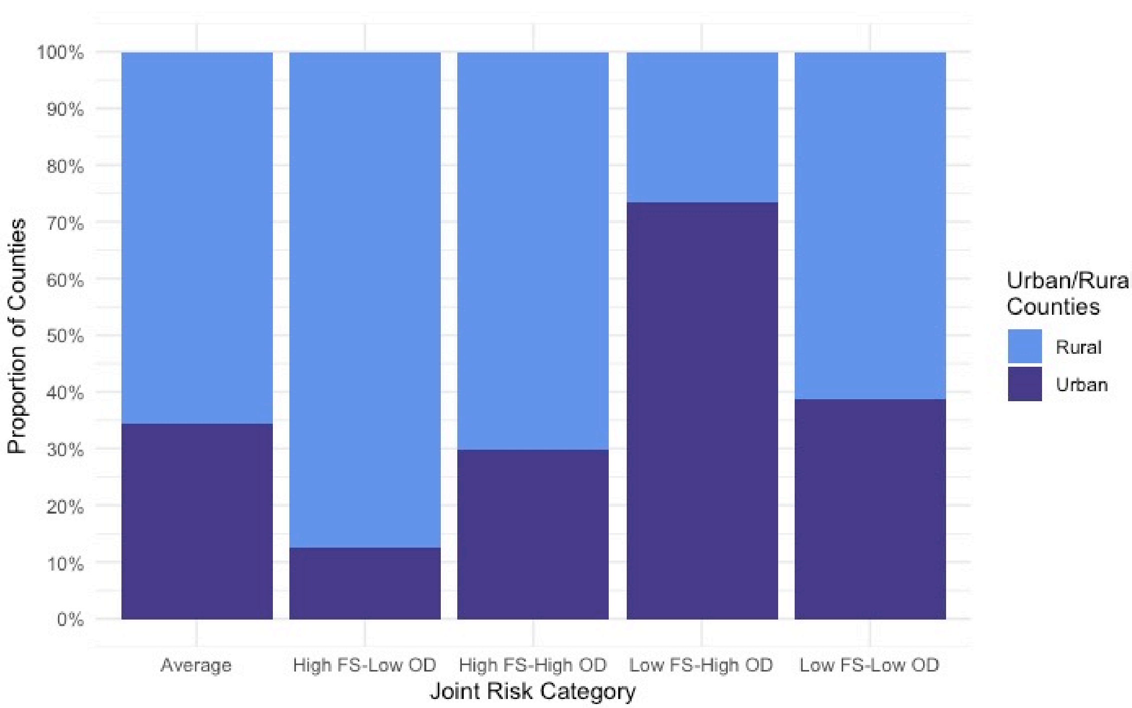


Figure 6: Quintiles of Raw Opioid Overdose Death SMRs by US County

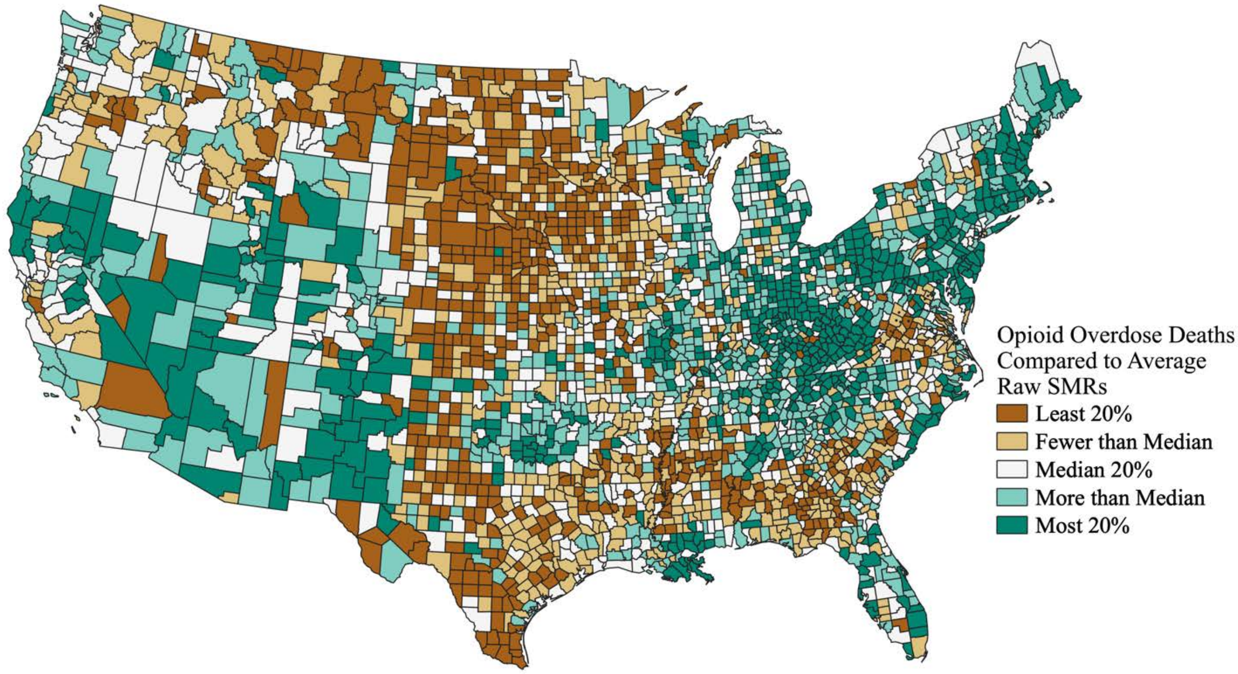


Figure 7: Quintiles of Raw Firearm Suicide Death SMRs by US County

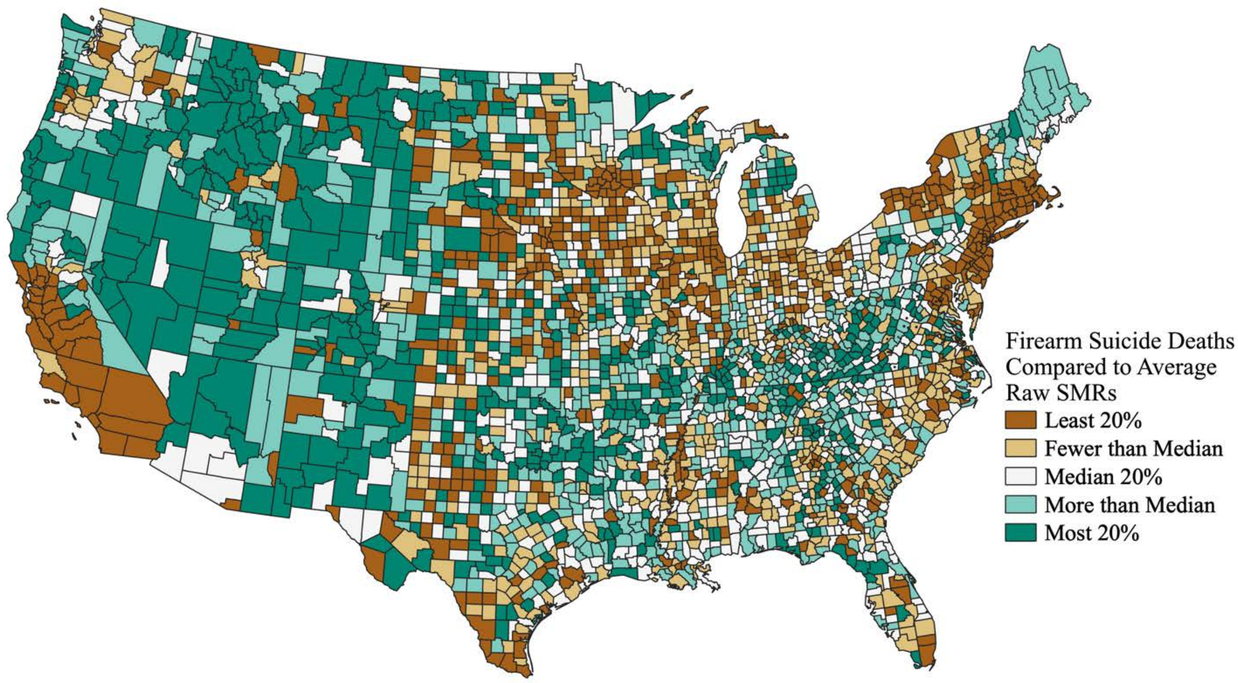
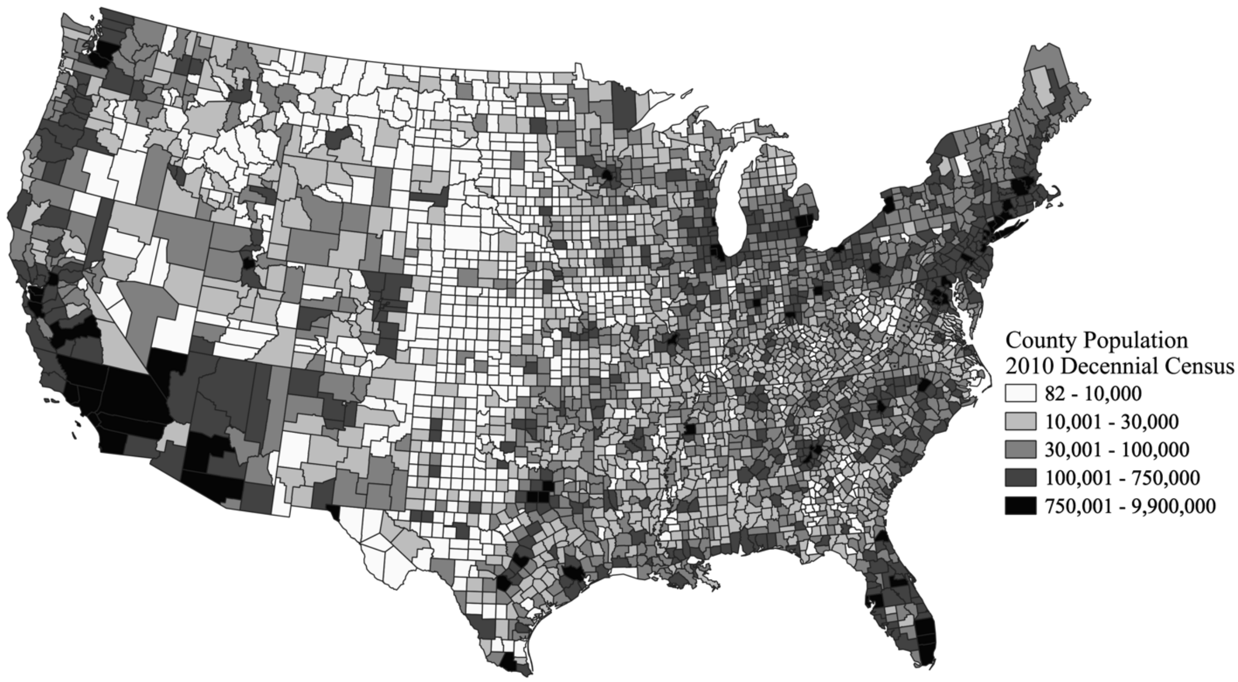


Figure 8: County Population from the 2010 Decennial Census



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Appendix: Supplementary Analysis of Raw SMR Values

Figure 1: County Firearm Suicide and Opioid Overdose Death Raw SMRs Compared to the Median Raw SMR for Each Outcome

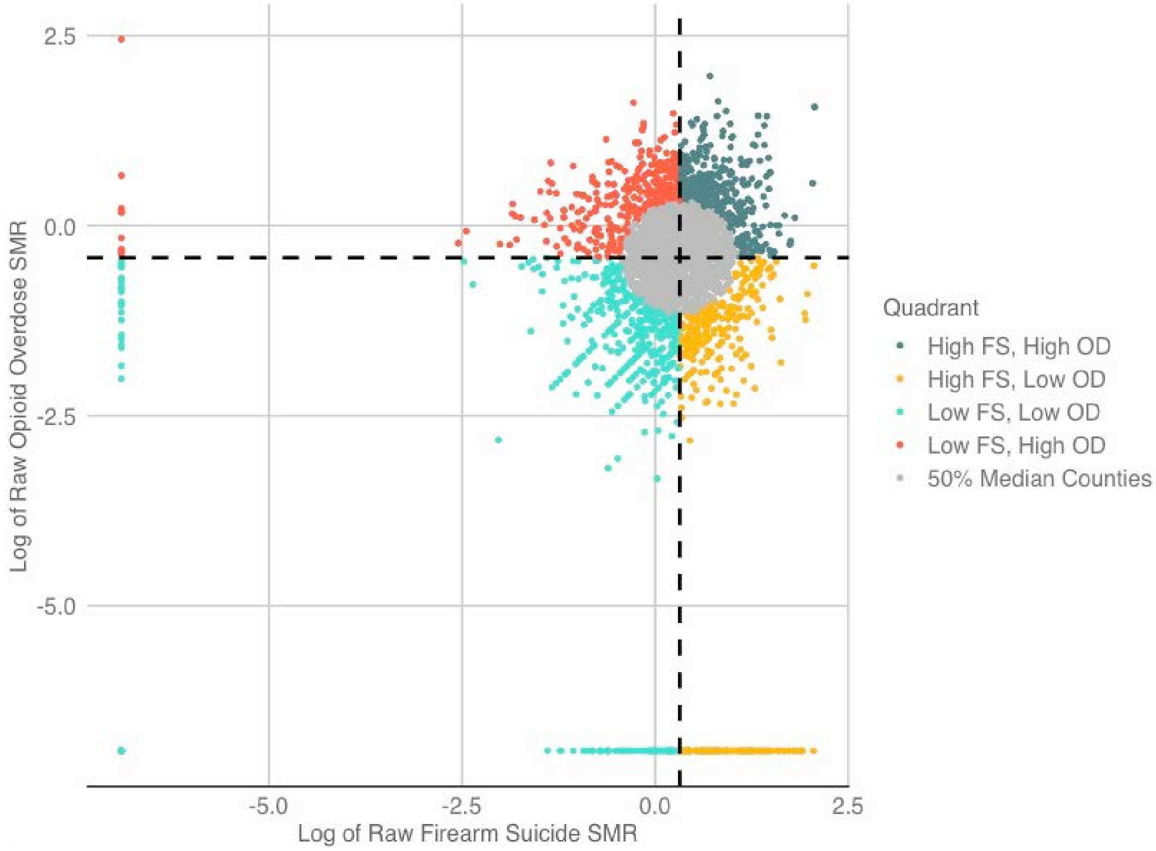

Figure 2: 50 Percent Most and Least Burdened Counties in the United States by Firearm Suicide and Opioid Overdose Death Raw SMRs