INVESTIGATING THE SPATIAL RELATIONSHIP BETWEEN SUICIDE AND RACE/ETHNICITY: THE CASE FOR ALTERNATE RATE ADJUSTMENT TECHNIQUES IN MEDICAL GEOGRAPHY

Katherine A. Lester, M.S.

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APPROVED:

Joseph Oppong, Committee Chair
Chetan Tiwari, Committee Member
Jannon Fuchs, Committee Member
Prathiba Natesan Batley, Committee Member
Armin Mikler, Committee Member
Jyoti Shah, Chair of the Department of Biological Sciences
John Quintanilla, Interim Dean of the College of Arts and Sciences
Victor Prybutok, Dean of the Toulouse Graduate School
Lester, Katherine A. *Investigating the Spatial Relationship between Suicide and Race/Ethnicity: The Case for Alternate Rate Adjustment Techniques in Medical Geography*. Doctor of Philosophy (Environmental Science), December 2022, 89 pp., 7 tables, 22 figures, chapter references.

This work explores potential distortions created by race and ethnicity on the visualization, interpretation, and understanding of the spatial distribution of suicide in the United States. Due to radically different suicide rates among racial/ethnic groups, traditional crude or age-adjusted rates may introduce statistical confounding in both linear and spatial models. Using correlation, choropleth mapping, hot spot analysis, and location-allocation modeling, this work shows how traditional methods of health system planning may unintentionally overlook elevated risk in minority-dominated areas like inner cities, the Texas/Mexico border region, and the Deep South. The final chapter introduces a simulation protocol for examining potential distortions in datasets to identify spatial and non-spatial distortions created by the underlying population composition. Methodologically, this dissertation contributes to the discourse on place context versus population composition. More generally, this research points to potential hazards to creating a more inclusive and equitable healthcare system.
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CHAPTER 1
INTRODUCTION

This dissertation explores the potential confounding effect of race and ethnicity on the visualization, interpretation, and understanding of the spatial distribution of suicide. This chapter provides an overview of the project, an outline of its organization, an introduction to the relevant literature, and identifies the objectives and research gaps this study will fill.

Background

Researchers have used a spatial perspective to understand mental and behavioral health issues since Emile Durkheim’s *Suicide: A Study in Sociology*, first published in 1897 (Durkheim 2006). However, until the late 1990s, psychology was rarely incorporated under the larger umbrella of medical geography. Early studies performed by non-geographers were typically riddled with common errors such as the small numbers problem, or rate instability caused by insufficient case counts, often creating misleading patterns (Waller and Gotway 2004). Another common pitfall is the issue of scale including the modifiable areal unit problem, or the tendency for patterns to change as unit boundaries change (Dark and Bram 2007). Over the past thirty years medical geographers have applied increasingly complex methods to mental health data including multiscale modeling (Cutchin and Churchill 1999), structural equation modeling (Franzini et al. 2005), and Bayesian approaches (Rossen et al. 2018). However, increasing complexity in analytical approaches has not yielded much more explanation than the most basic mapping and correlation exercises.

One topic that has received minimal attention from geography is the intersection of race/ethnicity and behavioral health outcomes, especially homicide and suicide. In the United
States, race is the number one predictor of whether a violent person will commit suicide or homicide, more than age, gender, presence of gun, or mental health issues (Fridel and Zimmerman 2019). Figure 1.1 shows these dramatic differences. Though many studies include race/ethnicity as one dependent variable (Cosby et al. 2019; Steelesmith et al. 2019; Rossen et al. 2018; Al-Sayegh et al. 2015; Branas et al. 2004; Dohrenwend et al. 1992) and some claim to control for it (Cosby et al. 2019; Anestis and Anestis 2015), many researchers believe more direct attention is needed in this area (Rossen et al. 2018; Smith and Kawachi 2014; Bills and Li 2005).

![Figure 1.1: Homicide and suicide rates by race/ethnicity, 1999-2019 (CDC 2022).](image)

Suicide is generally poorly understood. In a scoping review of 50 years of research, Franklin et al. (2017) found that there has not been much progress in identifying suicide risk in an individual. At best, clinicians can identify a 10 percent increase in risk. The need for exploration of suicide risk at wider scales is clear (Amaddeo, Salazzari, and Salinas-Perez 2014). However, suicide presents geographers with several unique challenges. Suicide itself is
somewhat difficult to define. Sociologists conceptualize it as a disconnect between a person’s goals or desires and the achievement of these goals. Therefore, suicide is a practical solution to this frustration (Shneidman 1985; Leighton 1959). The economists’ definition is clearly presented by Hamermesh and Soss (1974): “We assume that an individual kills himself when the total discounted lifetime utility remaining to him reaches zero (p. 85).” Noted psychologist Sigmund Freud argues that suicide is the companion to homicide; both stem from excessive aggression, but suicide is directed internally (Freud 2005). Within neuroscience, suicide is found to run in families, and hypothesized to be the result of poor serotonin uptake and prolonged exposure to the stress hormone cortisol (Al-Sayegh 2015; Preti 2011). The ICD-10 codes for suicide simply define it as intentional self-harm; the interpretation of this definition is left to coroners (CDC 2022).

In any case, decades of spatial studies on suicide have returned weak and contradictory results. In a landmark study, Hood-Williams (1996) examined the suicide research available at the time and discovered most studies took a simple risk-factor approach, correlating a wide array of dependent variables with suicide rates. In the worst-case scenario this quickly becomes “fishing” for significant results. Ultimately, Hood-Williams concludes that a risk-factor approach does not constitute a theory at all. He writes, “We are in a jumble of facts. This is a crude empiricism in which disconnected bits of data are mistaken for concepts and there is no ordering into any rational, explanatory framework,” (Hood-Williams 1996, p. 170). While Hood-Williams called for more theoretical reflection, a risk-factor approach remains the norm 25 years later. In fact, possibly due to decades of weak results, many of these risk factors have become more difficult to justify. Examples include elevation (Ha and Tu 2018), weather (Moore
et al. 2018), and even the popularity of country music (Snipes and Maguire 1995). Table 1.1 displays some of the explanatory variables used in these studies.

**Table 1.1: A selection of suicide risk factors from previous research**

<table>
<thead>
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<th>Variable</th>
<th>Citation</th>
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<td>Lund et al. 2015; Hood-Williams 1996</td>
</tr>
<tr>
<td>Stressful life events</td>
<td>Silva, Loureiro, and Cardoso 2016; Hirsch and Cukrowicz 2014; Hood-Williams 1996</td>
</tr>
<tr>
<td>Divorce</td>
<td>(Hood-Williams 1996)</td>
</tr>
<tr>
<td>Unemployment</td>
<td>Stein et al. 2017; Silva, Loureiro, and Cardoso 2016; Goetz, Davlasheridze, and Han 2015; Hood-Williams 1996</td>
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<tr>
<td>Veteran</td>
<td>Cerel et al. 2015; Hood-Williams 1996</td>
</tr>
<tr>
<td>Drug use</td>
<td>Stein et al. 2017; Hirsch and Cukrowicz 2014; Hood-Williams 1996)</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>Cosby et al. 2019; Veling et al. 2015; Hirsch and Cukrowicz 2014; Branas, Richmond, and Schwab 2004</td>
</tr>
<tr>
<td>Rural/Urban</td>
<td>Rossen et al. 2018; Silva, Loureiro, and Cardoso 2016; Hirsch and Cukrowicz 2014</td>
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<tr>
<td>Agricultural employment</td>
<td>Hirsch and Cukrowicz 2014</td>
</tr>
<tr>
<td>Gender</td>
<td>Fountoulakis and Gonda 2017; Canetto 2017; Silva, Loureiro, and Cardoso 2016; Hirsch and Cukrowicz 2014</td>
</tr>
<tr>
<td>Poor self-esteem</td>
<td>Hirsch and Cukrowicz 2014</td>
</tr>
<tr>
<td>Impulsivity</td>
<td>Hirsch and Cukrowicz 2014</td>
</tr>
<tr>
<td>Mental illness</td>
<td>Wang et al. 2018; Fountoulakis and Gonda 2017; Elliott, Naphan, and Kolenburg 2015; Hirsch and Cukrowicz 2014</td>
</tr>
<tr>
<td>Migration/Mobility</td>
<td>Silva, Loureiro, and Cardoso 2016; Veling et al. 2015; Breault 1986</td>
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<tr>
<td>Social support</td>
<td>Stein et al. 2017; Silva, Loureiro, and Cardoso 2016; Goetz, Davlasheridze, and Han 2015</td>
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<tr>
<td>Economic depression</td>
<td>Cosby et al. 2019; Stein et al. 2017; Bando and Lester 2014</td>
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<tr>
<td>Health insurance/access</td>
<td>Silva, Loureiro, and Cardoso 2016</td>
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<tr>
<td>Temperature</td>
<td>Moore et al. 2018; Talaei et al. 2014</td>
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<tr>
<td>Variable</td>
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<tr>
<td>Atmospheric pressure</td>
<td>Moore et al. 2018; Talaei et al. 2014</td>
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<tr>
<td>Humidity</td>
<td>Moore et al. 2018; Talaei et al. 2014</td>
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<tr>
<td>Education</td>
<td>Cosby et al. 2019; Silva, Loureiro, and Cardoso 2016; Goetz, Davlasheridze, and Han 2015</td>
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<tr>
<td>Sunshine</td>
<td>Makris et al. 2016; Goetz, Davlasheridze, and Han 2015</td>
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<tr>
<td>Poverty</td>
<td>Piatkowska 2020; Cosby et al. 2019; Silva, Loureiro, and Cardoso 2016; Goetz, Davlasheridze, and Han 2015; Veling et al. 2015; Kirkbride et al. 2012</td>
</tr>
<tr>
<td>Religion</td>
<td>Silva, Loureiro, and Cardoso 2016; Moore 2015; Foo et al. 2014; Jung and Olson 2014; Osafo et al. 2013; Breault 1986</td>
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<tr>
<td>Genetic variation</td>
<td>Fountoulakis and Gonda 2017</td>
</tr>
<tr>
<td>Homicide</td>
<td>Fountoulakis and Gonda 2017; Leenen and Cervantes-Trejo 2014; Bando and Lester 2014</td>
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<td>Time of day</td>
<td>Branas, Richmond, and Schwab 2004</td>
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<tr>
<td>Vacant housing stock</td>
<td>Branas, Richmond, and Schwab 2004</td>
</tr>
<tr>
<td>Population density</td>
<td>Veling et al. 2015; Kirkbride et al. 2012; Branas, Richmond, and Schwab 2004</td>
</tr>
<tr>
<td>Infant mortality</td>
<td>Piatkowska 2020</td>
</tr>
<tr>
<td>Voter turnout</td>
<td>Veling et al. 2015</td>
</tr>
<tr>
<td>Crime</td>
<td>Veling et al. 2015</td>
</tr>
<tr>
<td>Elevation/Altitude</td>
<td>Ha and Tu 2018; Brenner et al. 2011</td>
</tr>
<tr>
<td>Season</td>
<td>Moore et al. 2018</td>
</tr>
<tr>
<td>Age</td>
<td>Canetto 2017; Silva, Loureiro, and Cardoso 2016</td>
</tr>
<tr>
<td>Geomagnetic fields</td>
<td>Nishimura et al. 2014</td>
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<tr>
<td>Political party</td>
<td>Kposowa 2013</td>
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Since explanatory power for suicide is low and the race/ethnicity pattern is so prominent, it is critical to focus attention squarely on this issue. Race/ethnicity should not just be another one of Hood-William’s “jumble of facts” (1996). Race/ethnicity is a complex variable, potentially signifying differences in culture, socio-economic status, and historical trauma. Race/ethnicity is located both within an individual and reflected back to them by their environment. It interacts with nearly every other potential risk factor. This is a classic context
verses composition issue (Meade and Emch 2010; Franzini et al. 2005).

Race/ethnicity is both a contextual and compositional factor in suicide research. Black and Hispanic Americans are nearly half as likely to receive specialty mental health care as their white neighbors; both structural racism within the medical community and individual health seeking practices are likely to blame (Alegria et al. 2002). The way mental illness is interpreted by providers often changes depending on the race/ethnicity of the patient, in classic example of structural violence and discrimination (DeVerteuil 2015; Corrigan et al. 2005). Meanwhile, self-rated mental health is lower in communities with a high perception of racism (Franzini et al 2005), and Black, Hispanic, and Asian students have been shown to have higher rates of suicidal ideation than white students (Sa et al. 2020). A recent study of veterans found that despite overall higher rates of suicide in rural areas, the rural/urban differences disappeared in both Black and white populations, once they accounted for race (Peltzman et al. 2021).

Race/ethnicity highlights the need for thinking deeply about the variance within spatial units in addition to the variance among them. For example, a community with high overall social capital (a common resilience factor in suicide research) may be harmful for minority groups, if the majority group is intolerant and united (Goryakin et al. 2014).

Figure 1.2 shows a conceptual framework based on Bronfenbrenner’s (1977) nested systems model from developmental psychology combined with geography’s political ecology framework emphasizing money, history, and power (Hirsh and Curkowicz 2014; Kalipeni and Oppong 1998). This model incorporates some of the risk factors from Table 1, but situates them within a broad understanding of the physical, social, and political environment. While the framing of context versus composition is a helpful simplification, Figure 2 captures ecology’s
view of the individual defined by J. Baird Callicott: “…one's self, both physically and psychologically, gradiently emerges from its central core outwardly to the environment. One cannot, thus, draw hard and fast boundaries between oneself, either physically or spiritually, and the environment (1986, p. 315).” Every suicide is the result of some intersection of historical, cultural, behavioral, and individual risks, and race/ethnicity appears to be an important determinate for when and how these outcomes emerge.

Figure 1.2: A nested systems framework for suicide research
The context versus composition question is not new. Medical geographers are universally trained in age-adjustment techniques, which use rate calculation to remove the compositional effect of age (Pickle 2009; Waller and Gotway 2004; Pickle and White 1995). For example, finding that an older community has higher rates of cancer than a younger community is not an interesting result for a degenerative disease. The age composition must be accounted for in order to find community-level influences.

In the case of suicide, race/ethnicity is a larger influence than age (Figure 1.3). Race/ethnicity also has a more dramatic spatial pattern than other demographic characteristics like age or gender. In the United States, 898 counties are more than 95% non-Hispanic white, while 88 counties are majority Black and 53 are majority Hispanic (CDC 2022). When using statistics solely reliant on central tendency measures, the potential for the majority group to eclipse patterns in minority populations is immense.

![Figure 1.3: Comparing suicide rates across ages and race/ethnicity categories, 1999-2019. (CDC data)](image)

Prior research highlights three key facts: suicide rates vary dramatically among
racial/ethnic groups, the spatial distribution of race/ethnicity is far from uniform, and race/ethnicity influences an individual’s experience of a vast array of hypothesized suicide risk factors and causal mechanisms. These three facts suggest a large potential for statistical confounding in suicide research using traditional approaches. A confounding variable is related to two variables of interest (for example, suicide and poverty) which obscures the relationship between them, leading to misinterpretation (MacKinnon, Krull, and Lockwood 2000). Adjusting for this confounder removes the noise so the researcher can better see the true patterns. While more recent studies have highlighted the need for more race/ethnicity-focused studies of suicide geography (Platt et al. 2022; Spark et al. 2022; Wulz et al. 2021), the statistical confounding potential of race/ethnicity has not been directly explored in this context.

Research Gaps

The key gaps in knowledge this dissertation intends to fill are:

- Does race/ethnicity need to be directly addressed in suicide studies? If it is not explicitly incorporated into analysis, what problems may arise?
- Does race/ethnicity create a confounding effect for the interpretation of spatial patterns of suicide? In what conditions? Does this effect change at different scales? How might such an effect influence decision-making?
- Does race/ethnicity distort the relationship between suicide mortality and explanatory dependent variables?
- Is vulnerability to suicide acting at the individual or community level? In other words, how can researchers separate compositional and contextual contributors?
- How can researchers identify possible compositional confounding in their data? Can the impact of rate-adjustment be measured?

Goals and Objectives

The overall goal of this research is to explore the interaction of race/ethnicity and
suicide to better understand potential distortions and make recommendations about how and when a race/ethnicity-focused method may be most appropriate. The specific objectives within this goal are:

1. Provide an alternative and inclusive approach to identifying communities with high mental distress.
2. Evaluate the efficacy of race/ethnicity adjustment in the use of general linear model statistics.
3. Create a protocol for diagnosing compositional effects in health data.

Objective 1: Provide Alternative Approach to Disease Mapping

Race/ethnicity is critical for understanding self-harm behavior. Many researchers include race/ethnicity as part of their analyses. Others have called for more research in this area. However, the impact of race/ethnicity on the interpretation of geographic decision-making tools remains unexplored. Relevant research questions are:

- Does race/ethnicity composition influence the spatial patterns of self-harm?
- How does the perception of relative risk change after race/ethnicity adjustment?
- Do patterns change at the national scale? State? City?
- Why are these patterns changing in this manner?

Objective 2: Evaluate the Effect of Race/Ethnicity Adjustment in Relational Models

Most research on suicide links explanatory factors with mortality outcomes to identify community characteristics associated with elevated levels of self-harm, with the goal of intervention to reduce risk. Race/ethnicity is a common explanatory factor in these models. However, when race/ethnicity is used as a dependent variable, there is no way to separate composition from context. Relevant research questions are:
• Does race/ethnicity adjustment change the correlation between homicide mortality and suicide mortality, when compared to age-adjusted data?

• Can race/ethnicity adjustment provide a means for separating contextual and compositional contributions of race/ethnicity to suicide and homicide mortality?

Objective 3: Create a Protocol for Diagnosing Compositional Effects in Health Data

While age-adjustment is standard practice, it is rarely measured. Moreover, other forms of rate-adjustment may be more appropriate for different data. A test for compositional confounding would supply an overview of potential issues with the data and provide effect sizes to justify selected rate-adjustment methods. Relevant research questions are:

• How can compositional effects be separated from random variance?
• Can the strength of the compositional distortion be measured?
• How can researchers compare confounding effects across compositional categories?

Study Design

To examine the influence of race/ethnicity on the spatial patterns of suicide mortality, this study compares rates before and after race/ethnicity adjustment. In this instance, indirect race/ethnicity adjustment is the best option due to wide variations in population structure across counties. Direct age adjustment, which applies local rates to a global population structure, requires stable rates in all bin categories (in this case race/ethnicity groups). Because many counties do not have significant minority populations, the units required for direct adjustment would most often be the size of states. For a higher spatial resolution indirect adjustment is better. Indirect adjustment applies global rates to local population structures to create an expected suicide rate. This expected rate can then be compared to the observed non-adjusted rate using a standardized mortality ratio (SMR). All disease and population data comes
from the Centers for Disease Control and Prevention (CDC), for the time period between 1999-2019. Both state and county scales are employed throughout the study.

To identify distortions in visualization techniques (objective 1), age-adjusted rates and race/ethnicity adjusted SMRs are applied to three techniques common in public health analysis: choropleth mapping, Getis-Ord hotspot analysis, and location-allocation modeling. The resulting patterns are compared to visually identify where race/ethnicity adjustment alters the interpretation. This process is repeated at three scales: national, state (Texas), and metropolitan (Richmond, Virginia).

To examine potential confounding effects of race/ethnicity in GLM models (objective 2), this study explores the correlation between homicide and suicide mortality both before and after race/ethnicity adjustment. Additionally, both adjusted and non-adjusted rates are correlated with ecological race/ethnicity variables, such as percent Black. This analysis provides information on the nature of the context verses composition discussion represented by the nested systems diagram in Figure 2.

Finally, to create a diagnosis protocol for compositional distortions in health data (objective 3), this study uses a simulation protocol using the data from the CDC. Using R, 600 simulated data sets are created based on CDC numbers and random perturbation. These data sets are compared to the observed rates to determine how well age, race/ethnicity, and gender can predict spatial patterns. Moran’s I is then used to identify spatial clustering patterns to further identify regional biases created by the inclusion or omission of different compositional variables.
Organization of the Thesis

This thesis contains five chapters, including this introduction. Chapter 2 explores three common visualization and planning techniques both with and without race/ethnicity adjustment. Chapter 3 examines the relationships among homicide, suicide, and race/ethnicity using both race/ethnicity adjustment and county-level correlations. This chapter directly addresses the issues of confounding and context verses composition. Chapter 4 provides a potential diagnostic tool for measuring compositional confounding effects by employing a simulation program. Finally, chapter 5 summarizes the findings and applications of this study while suggesting potential avenues for further research.

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CHAPTER 2
CORRELATION, COMPOSITION, AND CONTEXT: EXPLORING RACE/ETHNICITY DISTORTIONS IN BIVARIATE MODELS

Abstract
Suicide and homicide comprise the vast majority of lethal violence deaths in the United States, yet the relationship between them remains elusive. This paper argues that one reason geographers may have difficulty identifying clear patterns is the confounding effect of race and ethnicity. Using race/ethnicity adjusted mortality rates, this research shows how a non-significant relationship between these two outcomes becomes a positive relationship after accounting for race/ethnicity. Spatial patterns shift dramatically post-adjustment, especially in minority-dominated regions. Comparing correlations between both crude and adjusted rates with ecological demographic factors facilitates a discussion on the nuances of composition versus context. Results show how failure to account for race/ethnicity may create misleading findings for researchers in the future.

Introduction
More than fifty thousand Americans die from lethal violence every year, yet the patterns and ecological drivers of suicide and homicide remain unclear. Shaped by social, cultural, and economic forces, lethal violence and the form it takes changes dramatically based on group membership. In the United States, clear differences persist among racial/ethnic categories. These differences may distort or confound the traditional tools of medical geography. This paper focuses on race/ethnicity and its effect on the spatial relationship between suicide and homicide in the United States.
Literature Review

The relationship between homicide and suicide is a long-standing area of research. Sigmund Freud conceptualized homicide and suicide as arising from similar circumstances; the difference is whether the resulting aggression is turned inward or outward (Freud 2005). This paradigm is still dominant in modern conceptual frameworks. Within the social sciences, suicide and homicide are not typically considered psychological disorders. Instead, these actions are practical solutions to personal problems (Shneidman 1985). The dominant model in this research is the stream analogy of lethal violence, which argues that homicide and suicide arise from a common source of violence, but the difference between the two is controlled by social forces (Unnithan et al. 1994; Bills and Li 2005).

For geographers this creates a technical problem. If similar circumstances lead to both types of violent death, then they should overlap or correlate with similar community characteristics. However, if the social forces separating homicide from suicide are acting at a larger geographical scale, then homicide and suicide might be found in completely different regions. Prior research reveals a wide range of relationships between suicide and homicide depending on region, scale, and time period. Globally, there is no significant correlation between a country’s homicide and suicide rates (Bills and Li 2005). However, among European nations there exists a strong positive relationship, while in the Americas the relationship is negative or random (Bills and Li 2005; Fountoulakis and Gonda 2017). At the finer scale of states and counties, suicide and homicide are positively correlated in Mexico (Leenen and Cervantes-Trejo 2014), negatively related in Brazil (Bando and Lester 2014), and unrelated in Australia (Lee and Pridmore 2013). In the United States, county-level analysis showed that
firearm-related homicide and suicide are negatively related but there is no similar relationship for homicide and suicide by other means (Branas et al. 2004). At an even finer scale, Branas, Richmond, and Schwab (2004) found a negative correlation between the two outcomes at the scale of urban neighborhoods.

Theoretically, as the gating mechanisms of homicide and suicide are incorporated into analysis, the spatial relationship between the two should align more closely. Currently, the most common research on this topic focusses on poverty and economic exclusion (Bando and Lester 2014; Huisman and Oldehinkel 2009; Piatkowska 2020). However, a longitudinal study found that race has a larger impact on the probability of suicide versus homicide than economic issues, age, gender, presence of gun, or poor mental health (Fridel and Zimmerman 2019).

Figure 2.1: Homicide and suicide rates by race/ethnicity, 1999-2019. (CDC 2022)

In the context of the United States, the effect of race/ethnicity on violence mortality and the homicide/suicide ratio is clear in the mortality data presented in Figure 2.1. Black Americans are three times more likely to die of lethal violence than their Asian/Pacific Islander
(API) counterparts. Homicide comprises 79 percent of black violent mortality, but only 14 percent of non-Hispanic white (NHW). Some researchers have included race/ethnicity variables as part of a larger regression model (Branas et al. 2004) while others who have not included race/ethnicity have identified it as a limitation (Bills and Li 2005). However, race/ethnicity has not yet been at the core of a spatial analysis on the relationship between these outcomes.

In 2015, Geoffrey DeVerteuil published a paper imploring the medical geography community to reconsider its approach to violence. He highlights a few critical components. Violence is harmful, inhibiting individuals and/or communities, including social and emotional dimensions. Violence is an ongoing process linked to social and collective structures. Finally, violence is inherently spatial and occurring at multiple scales. He challenges the discipline to think harder about simply applying traditional tools to this emerging research area, quoting Waquant (2004): “Medical geography, with its biomedical model and focus on disease ecology, spatial analysis of communicable diseases, and health care provision, has treated violence more as a localized hazard while blind to wider social structure and cultural meaning (p. 322).” An emerging body of work seeks to marry the traditional, robust, and time-tested quantitative techniques of medical geography with the peculiar circumstances of violence, behavior, and mental distress. This paper is a response to this challenge.

This paper addresses several gaps by exploring the impact of both the compositional and contextual contributions of race/ethnicity to suicide and homicide mortality in the United States. Specifically, we investigate the relationship between homicide and suicide at the county equivalent scale and compare results before and after race/ethnicity adjustment. Ultimately, we seek to separate context from composition to reveal a more theoretically nuanced view of
the role race/ethnicity plays in violent deaths.

Methods

Data Preparation

Both suicide and homicide are relatively rare health outcomes. The raw number of cases in most counties is too small to be statistically reliable. Therefore, counties were aggregated using a protocol from Sun and Wong (2017). The Centers for Disease Control consider rates calculated with fewer than 20 cases unreliable. Therefore, using data from the CDC Wonder database, units were aggregated until they contained at least 20 cases of suicide and 20 cases of homicide during the time period of 1999-2019 (CDC 2021). Large units, like major cities, remain independent observations while smaller counties are aggregated to maximize compactness and avoid crossing state lines.

Rate Calculation

To preserve spatial detail while using race/ethnicity data, this project employs indirect rate adjustment. The indirect adjustment method applies national rates to local population structure and can be interpreted as the expected rate, given the population composition (Waller and Gotway 2004). The indirectly adjusted weight is compared with the crude rate to compute standardized mortality ratios (SMRs). The SMR measures how the observed crude rate deviates from the expected rate. These numbers can be interpreted as the remaining variance, once the effect of population composition is removed.

This analysis compares age-adjusted SMRs with age and race/ethnicity SMRs. The age groups are 15-29, 30-44, 45-59, and 60 plus. The five race/ethnicity groups used in this analysis
are: Non-Hispanic white (NHW), Black, Hispanic white (HW), Asian-Pacific Islander (API), and American-Indian/Alaska Native (AIAN). These groups are easily retrievable from both the CDC and the US Census and have been shown in prior research to exhibit different behaviors around violence.

Analysis

First, we explore the contribution of population composition. Once both types of SMRs are calculated for suicide and homicide, Pearson’s correlations are used to compare the relationship between outcomes at the national scale, census region scale, and at various levels of urbanization. These rates are also used to create choropleth maps to identify regions where suicide and homicide overlap or diverge. The same process will be used for SMRs both before and after race/ethnicity adjustment.

Second, we incorporate race/ethnicity variables to further explore the contextual ecological contributions of race/ethnicity. Using population data from the CDC Wonder database, crude rates, adjusted rates, and SMRs are correlated with percent NHW, percent black, percent API, percent AIAN, and percent Hispanic white. Correlation between the ecological variables and age-adjusted SMRs demonstrate the results of traditional analysis methods, while the correlations post-race/ethnicity-adjustment show how these relationships change once the effect of race/ethnicity composition is removed.

Results

At the national level, there is no significant correlation between homicide and suicide mortality rates (Table 2.1). However, there are significant relationships at the census region
level. Suicide and homicide are positively correlated in the West and Midwest and negatively correlated in the South and Northeast. These relationships are generally weak. Additionally, no significant relationship exists between suicide and homicide at any level of urbanization.

Table 2.1: Correlations between Age-adjusted suicide SMRs and Age-adjusted Homicide SMRs.

<table>
<thead>
<tr>
<th>Census Region</th>
<th>Correlation Age-adjusted</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>.040 (.089)</td>
<td>1783</td>
</tr>
<tr>
<td>West</td>
<td>.397</td>
<td>235</td>
</tr>
<tr>
<td>Midwest</td>
<td>.283</td>
<td>411</td>
</tr>
<tr>
<td>South</td>
<td>-.239</td>
<td>969</td>
</tr>
<tr>
<td>Northeast</td>
<td>-.271</td>
<td>166</td>
</tr>
<tr>
<td>Large Central Metro</td>
<td>-.104 (.464)</td>
<td>52</td>
</tr>
<tr>
<td>Large Fringe Metro</td>
<td>.105 (.127)</td>
<td>211</td>
</tr>
<tr>
<td>Small/Medium Metro</td>
<td>.065 (.137)</td>
<td>518</td>
</tr>
<tr>
<td>Micropolitan/Non-core</td>
<td>.012 (.693)</td>
<td>1002</td>
</tr>
</tbody>
</table>

Note: Correlations are significant at 99% confidence unless otherwise noted.

Figure 2.2 shows the distribution of lethal violence mortality, classified by age-adjusted homicide and suicide SMRs. In the northern tier of states, suicide dominates while the southern tier generally exhibits high rates of both. The deep south is characterized by low suicide and high homicide rates. Suicide rates increase in the upper South, but homicide rates do not, creating a band of high suicide and high homicide from West Virginia to Oklahoma. The urban northeast and Midwest are characterized by large areas of low overall violence, studded with high homicide/low suicide urban centers. Nevada, New Mexico, and Arizona exhibit high rates of both homicide and suicide, while the upper mountain west is dominated by high suicide and low homicide. Central California is another region of high homicide and low suicide, while urban
areas exhibit lower levels of violent death. The stability of these patterns once the contribution of race/ethnicity is removed is discussed in the next section.

After exploring the relationship between homicide and suicide using age-adjusted SMRs, we repeated the analysis using age and race/ethnicity-adjusted data. Race/ethnicity adjustment provides a method for removing the noise caused by expected patterns created by diverse population structures across units.

First, we examined the adjusted (expected) suicide rates based on age and race/ethnicity composition. The correlation between expected suicide and expected homicide is strong and negative \( (r = -0.850, p < 0.001) \). Then we examined the correlation between rare and race/ethnicity-adjusted SMRs. The correlation between suicide SMRs and homicide SMRs is moderate in strength and positive in direction \( (r = 0.456, p < 0.001) \). While age-adjusted homicide
cannot be used to predict age-adjusted suicide, race/ethnicity-adjusted homicide SMRs predict 20.7 percent of the variance in race/ethnicity-adjusted suicide SMRs.

Once race/ethnicity composition is accounted for, there is a positive relationship in every census region (Table 2.2). The relationships in the West and Midwest become nearly twice as strong. A positive relationship between homicide and suicide SMRs also exists at every urbanization level and is particularly strong in the large fringe metro countries.

**Table 2.2: Correlations between homicide and suicide, comparing two rate calculation methods.**

<table>
<thead>
<tr>
<th>Census Region</th>
<th>Correlation Age-adjusted</th>
<th>Correlation Age and Race/ethnicity-adjusted</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>.040 (.089)</td>
<td>.473</td>
<td>1783</td>
</tr>
<tr>
<td>West</td>
<td>.397</td>
<td>.565</td>
<td>235</td>
</tr>
<tr>
<td>Midwest</td>
<td>.283</td>
<td>.559</td>
<td>411</td>
</tr>
<tr>
<td>South</td>
<td>-.239</td>
<td>.322</td>
<td>969</td>
</tr>
<tr>
<td>Northeast</td>
<td>-.271</td>
<td>.255</td>
<td>166</td>
</tr>
<tr>
<td>Large Central Metro</td>
<td>-.104 (.464)</td>
<td>.321</td>
<td>52</td>
</tr>
<tr>
<td>Large Fringe Metro</td>
<td>.105 (.127)</td>
<td>.534</td>
<td>211</td>
</tr>
<tr>
<td>Small/Medium Metro</td>
<td>.065 (.137)</td>
<td>.439</td>
<td>518</td>
</tr>
<tr>
<td>Micropolitan/Non-core</td>
<td>.012 (.693)</td>
<td>.488</td>
<td>1002</td>
</tr>
</tbody>
</table>

*Note: All correlations are significant at 99% unless otherwise noted.*

Figure 2.3 shows a map of lethal violence using age and race/ethnicity-adjusted homicide and suicide SMRs. Compared to Figure 2.2, fewer units show either high homicide/low suicide or high suicide/low homicide, supporting the correlation results suggesting increased alignment. While a cluster of high suicide/low homicide units still appears in the central mountain region, Montana, Oregon, Washington, and the Dakotas now also show average or higher than expected homicide rates, given the population composition. In the upper Midwest and urban northeast, more counties exhibit low/low behavior, though the high
homicide urban areas remain largely unchanged. The highly Hispanic counties in central California and south/west Texas reveal higher suicide than expected; in Texas these counties switch entirely from homicide characterized counties in Figure 2.2 to suicide characterized in Figure 2.3. The most noteworthy difference between the maps is in the South. The solid high homicide/low suicide band from Figure 2.2 disintegrates in Figure 2.3. While higher than expected homicide is still an issue along the Mississippi river, pockets of higher than expected suicide and lower than expected homicide appear in central Georgia and Virginia. The band of high violence from West Virginia to Oklahoma remains, but a cluster of high homicide/low suicide appears in Eastern Kentucky and West Virginia.

![Figure 2.3: Classification based on suicide and homicide SMRs](image)

Race/ethnicity adjusted SMRs capture the contribution of composition to suicide and homicide rates. This largely comprises factors working at the individual level. To assess
contextual community contributions, race/ethnicity must be revisited at the ecological level.

Suicide and homicide SMRs were correlated with county-level race/ethnicity composition factors to explore this effect. Table 2.3 shows the correlation results for each pair of variables.

Figure 2.4 shows the same information in graphical form.

Table 2.3: Correlation Coefficients between three types of rates for violent deaths, suicide, and homicide.

<table>
<thead>
<tr>
<th></th>
<th>Age-Adjusted SMR</th>
<th>Adjusted/Expected Rate (Composition)</th>
<th>Race/ethnicity adjusted SMR (Context)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suicide</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% NHW</td>
<td>.154</td>
<td>.964</td>
<td>-.199</td>
</tr>
<tr>
<td>% Black</td>
<td>-.332</td>
<td>-.737</td>
<td>-.079</td>
</tr>
<tr>
<td>% HW</td>
<td>-.065</td>
<td>-.519</td>
<td>.140</td>
</tr>
<tr>
<td>% API</td>
<td>-.191</td>
<td>-.282</td>
<td>-.099</td>
</tr>
<tr>
<td>% AIAN</td>
<td>.527</td>
<td>ns</td>
<td>.548</td>
</tr>
<tr>
<td>Homicide</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% NHW</td>
<td>-.604</td>
<td>-.789</td>
<td>-.134</td>
</tr>
<tr>
<td>% Black</td>
<td>.710</td>
<td>.969</td>
<td>.067</td>
</tr>
<tr>
<td>% HW</td>
<td>ns</td>
<td>.062</td>
<td>ns</td>
</tr>
<tr>
<td>% API</td>
<td>-.079</td>
<td>ns</td>
<td>-.125</td>
</tr>
<tr>
<td>% AIAN</td>
<td>.178</td>
<td>ns</td>
<td>.324</td>
</tr>
</tbody>
</table>

Note: All results are significant at 99% confidence.

In Figure 2.4, the correlations between age-adjusted SMRs and demographic variables are represented by dark gray bars. These are the results we would obtain from a traditional analysis. Figure 2.4A shows the results for overall lethal violence mortality. There are weak negative associations between violence and percent NHW and API, a weak positive association with percent Black, and a moderately strong association with percent AIAN.
Figure 2.4: Correlation coefficients between three types of mortality rates and race/ethnicity composition variables. A: Violence, B: Suicide, C: Homicide.
The second set of correlations, represented in blue in Figure 2.4A, show the association between indirectly adjusted (or expected) rates and demographic characteristics. If the relationship between violence and race/ethnicity is entirely dependent on composition, then the correlation between observed (crude rates) and expected (adjusted rates) should be roughly equal. As Figure 2.4A shows, this is often not the case. Additionally, if composition alone explains the spatial pattern of mortality, then the relationship between demographic variables and SMRs, or the remaining variance once the effect of composition alone is removed, should be zero. The relationship between demographic variables and age and race/ethnicity-adjusted SMRs is represented by the red bars in Figure 2.4.

Figure 2.4B shows this analysis for suicide mortality alone. A small positive association between suicide mortality and percent NHW was observed in crude rates, yet the anticipated effect was nearly five times larger based on compositional characteristics. Once composition is accounted for, there is a negative relationship between suicide and SMRs, indicating some mitigating resilience in white communities. There is also a small but significant negative association between percent Black and suicide mortality, though again, most of the negative relationship between percent Black and crude rates is explained by composition alone. Similar to lethal violence, the relationship between percent HW and suicide was predicted to be much stronger than observed. Once composition is removed, there is a positive association between suicide mortalities and percent HW. Once again, high rates of suicide mortality in AIAN communities is entirely explained by context, with no contribution from composition.

Finally, Figure 2.4C shows the associations between race/ethnicity and homicide mortality. The moderately strong relationship between percent NHW and homicide is mostly
explained by composition, though there is a small negative contextual effect. The association between percent Black and homicide mortality is moderately strong and positive, and also primarily accounted for by composition. Though there is a significant positive association between SMRs and percent black, the effect is very small. Composition was not predicted to contribute to lower homicide rates in units with larger proportions of API, so the small observed negative association is attributed to context. In fact, despite large differences in both observed and expected associations with homicide, percent NHW and percent API have similar contextual contributions based on SMRs. Once again, elevated rates in areas with higher proportions of AIAN are not anticipated by the adjusted rates, revealing primarily contextual contributions to homicide in these areas.

Discussion

The stream analogy of lethal violence suggests critical branching points differentiating suicide from homicide. Adjusting for these pivotal factors should lead to closer alignment of homicide and suicide mortality, paving the way for more fruitful investigations of the shared causes of lethal violence. The results of this paper support race/ethnicity as one of these critical intersections. Prior to race/ethnicity adjustment, there is a random spatial relationship of suicide and homicide mortality at the county equivalent scale. However, post-adjustment SMRs bring these outcomes closer into alignment, identifying more communities with higher than expected rates of both.

Some of the most recognizable regional differences in homicide and suicide diminish post-adjustment. The high homicide/low suicide belt of the American South splinters into a jumble of mixed outcomes. This suggest that the apparent homogeneity of this region was
mostly an artifact of its racial/ethnic composition (specifically high proportions of Black residents). The mountain west is generally considered a high-suicide/low-homicide outlier, but race/ethnicity adjustment suggests this characterization is also related to population composition (in this case dominantly NHW). Instead, this region is dominated by higher than expected suicide and homicide rates, a fact which may change some of the theories about America’s suicide belt.

Equally as noteworthy, some regions changed very little post adjustment. The urban northeast is a pocket of low lethal violence, even when population composition is factored in. The rural Midwest similarly has lower than expected rates of lethal violence, but midwestern urban areas suffer from high rates of homicide in both crude and adjusted situations. There is also a consistent band of lethal violence from West Virginia through Oklahoma.

Race/ethnicity adjusted rates and SMRs eliminate the noise caused by diverse population structures, allowing for clearer analysis of potential contributing factors. In this paper we used these rates to examine the additional contextual contribution of race/ethnicity. The benefit of this dual approach of composition and context is highlighted by the findings for AIAN and black mortality rates. Both groups are associated with higher than average rates of lethal violence, but how and why is quite different.

Black rates of homicide are extraordinarily high. Yet, composition explains almost all of the association between crude homicide and percent black. There is no contextual contribution of percent Black to community homicide rates and a small but significant negative effect on suicide rates. This suggests that the forces leading to high Black homicide mortality are acting
on individuals evenly across the study area. Higher densities of Black residents do not increase the contextual risk of violence.

However, the situation with AIAN-associated violence is much different. National rates of homicide and suicide among AIAN are close to the overall national average. Therefore, composition does nothing to explain why percent AIAN is strongly related to high rates of both suicide and homicide. Instead, the explanation for this effect is entirely contextual. People living in areas dominated by AIAN residents (they may be AIAN or some other race/ethnicity) are dying of both suicide and homicide at a much higher rate than expected. In the United States, counties with high proportions of AIAN are usually rural. High proportions of AIAN are also associated with the reservation system, notoriously linked to poverty, poor opportunity, and brain drain.

Similarly, proportion Hispanic white is positively associated with higher than expected suicide rates, after controlling for population composition. Counties with high proportions of HW are found primarily along the Mexico border and through the agricultural regions of the southwest. These areas have higher than average likelihood of several factors thought to contribute to suicide: poverty, social disorganization, and poor access to healthcare. Again, proportion HW as a contextual variable does not mean Hispanic people are necessarily committing suicide at a higher rate. It means that areas with a higher proportion of HW are, for some reason, more at risk of suicide than average. However, unlike regions with high proportion AIAN, this effect does not extend to homicide.

Counties with high proportions of NHW residents exhibit small negative contextual effects on violence. White counties are more likely to have higher levels of wealth, more stable
social networks, and more opportunities, even though individual NHWs have a higher risk of suicide than any other group. Percent NHW is the most commonly used race/ethnicity variable in suicide geography research, but rarely is it treated with much care. The positive correlation between NHW and crude suicide rates is deceptive; it contains both compositional and contextual data with very different dynamics. High composition NHW will lead to higher observed suicide rates, but the whitest communities will also have a contextual force acting the opposite way to slightly inhibit rates.

This dynamic highlights the potential confounding issues associated with analyses disregarding or minimizing the impact of race/ethnicity. For example, does poverty contribute to suicide rates? It is nearly impossible to answer that question without first accounting for the fact that the richest counties will inevitably have high suicide rates just because of the race/ethnicity of the people who live there. We know that many of the socioeconomic indicators used for research in the United States are influenced or distorted by historical inequities and cultural differences represented by race/ethnicity. Given our poor understanding of suicide and homicide from an ecological perspective, this kind of nuanced theoretical richness is important.

These results are important for three reasons. First, they open the door for a more nuanced understanding of the spatial relationship between race/ethnicity and violence incorporating the important distinction between composition and context. Second, they show the potential of using race/ethnicity-adjusted SMRs to examine potential contributing factors like poverty, mobility, and social connection, variables often patterned by race/ethnicity themselves. Third, this distinction between context and composition can inform better tailored
interventions. For example, many AIAN communities are currently incubators for violence, but majority black communities are not, and therefore may require a different approach.

Conclusion

In the United States, race/ethnicity is a critical fork in the stream analogy of lethal violence. As researchers across disciplines work to explain this effect, geographers must determine how to incorporate this information fully into our research. Failure to address the issue may lead to missing important similarities between suicide and homicide and among communities that foster increased violence. Researchers may choose to include race/ethnicity as a dependent variable, but they should be aware that this technique cannot account for important differences in compositional and contextual contributions. The ultimate goal is to create a more equitable and inclusive quantitative framework for exploring the geography of violence and other health outcomes disproportionately affecting one race/ethnicity group more than another.

This study has several limitations. Aggregation is helpful for including the entire population, but introduces potential issues caused by the modifiable areal unit problem. This study focuses on mortality data, which means information on the perpetrators of homicide is missing. Additionally, we have only analyzed the numbers at one scale, and as previous literature shows, the relationship between suicide and homicide may change dramatically from one scale to the next. Future research should replicate this study at multiple scales and using different aggregation schemes to determine the stability of these results. Future work should also incorporate commonly used explanatory variables like poverty, unemployment, and mental health to explore how these relationships are tied to the race/ethnicity issue.
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CHAPTER 3

SPATIAL MODELING AND THE CONFOUNDING EFFECT OF RACE/ETHNICITY

Abstract

Traditional visualization techniques conceal risk in minority communities because of the relatively small number of cases. A need exists for a visualization approach that reveals the relative risk in such communities to facilitate appropriate planning for intervention. Race/ethnicity adjustment provides a valuable tool for revealing distressed minority populations and, thus, accommodating the issues presented by population composition. This paper examines how adjusting for race/ethnicity impacts the visualized spatial patterns of suicide mortality. Using GIS and statistical analysis, we compare county-level crude suicide mortality with race/ethnicity adjusted mortality rates at three different geographic scales. We illustrate the difference in visualized community distress using a simple p-median location-allocation model for siting facilities to address perceived distress. The results reveal clear differences in location of service facilities as well as allocation of need to service. Researchers must be intentional in highlighting the needs of small minority populations that tend to be overshadowed by the large numbers of the majority population.

Introduction

Rates of suicide vary widely across racial/ethnic groups in the United States but the visualization approaches employed often conceal, rather than reveal, these differences in geographic space. Consequently, the high rates among minority groups are rarely apparent. This paper compares suicide data before and after race/ethnicity adjustment across three geographic scales using three common methods: choropleth mapping, Getis-Ord hot spot
analysis, and location-allocation modeling. The results reveal that different adjustment techniques produce contrasting perceptions of risk in minority-dominated areas like cities, border regions, and the American Deep South.

**Background**

For centuries, self-harm has been at the center of contentious debates over free will, ethics, morality, nature versus nurture, and a host of other issues. Today, suicide is the 11th leading cause of death in the United States, yet applied understanding of the community drivers of risk remains poor (CDC 2022; Franklin et al. 2017). As public health attempts to grapple with mental health, suicide must be part of the conversation. However, suicide data comes with some serious issues and cannot be used as a proxy variable for mental distress in its raw form. In this section I will highlight some of the issues with this data.

The first concern is the simple issue of definitions. The ICD-10 uses the definition of “intentional self-harm,” but the issue of intent is unclear. Without a suicide note, coroners must determine whether to classify a death as a suicide, accident, or undetermined. This decision varies across municipalities. Some rely on psychological autopsies, a somewhat controversial practice. Mental illness and substance abuse may contribute to the circumstances leading to suicide, but they are not sufficient nor necessary (Thornton et al. 2016). Some may consider risky behavior leading to death suicidal, such as drug overdoses. Other may rely on a note, while some may avoid classifying deaths as suicides to avoid social issues like shame in the decedent’s family or economic consequences like the nullification of life insurance policies. Within the social sciences, suicide is not typically considered a psychological disorder. Instead, it is framed as a practical solution to perceived problems (Shneidman 1985). This theory assumes
some form of rational decision making, which is at odds with biological explanations implicating genetics, psychosis, and other neurological dysfunction (Preti 2011; Tidemalm et al. 2011; McGuffin et al. 2010; Hamermesh and Soss 1974).

In any case, the variety of definitions and explanations for suicide create measurement error issues. Though suicide is a relatively common cause of death, finer scales of space or time may only have a small number of observations, amplifying measurement error. Processing this data requires directly addressing the small numbers problem, or rate instability caused by small samples (Waller and Gotway 2004). The easiest way to accommodate small numbers is to widen the time span or choose a larger spatial support. Some studies choose to employ smoothing methods to overcome this obstacle (Cutchin and Churchill 1999). Failing to accommodate the small numbers problem can easily create misleading results.

The modifiable areal unit problem (MAUP) is related to the small numbers problem. If researchers choose to change the spatial units or aggregate into new units, the results may change (Dark and Bram 2007). Suicide is influenced by variables at the neighborhood, state, and national scales. The choice of scale and the choice of boundaries used may change the results significantly. Many authors have written on the need to analyze more than one scale at a time, and multiple permutations of aggregated regions may be used to address the MAUP.

Perhaps the largest challenge to suicide research is the issue of equifinality; there is no one path to suicidal behavior (Cutchin and Churchill 1999). Compensating for multiple routes to the same outcome is difficult both theoretically and methodologically. Rates vary widely by age, gender, race, and ethnicity. Causes may include chronic illness, extreme mental distress, social isolation, and lack of economic opportunity. The likelihood of these stressors and the filter
through which they are viewed are both dependent on the culture, class, and history of each individual as well as the characteristics of their environment. Within a geographic area, all of these dimensions are occurring at once, and our challenge is to separate the emergent contextual effects from those created by population composition.

Some clarity is provided by age-adjustment, which compensates for the statistical noise caused by variations in population structures (Pickle 2009; Waller and Gotway 2004; Pickle and White 1995). For example, prostate cancer rates increase dramatically with age. Crude rates would highlight areas with a lot of older people. There is nothing wrong or inaccurate about these rates. However, most geographic analysis seeks to go further by identifying areas where cancer rates are higher than expected, given the population composition. Age-adjusted rates are more easily comparable across space and may reveal communities with elevated risk that were previously obscured.

While suicide rates do vary by age, the differences are much larger between race and ethnicity groups (Figure 3.1). Non-Hispanic white (NHW) rates of suicide are two to three times higher than rates among black, Hispanic, or Asian-Pacific islander (API) groups. Because NHWs comprise 70 percent of the population, they dominate representations of suicide mortality. A black community would have to commit suicide at a rate 2.6 times higher than expected to match an average NHW community. This effect is likely magnified in some places by the high concentration of non-NHW people in the South, West, and urban areas (Figure 3.2).

If minority risk is hidden behind the noise created by NHW-rates, these communities may not receive the attention and mental health resources they need. Additionally, further analysis of the ecological contributors to suicide may align more closely with the characteristics
of NHW communities instead of identifying suicide-specific variables that transcend race/ethnicity. Therefore, this paper investigates the use of race/ethnicity-adjustment on the visualization of suicide mortality data in the United States. We use three common visualization techniques (choropleth mapping, hotspot analysis, and location-allocation) at three separate scales (national, state, and city) to explore the effect of adjustment on the patterns of self-harm mortality.

Figure 3.1: Comparing suicide rates across ages and race/ethnicity categories, 1999-2019. (CDC data)

Figure 3.2: Race/Ethnicity composition by Census District and urbanization category, 1999-2020. (CDC data)
Methods

Data is from the CDC detailed mortality database (Centers for Disease Control and Prevention 2021). The time period is 1999-2019, allowing for the maximum number of cases per county using the ICD-10 code classification. The racial/ethnic groups used here are: Black, Asian-Pacific Islander (API), American Indian/Alaska Native (AIAN), non-Hispanic white (NHW), and Hispanic or Latino white. All five groups have been shown to display different behaviors around suicide and these classifications can be bridged between CDC data and US Census data.

Suicide is a relatively rare health outcome, and many counties do not have a stable number of cases. Suicide studies at the county level are highly vulnerable to the small numbers problem. However, some statisticians warn against using smoothing when using indirectly-adjusted rates or standardized mortality ratios (Pickle and White 1995). This project employed a protocol based on Sun and Wong (2017) which uses selective aggregation to preserve independent observations. Units must have 25 cases of suicide during the time period, in line with the National Household Survey on Drug Abuse (Klein et al. 2002). Counties with fewer than 25 cases become candidates for aggregation.

Candidate counties were merged based on two criteria following Sun and Wong (2017). The first was compactness. The second was urbanization. The clearest pattern in prior research is the urban/rural divide (Rossen et al. 2018; Steelesmith et al. 2019; Stein et al. 2017). Therefore, counties with similar classifications were grouped together as much as possible to preserve this feature. After aggregation, the initial dataset of 3,147 counties is condensed to 2,730 county equivalents, comprising 2,627 unique counties and 290 aggregated units.

Results of geographic analysis may be different at different scales (Cutchin and Churchill
1999; Breault 1986). Therefore, this paper explores effects at three different geographic scales: national, state, and metropolitan statistical area (MSA). Texas was selected to illustrate the state level analysis due to its large size and diversity. Due to its relatively compact spatial units and unique characteristics, containing four independent cities of varying racial/ethnic composition in addition to peripheral suburban and rural counties, Richmond, Virginia was selected as the MSA case. Figure 3.3 compares suicide rates by race/ethnicity across the three scales.

![Figure 3.3: Age-adjusted suicide rates at three scales. With the notable exception of AIAN, the differences between racial/ethnic categories is remarkably stable.](image)

This research investigates two different rate calculation methods: standard age-adjusted (AAR) and race/ethnicity-adjusted (REAR). The use of race-adjusted disease rates is uncommon, but not unprecedented. Wu and Shete (2020) used indirect race-adjustment to explore sudden infant death mortality in North Carolina. Though they only used white and non-white bins, they discovered important changes in the spatial patterns observed previously.

AAR are obtained directly from the CDC Wonder database. The algorithm is a direct-
adjustment technique (local rates applied to national population structure). However, suicide rates by race/ethnicity are extremely unstable at the county level, eliminating the possibility of using direct adjustment. Smith and Kawachi (2014) attempted a state-level exploration of suicide by calculating rates by gender and race/ethnicity, but quickly discovered samples so small that only white men and women and Black men made it into the final analysis. Therefore, indirect adjustment is ideal to preserve detail and avoid the small numbers problem (Pickle and White 1995). Indirect adjustment applies national rates to local population structures. The indirectly race/ethnicity-adjusted rate (REAR) is interpreted as the expected rate given the racial/ethnic composition of the spatial unit (Waller and Gotway 2004). The AARs and REARs are also expressed as standardized mortality ratios (SMRs). SMRs based only on AARs (SMR<sub>aa</sub>) compare the observed local AAR to the national AAR. SMRs based on the REARs (SMR<sub>rea</sub>) compare the observed AAR to the REAR, as shown in Table 3.1 (Waller and Gotway 2004). AARs are used for all inputs into the race/ethnicity-adjusted condition.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race/Ethnicity Adjusted Rate (REAR)</td>
<td>((NH\text{\text{W national AAR}} \times \text{county proportion NH\text{\text{W}}}) + (\text{Black national AAR} \times \text{county proportion black}) + (\text{AIAN national AAR} \times \text{county proportion AIAN}) + (\text{API national AAR} \times \text{county proportion API}) + (\text{Hispanic national AAR} \times \text{county proportion Hispanic}))</td>
</tr>
<tr>
<td>Standardized Mortality Ratio, Age-Adjusted (SMR&lt;sub&gt;aa&lt;/sub&gt;)</td>
<td>(\frac{\text{Local AAR}}{\text{National AAR}} \times 100)</td>
</tr>
<tr>
<td>Standardized Mortality Ratio, Race/Ethnicity Adjusted (SMR&lt;sub&gt;rea&lt;/sub&gt;)</td>
<td>(\frac{\text{Local AAR}}{\text{Local REAR}} \times 100)</td>
</tr>
</tbody>
</table>

Three techniques commonly used in health system planning were chosen to compare conditions. The first is simple choropleth maps, the most common visualization technique used
by public health departments like the CDC. These maps allow for visual inspection of data and comparisons among units. The units selected are states for national maps, mental health authority regions for Texas, and county equivalents for the Richmond MSA.

The second technique is Getis-Ord Gi* hot spot analysis. Hot spot analysis uses smoothing algorithms to identify statistically significant areas of high and low rates (AkliluToma, Senbeta, and Bezabih 2021; Kumar et al. 2018). This analysis uses a spatially adaptive filter to accommodate the vast difference in county size across the United States. County-equivalent data is used at all three scales.

Finally, location-allocation analysis is used to determine if race/ethnicity can distort the identification of communities and sites requiring intervention. The p-median optimization criteria is applied to create the most equitable distribution of sites (Murad et al. 2021; Cirino et al. 2016). The input network is created by overlaying a fishnet grid (10-mile grid for national, 5-mile grid for Texas, 1-mile grid for Richmond). The weighting criteria for the national and state models are the SMRs, unweighted for population. At a large scale, the goal is more likely to be identifying communities with characteristics contributing to increased suicidal behavior. Therefore, weighting by population is inappropriate and will always pull sites into urban areas. However, at the smallest scale, clinic location is a more likely goal. For the MSA the demand surface is census blocks weighted by population and the county-level SMRs. A somewhat arbitrary number of sites is selected for each scale (50 at the national scale, 10 at the state and MSA).

Results

Figure 3.4A compares the resulting state-level choropleth maps with and without
race/ethnicity adjustment. Post-adjustment, SMRs increase in Hawaii, California, and across the South. SMRs decrease in New England and the upper Midwest. SMRs in the western suicide belt states remain high, but ratios slightly decrease in Utah, Idaho, and Oregon.

**Choropleth Maps**

![Choropleth Maps](image)

**Getis-Ord Gi* Hot Spot Maps**

![Getis-Ord Gi* Hot Spot Maps](image)

**Figure 3.4: National Choropleth and Hot Spot Maps.**

Figure 3.4B shows the hot spot maps based on county-level data and reveal a similar pattern, most notably the disappearance of the large cold spot across the southeast and smaller
cold spots in Texas and California. The southern tier of the United States comprises the most racially and ethnically diverse regions in the country. The southeast from East Texas to Virginia contains many black-majority counties, especially in the “cotton belt” which is clearly visible as the cold spot in the first map. Because the average rate of suicide among Black Americans is quite low, we should expect crude and age-adjusted suicide rates in these regions to be low. However, when the effect of race/ethnicity is accounted for, the southern cold spot disappears, and states like Louisiana, Mississippi, and South Carolina emerge as places with higher than expected suicide mortality. The effect of population composition obscured some of these potential trouble spots.

In contrast, we should expect higher suicide rates where a large proportion of the population is NHW. However, there is a large cold spot from the urban Northeast across the upper Midwest, despite a large NHW majority in most counties. After race/ethnicity adjustment, this cold spot grows. The suicide cold spot in the Northeast is confirmed; there is a real, powerful inhibiting effect in this region, especially in the New York/Boston area.

Results of the national location-allocation models are shown in Figure 3.5. Figure 3.5A compares the two. Many selected communities on the West Coast, East Coast, and Great Plains remain the same. Figure 3.5B shows the distance of each site selected in the race/ethnicity adjusted environment from the closest site in the age-adjusted model. Seventeen sites remain the same in each condition. The mean distance between new and old sites is 44.6 miles. However, there are two major changes.
Figure 3.5: Location-allocation results at the national scale. (A) at top shows the shared and unique sites before and after race/ethnicity adjustment. (B) at bottom shows the distance between the sites in the first and second condition.
One site is removed from Idaho and moved to New Mexico, reflecting the changes in the choropleth maps (Figure 3.4A). The new site in northern New Mexico is located in an area dominated by AIAN, with a low proportion of NHW. This site is 182.7 miles away from any services in the age-adjusted condition. Additionally, one site is removed from the central Midwest and added in Texas near Houston. Both new sites were removed from areas in Idaho and Missouri with high proportions of NHW. These changes reflect the general shift towards the South and Southwest created by race/ethnicity adjustment.

At the state scale, rates were re-calculated using state averages instead of national. Texas was selected because of its large size and diverse population.

Figure 3.6A shows SMRs for the 39 local mental health authority regions created by the Texas Department of State Health Services. In the age-adjusted condition, suicide rates are exceptionally low at the southern Texas/Mexico border. Below-average rates are also found in and around major urban areas in West Texas (El Paso), North Texas (DFW), and the upper Gulf Coast (Houston). The most elevated rates are along the northern and eastern borders. However, after race/ethnicity adjustment, rates along the southern border more closely reflect the expected rates. The most elevated risk is in non-urban South and East Texas. North Texas no longer stands out against the rest of the state. Additionally, the relationship between suicide and the largest cities changes, with the exception of the DFW area. Suicide rates in Houston are no longer below expected. The southern cities of Corpus Christi and San Antonio display higher-than expected suicide rates, despite appearing average in the age-adjusted condition. El Paso in far west Texas appears below average before adjustment and above expected after.
Figure 3.6: Choropleth and hotspot maps of Texas
Figure 3.7: Location-allocation results for Texas. Figure 7A shows site locations before and after race/ethnicity adjustment. Figure 7B shows the distance between clinics in the two conditions.
Figure 3.6B shows the results of the hot spot analysis using county-level data. Without race/ethnicity-adjustment, North Texas shows a wide-spread area of hotspots while deep South Texas is a cold spot at 99 percent confidence. However, once adjusted, South Texas is the primary hotspot, while a series of statistically weaker cold spots wind though the central part of the state.

Figure 3.7 shows the effect this change has on the location-allocation model. Only two sites are shared between conditions. The average distance a site moves between conditions is 32.2 miles. The site north of Dallas-Fort Worth moves from rural Wise County to the more urban/suburban Denton County. The four sites in southern Texas move closer to the Hispanic-dominated border region. The biggest difference is the site selected in Corpus Christi by the age-adjusted model moves to the center of the South Texas hot spot identified in Figure 13B. Without race/ethnicity adjustment, this site is 80.0 miles from the nearest site in the age-adjusted condition.

The southern, western, and border regions of Texas are dominated by Hispanic populations, generally a lower-risk group for suicide. North and East Texas have much larger proportions of NHW, so the pattern in Figure 3.6A should be expected. However, this pattern dissipates after race ethnicity adjustment. In the location-allocation model, the Corpus Christi site and the sites east and west of San Antonio shift towards the border areas. All these results suggest higher risk and demand in these primarily Hispanic communities that was previously hidden.

Figures 3.8 and 3.9 show results for the Richmond, Virginia metropolitan statistical area. This MSA is unique because it contains four different cities with varying racial/ethnic
composition. Prior to race/ethnicity adjustment, the areas with low SMRs are the central city of Richmond, its closest suburban counties, the secondary city of Petersburg south of Richmond, and one southeastern outlying county (Figure 3.8A). However, post-adjustment, the cities are all above expected, and only the northern suburban counties of Henrico and Goochland are below expected. The City of Richmond has a higher SMR than its neighboring suburbs and Petersburg jumps from the lowest class to the highest class post-adjustment. This change is due to a high proportion of black residents and relatively high suicide rates. In this unit, black suicide rates are 36 percent above the black MSA rate and NHW suicide rates are 107 percent higher than the overall NHW rate. This distress was hidden pre-adjustment.

Figure 3.8B shows the results of the hot spot maps. Results are not very strong, most likely due to the smaller number of units, but echo the patterns shown in the choropleth maps.

Figure 3.9 shows the impact this change has on locating fine-scale interventions. This location-allocation model, unlike the previous two, is weighted both by population at the block group level, and SMRs at the county level. The average distance between sites in the two conditions is 3.03 miles. The minimum distance is 2.1 miles. One site disappears from the far eastern periphery and reappears in the City of Richmond. Another site moves from suburban Chesterfield County south of Richmond to the cluster of small cities including Petersburg. The site located in Hopewell post-adjustment is 4.8 miles from the closest services located using age-adjusted data. This suggests that age-adjusted weights are potentially bypassing urban issues due to high proportions of minority residents.
Figure 3.8: Choropleth and hot spot maps for Richmond, VA
Figure 3.9: Location-allocation results for Richmond, VA
Discussion

Spatial analysis is a valuable tool for public health planning. Maps, cluster analysis, and location-allocation modeling can provide insight for identifying high-risk communities, distributing resources, and capacity building. However, these tools cannot take the place of critical data evaluation. This paper presents several examples of how race/ethnicity may contribute to misleading conclusions.

The influence of race/ethnicity is clear even at the coarsest scale. Southern states generally have higher than expected suicide rates, given the diverse population composition. The pattern is reversed in the NHW-dominated northern states from Nebraska to Massachusetts. Once the effect of race/ethnicity was removed from the location-allocation model, the center of gravity shifted towards the minority-dominated southern tier of states. Two sites were removed from the northern states and placed in Texas and New Mexico, further highlighting potential unmet need in the south-central United States.

These differences are not as clear without race/ethnicity adjustment, which could lead to the omission of Mississippi, Texas, and Louisiana as states with an elevated need for mental health resources. In fact, according to research conducted by Mental Health America, these states rank second, third, and ninth respectively on their list of states with the highest prevalence of mental illness (Mental Health America 2022). Currently, they also rank 48th, 51st, and 41st on access to mental health services. Yet, both Mississippi and Louisiana are part of the highly significant cold spot identified using age-adjusted county-level data. At the coarse scale of states, much data is available to “ground truth” these maps. However, these distortions continue at smaller scales where other reliable mental health data is rare to non-existent. In
one 2022 study, significant black youth suicide clusters were identified in the southeast United States, which would not have appeared if they had not racially stratified their data (Platt et al. 2022).

In Texas, age-adjusted data shows a clear gradient in suicide trends from high in the north to low in the south. This gradient closely follows the demographic pattern with large NHW-majorities in the north and Hispanic-majority counties in the south. Once adjusted for race/ethnicity, this pattern disappears from the choropleth maps. When cluster analysis is applied, the pattern reverses, revealing a hotspot of unmet need in the deeply Hispanic south. The location-allocation model shows how several clinics move towards the border region post-adjustment, including one which moves to the center of the newly-identified southern hotspot. These changes are important for identifying the quantity and distribution of need. However, they also have consequences for the type of services and providers needed. Culturally informed and bilingual care is notoriously difficult to access (Alegria et al. 2002). If need is identified in areas with large proportions of Hispanic, Black, Asian, or AIAN residents, the health authority can put their power behind finding and cultivating the necessary talent to adequately address the needs of these groups. If mis-specified models continue to emphasize majority NHW regions like North Texas, the access issue is more than geographical; it becomes cultural.

The issue of race/ethnicity is perhaps clearest at the fine level of the MSA. In the United States, cities are usually more racially diverse than rural areas. Therefore, because suicide mortality is generally higher in NHW communities, issues in urban areas are easily overlooked. The Richmond MSA is an excellent example of the dynamics at play. Prior to race/ethnicity adjustment, the pattern closely resembles a bull’s eye; rates are below average in the most
urban and suburban areas and increase quickly into the rural periphery. However, post-
adjustment, the pattern changes substantially. Lower than expected rates ring the central city,
which has a higher-than-expected suicide rate, even when compared to its suburban neighbors.
The location-allocation model calls for double the resources in these urban areas post-
race/ethnicity adjustment. The larger the proportion of minorities, the higher the probability of
distortion, as in the case of Petersburg. Petersburg is an area of very high suicide rates among
both Black and white residents, but still appears well below expected in the age-adjusted
condition. Without a race/ethnicity-conscious approach, Petersburg will likely remain
underserved.

Conclusion

This paper contributes to a growing body of literature on the geography of suicide, the
relationship between suicide and race/ethnicity, and the application of traditional methods of
medical geography to violence and behavioral health. These results demonstrate how
population composition may distort our perception of health outcomes potentially leading to
misleading conclusions about etiology, risk, and intervention.

There is no one correct map. However, it is extremely important to be cautious of the
ultimate goal of any of these tools. What is the goal of this analysis? Are we trying to reach the
most people at risk of suicide specifically or the most people with high levels of psychic
distress? Is the goal to identify where suicide is highest or what type of communities are
contributing to higher suicide rates? All these questions are valid, but it is important to think
critically when using health data with a large degree of distortion. For example, a researcher
working in the upper Midwest region may choose to use age adjustment and include
race/ethnicity as a dependent variable, but a researcher in the South might find race/ethnicity adjusted rates easier to interpret and explain. Health system planners should be aware of these issues and prepared to explore tools like race/ethnicity adjustment as part of their assessments.

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CHAPTER 4

USING STATISTICAL SIMULATION TO JUSTIFY RATE-ADJUSTMENT TECHNIQUES

Abstract

When disease rates are investigated geographically variations in population composition may result in a confounding effect. Typically, age-adjustment is used to compensate for this distortion. However, the applicability and effect size of age-adjustment is rarely tested or reported. Additionally, some diseases may require a different adjustment scheme based on sex or race/ethnicity. US suicide and cancer data are used as case studies. Simulated crude, age-adjusted, sex-adjusted, and race/ethnicity-adjusted rates are used to predict the true rates in a regression analysis. Then, Moran’s I is used to explore spatial bias. Cancer results show how this method can measure the contribution of age-adjustment where appropriate. Suicide results show what happens when age does not confound disease rates, but a different variable (race/ethnicity) is a more powerful predictor. This diagnostic methodology provides justification for rate adjustment, an effect size for any adjustment method, and an opportunity to explore patterns prior to model specification.

Introduction

Disease rates are the primary tool used to compare health outcomes across spatial units; however, differences in populations structure may lead to erroneous conclusions and confounding effects in statistical analyses. Health geographers and epidemiologists rely on adjusted disease rates to reduce variance in the data caused by population structure. Currently, age-adjustment is used in nearly every context. This is problematic for two reasons. First, age-adjustment may not add any explanation to data, but it requires slicing the data into thinner
pieces, thereby magnifying the small numbers problem. Second, and more importantly, there are multiple ways to adjust data that may fit some health outcomes better than age-adjustment. Some disease outcomes may not be influenced by age at all, but by race or sex. This paper introduces a diagnostic tool for understanding the influence of different population structures on any given health outcome. In this case, suicide and cancer are used as comparative case studies.

Rate adjustment may be direct or indirect. Direct adjustment applies a national population structure to local rates, while indirect adjustment applies national rates to local population structures (Pickle and White 1995). Epidemiology literature suggest that this population structure could be based on age, sex, race, or any other grouping for which rates are available (Waller and Gotway 2004). However, the use of adjustment methods other than age-adjustment are rare. In fact, the standard medical geography textbooks by Meade and Emch (2010) and Emch, Root, and Carrel (2017) barely explain age-adjustment, only mentioning it in passing as though age-adjustment is the only option. Much has been written about the difference between direct and indirect age-adjustment (Pickle and White 1995), and these studies show that the choice of adjustment method can dramatically change the interpretation of resulting maps. However, the question of whether different adjustment methods fit some health outcomes better remains unexplored.

Data and Methods

The analysis is divided into two sections: regression and spatial analysis. First, a crude (or random) condition is simulated, using the national distributions for cancer and suicide. The crude condition contains no county-specific information. Then, sex, age, and race/ethnicity-
adjusted rates are created using the indirect rate adjustment method and simulated rates drawn from the normal distribution for each group. The indirect adjustment method is more appropriate in this application because it avoids the small numbers problem and allows for a much large sample of counties. The simulated group-specific rate is weighted by the true county-specific proportion for each group, then all groups are summed together (Waller and Gottaway, 2004).

Cancer and suicide were chosen because both are top 10 causes of death in the United States but have very different etiologies. Data for cancer and suicide rates were obtained from the CDC Wonder mortality database. Data is at the county level, years 1999-2016. Cancer is defined as ICD-10 codes C00-C97, the malignant neoplasm category. Suicide is defined as intentional self-harm, or ICD-10 codes X60-X84. Subcategories for rate adjustment include male, female, age 15-29, age 30-44, age 45-59, age 60-74, age 75 plus, black, Asian-Pacific islander, American Indian/Alaska Native, white non-Hispanic, and white Hispanic. Both group distributions and county population proportions are based on the data from CDC Wonder. Only counties with a more than 20 total cases over the 1999-2016 period are included in the analysis (n = 3129 for cancer, n = 1923 for suicide).

To determine whether adequate number of repetitions have been generated, the method outlined by Koehler, Brown, and Haneuse (2009) is used to examine heteroskedasticity. Both cumulative root mean squared error (RMSE) and cumulative relative bias are computed for each condition. The number of repetitions for each outcome (cancer and suicide) is selected based on where the RMSE and relative bias appear to converge for each condition as the number of repetitions increase. Figure 4.1 shows an example of convergence plots.
Regression is used to test how well simulated rates can predict true rates (Cohen et al 2003). A bivariate regression model is run for each simulated data set. For each regression, $R^2$, $R^2$ confidence intervals, slopes, slope confidence intervals, RMSE, relative bias, and coverage rates (i.e. the percentage of estimated confidence intervals that contain the true value) are saved. All analysis is performed using $p = 0.5$. Then, these results are pooled using an ANOVA and presented using boxplots.

Spatial bias must also be included in the decision-making criteria. Moran’s I measure of autocorrelation is computed for each simulated data set and pooled using ANOVA. If the majority of simulations result in statistically significant results (clustered or dispersed), the average simulated rate for each county will be mapped using ArcGIS. The patterns are examined visually, revealing spatial patterns created by population structure alone. A flowchart
of this process is shown in Figure 4.2.

Figure 4.2: A flowchart showing the process for each of 4 conditions
Results and Discussion

To identify the most appropriate rate-adjustment method, a regression analysis was run to predict true rates from simulated rates. Then, the spatial patterns of the simulated data were examined using Moran’s I and basic mapping. The results of the analysis suggested 500 repetitions for cancer and 600 repetitions for suicide as being adequate to obtain stable estimates.

Once the number of repetitions was decided, a regression analysis was performed on each dataset between the simulated rates and the true rates. $R^2$, slope, RMSE, relative bias, and coverage were obtained for each individual analysis and pooled using ANOVA. Figure 4.3 shows boxplots for the pooled $R^2$ and pooled slope results. $R^2$ is the regression effect size describing the amount of variance explained in the true rates by the simulated rates.

Other measures of regression fit were also documented. Slope is the critical component of a regression model. Without a statistically significant slope, the regression model is useless at prediction. RMSE is a goodness of fit measure calculated using residuals. Relative bias is another goodness of fit measure based on the error of the model. Finally, coverage rate measures how often the confidence interval contains the true value. A 95% confidence interval is placed around each predicted value and if the true value falls within that range, that point is said to be covered.

Additional methods were used to examine the spatial patterns created by population distortions on disease rates. Moran’s I is a measure of spatial autocorrelation, indicating whether the pattern is clustered, dispersed, or random across space. In this case, Moran’s I is used to detect regional biases created by differences in population structure. Finally, maps
were created of the simulated rates to visually examine the exact location of these distortions.

Cancer

Figure 4.3 shows the pooled results of the cancer analysis. According to the $R^2$ results, age is the best predictor of cancer, consistently predicting more than half of the variance in true rates (52.59% on average). Simulated crude rates predicted none of the variance, as expected. Race/ethnicity was the second strongest predictor, but far less powerful than age, on average predicting only 4% of the variance in cancer rates. According to the 95% confidence intervals, 100% of AAR and RAR regressions resulted in a statistically significant $R^2$, while only 8.8% of sex-adjusted models were statistically significant, and only 3.4 of the crude simulated regressions were statistically significantly different from zero. The ANOVA results show a statistically significant and extremely strong effect sizes for $R^2$ ($\eta^2 > .999$).

When considering slope, all the simulations predicting cancer rates from AAR and RAR were statistically significant, but the strength of the slope is different between the two. The AAR (average slope = .768) are much stronger than the RAR (average slope = .200). Only 9.9% of SAR simulations resulted in a statistically significant result, and the average slope was -0.026. The ANOVA results showed a statistically significant and strong effect size for slope ($\eta^2 = .998$).

RMSE was also statistically significant with a large effect size in ANOVA ($\eta^2 > .999$). The results are quite like those for $R^2$ and slope (Figure 18). The average RMSE of cancer AAR (43.41) was 31% lower than random or SAR (RMSE = 63.04 for both) and 29.7% lower than RAR (61.77). Lower RMSE indicate more accurate parameter estimates. Relative bias, a similar statistic to RMSE, lends even more support to the primacy of age in cancer studies. The relative bias for the cancer AAR model (3.18) was about half the relative bias for random, SAR, and RAR.
models (6.51, 6.51, and 6.37, respectively). Again, the ANOVA shows strong statistically significant results ($\eta^2 > .999$).

Figure 4.3: Boxplots showing the pooled results of regression and Moran’s I analysis for cancer.
Visual inspection of Figure 4.3 shows that coverage was very low for random (2.90%) and SAR models (3.12%). Coverage improved somewhat in the RAR model (5.22%), but AAR coverage (15.41%) was three times higher than RAR. This means our age model is fitting three times more points than a model based on race/ethnicity and five times more points than random. ANOVA is once again strong and significant ($\eta^2 > .999$).

The regression results suggest that a cancer researcher must build age into their analyses. Traditional age-adjustment is most likely the best option. However, the question of spatial patterns remains. It is possible that by ignoring race/ethnicity, we risk introducing regional error into the analysis. Therefore, Moran’s I was performed on each individual simulated dataset. Table 4.1 shows the results. The true rates were clustered at a value of .027.

<table>
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<th>Adjustment Scheme</th>
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<td></td>
<td>p &lt; .001</td>
<td></td>
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<td>4.0%</td>
</tr>
<tr>
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<tr>
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<td>.040</td>
<td>0.2%</td>
<td>99.8%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

For cancer, both AAR and RAR models were consistently clustered (100% and 99.8%, respectively). Crude simulated rates and SAR were randomly distributed across space. Interestingly, both AAR and RAR rates were more clustered (higher values of I) than the true rates. The ANOVA analysis was highly statistically significant ($\eta^2 = .998$).

Since the two datasets were statistically significantly clustered (AAR and RAR) the results were mapped and inspected visually. Figure 4.4 shows the comparison between true rates, average simulated AAR and average simulated RAR.
Figure 4.4: Maps of cancer rates. True crude rates are at the top, followed by the average simulated rates from the AAR and RAR models.
Average simulated random rates will average out to a flat surface with the mean value, so any variation in the RAR and AAR maps is due entirely to population structure. The AAR map matches the true rates well, predicting higher rates in the great plains, Florida, northern Michigan, and parts of the southwest. It also predicts low rates in the mountain west, urban east coast, and Texas border regions. Average RAR rates also predict some of these patterns, especially lower rates across the southern tier of the United States, but with less specificity than the AAR.

Given that the patterns do not vary greatly between RAR and AAR, using only age-adjustment instead of age/race adjustment should not change the results very much. The magnitude of the difference between the two methods is clear from the regression models; age is the best choice. However, further analysis can continue knowing that race/ethnicity may be an important explanatory variable, and that sex is not creating phantom patterns in the data.

Suicide

The results for suicide are quite different from cancer. According to the R² results, race/ethnicity was the strongest predictor of crude suicide rates, though the effect is much smaller than for cancer (Figure 4.5). For suicide, 100% of RAR simulations resulted in a statistically significant R², with an average R² value of 3.10%. Only 10% of AAR simulations resulted in a significant model with an average R² of 0.08%. The results of sex-adjusted rates (SAR) are no different from random (average R² = .001, 4.8% significant simulations). The ANOVA results show a statistically significant and extremely strong effect size (ƞ² > .999). These results suggest that population variation is likely distorting suicide rates very little; however, it also indicates that age-adjustment may not be necessary.
Figure 4.5: Boxplots showing the pooled results of regression and Moran's I analysis for suicide
ANOVA results for slope are also strong ($\eta^2 > .999$). One-hundred percent of RAR simulations resulted in a statistically significant slope, with an average slope of .222. Only 11.3% of AAR and 5.5% of SAR regressions yielded statistically significant results (average slope = .034 and -.006, respectively). Again, the RAR model was statistically significant, but not especially strong.

RMSE was also significant with a large effect size in ANOVA ($\eta^2 > .999$). The average RMSE of suicide RAR (4.59) was only 1.5% lower than the average RMSE for crude, SAR, and AAR (4.67 for all). Likewise, the relative bias of the RAR model (7.71) was only slightly lower than the relative bias for crude, SAR, and AAR models (8.05, 8.05, and 8.04, respectively). Additionally, these values are quite high, compared to the results for cancer rates. This suggests a higher degree of systematic error in the race/ethnicity data. The ANOVA results relative bias were strong and statistically significant ($\eta^2 > .999$).

Random (3.94%) and SAR (3.88%) models have very poor coverage. Coverage improves slightly in the AAR model (4.27%). Coverage in the RAR model (6.38%) was 62% higher than the random model, though it still captures only a small fraction of the data. ANOVA results are strong ($\eta^2 > .999$).

Table 4.2 shows the results of the Moran’s I analysis of suicide. The ANOVA results show group membership determines statistically significant differences among the datasets ($\eta^2 > .999$). The true are highly clustered ($I = .110$). However, of the four simulated rates, only RAR resulted in reliably clustered results. In fact, every simulated dataset using RAR was statistically significantly clustered, with an average value of $I = .034$. 

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Table 4.2: Moran’s I results, suicide

<table>
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<th>Adjustment Scheme</th>
<th>Av. Moran’s I</th>
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<th>Clustered</th>
<th>Dispersed</th>
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<td>94.8%</td>
<td>3.8%</td>
<td>1.3%</td>
</tr>
<tr>
<td>Sex-Adjusted</td>
<td>- .000</td>
<td>94.3%</td>
<td>4.5%</td>
<td>1.2%</td>
</tr>
<tr>
<td>Age-Adjusted</td>
<td>- .000</td>
<td>94.2%</td>
<td>5.3%</td>
<td>0.5%</td>
</tr>
<tr>
<td>Race/Ethnicity Adjusted</td>
<td>.034</td>
<td>0.0%</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Figure 4.6: Maps of suicide rates. True crude rates are at the top, followed by the average simulated rates from the RAR model.

Figure 4.6 shows the true pattern of crude suicide rates and the average RAR map. RAR predicted high rates in the Appalachian and Ozark regions, and low rates in the deep south and
southern California. The pattern of average RAR represents the noise that will be removed if the researcher chooses to utilize race/ethnicity adjustment. These patterns match the true patterns of suicide closely. Therefore, even though the RAR model has a low effect size, when compared to the AAR model for cancer, it does a good job of predicting the spatial patterns of suicide. This may be compelling evidence for future research to use race-adjustment or some other approach incorporating race into the independent variable. Race-adjustment would remove the 3% of variance caused by the racial/ethnic composition of the counties, possibly removing some confounding effects and regional distortions.

Conclusions and Implications

The analysis outlined above identified the best-fit adjustment method for two different leading health outcomes. Age-adjustment is clearly the better choice for cancer. Age structure alone explains more than half the variance in cancer rates across US counties, and the clustered shape of the resulting simulated rates closely approximated the true shape of the data. Because race/ethnicity adjustment is also statistically significant in some parts of the analysis, researchers will need to decide whether to use age-adjustment alone or use both methods simultaneously. Using both age and race/ethnicity adjustment may over-smooth the data, introduce excess measurement error, and create theoretical difficulties in interpretation.

Though the effect size for suicide was much smaller than for cancer (the best-fit method only explains 3% of the variance), this analysis shows that age-adjustment is not a good option for suicide. Race/ethnicity can predict the true rates much better than age.

This analysis and these results show that the choice of an adjustment method is an important decision that must be considered. Nearly all the spatial research on suicide uses age
adjustment, but there is no compelling statistical reason to do so. In fact, by using the wrong adjustment method we are increasing the influence of other confounding variables. This method gives researchers a decision-making tool when deciding on an adjustment method or generating causative theories. More importantly, these results show that a one-size-fits-all approach to rate adjustment is not appropriate.

References

Centers for Disease Control; 2018; Underlying Cause of Death; CDC Wonder; https://wonder.cdc.gov/ucd-icd10.html


CHAPTER 5

CONCLUSION

Summary and Conclusions

This project explored the potential of race/ethnicity adjustment techniques to better understand the role of race/ethnicity on the spatial patterns of suicide in the United States. Results showed pockets of previously undocumented risk in central cities and across the American South. Race/ethnicity adjustment is a useful tool for broadening our understanding of health outcomes heavily skewed by race/ethnicity population composition.

Introduction

The overarching goal of this project was to explore the relationship between place, race/ethnicity, and suicide. Suicide is a behavioral health outcome with a different relationship to race/ethnicity and age composition than the more familiar health geography topics of infectious and degenerative diseases. Therefore, this project contributes to the growing body of knowledge on the connection between space, place, and mental health.

This project has three primary objectives. The first is to provide an alternative and inclusive approach to identifying communities with high mental distress. Suicide is one outcome of mental distress that is largely patterned by race/ethnicity. Therefore, the underpinning philosophy of this chapter is that race/ethnicity adjustment, in contrast to traditional age-adjustment, can provide a better picture of where the population is struggling with mental distress. This analysis employed standardized mortality ratios created by comparing expected rates created using indirect rate-adjustment techniques to the crude observed rates. Age-adjusted and race/ethnicity-adjusted results were compared to identify important geographic
differences between the methods.

The standardized mortality ratio methodology was also used to explore the second objective: evaluate the efficacy of race/ethnicity in the use of general linear models. This analysis had two primary components. First, homicide and suicide rates were compared pre- and post-race/ethnicity adjustment. This experiment examined how race/ethnicity adjustment alters relationships in a bivariate space. Then, suicide and homicide rates were compared with ecological measures of race/ethnicity to explore the possibility of separating context from composition.

The third objective was to create a protocol for diagnosing compositional effects in health data. By using indirect rate adjustment in a simulation protocol introducing randomness, crude rates were compared with predicted rates based on race/ethnicity, age, and gender. Both suicide and cancer mortality were analyzed to show the differences between a degenerative and a behavioral outcome. The results of these analyses are discussed in more detail in the next section.

Summary of Findings

Objective 1: Provide an Alternative and Inclusive Approach to Identifying Communities with High Mental Distress

Three common visualization techniques were used to explore the influence of race/ethnicity on perceived patterns of suicide and psychological distress. These methods were choropleth mapping, hotspot analysis, and location-allocation modeling. Results demonstrated that adjusting the data for race/ethnicity can dramatically change the perception of which communities are most vulnerable and therefore where to direct intervention efforts.
At the national level, the largest change was in the southern tier of the United States. Prior to race/ethnicity-adjustment, the coastal south from Virginia through Texas shows up as a highly significant cold spot for suicide mortality. However, post-adjustment this cold spot entirely disappears. A similar effect happens in urban California. Meanwhile, high rates of suicide in the mountain west and low rates in the northern states from Iowa to Massachusetts remain largely unchanged in the two conditions, suggesting these are durable patterns. However, health interventions at the national level using only age-adjusted data are likely to neglect the deep south and Texas border regions. Ongoing neglect of regions comprised of historically marginalized groups such as African-Americans and Hispanic immigrants is a clear example of structural violence.

Analysis at the Texas level reinforces the finding that race/ethnicity plays a critical role in suicide patterns in heterogeneous study areas. Intervention strategies based on age-adjusted data alone would funnel resources into the majority-non-Hispanic white (NHW) region of North Texas, while neglecting the Hispanic-dominated region in the South. However, once race-ethnicity adjustment is applied to the data, South Texas is the region with significantly higher suicide risk than expected, given the population composition. The location-allocation model pulls a clinic into this hotspot post-adjustment. Without accounting for race/ethnicity, this highly vulnerable region would be left without resources.

Finally, a similar effect happens at the city scale in Richmond, Virginia. At this fine scale the issue of urban representation becomes apparent. Because cities tend to be more diverse, their vulnerability to suicide is deemphasized in age-adjusted data. When adjusted with race/ethnicity, the cities show higher risk than the surrounding suburbs. In Petersburg, Black
suicide rates are elevated 36 percent above the metropolitan statistical areas (MSA) average Black suicide rate; the NHW rates are 107 percent higher. Yet, because Petersburg is 76 percent Black, the city shows up in the lowest risk quintile using age-adjusted data. After race/ethnicity adjustment, Petersburg is the highest-risk unit in the MSA. This has consequences for the distribution of resources and clinic location. Race/ethnicity adjustment is likely to have a larger impact at smaller scales.

Objective 2: Evaluate the Efficacy of Race/Ethnicity Adjustment in the Use of General Linear Model Statistics

The second objective aimed to explore the effect of race/ethnicity adjustment on the relationships between variables in a GLM model. I compared the relationship between suicide and homicide mortality before and after race/ethnicity adjustment. Then, to further explore the question of composition verses context, I explored the impact of race/ethnicity adjustment on the correlations between homicide/suicide and population structure.

According to the stream analogy of lethal violence, homicide and suicide should share some common sources of violence. However, previous research has shown no clear relationship between the two. In the case of county-equivalent data in the United States, 1999-2019, age-adjusted homicide and suicide rates have no significant correlation at the national level or at any urbanization classification. In the West and Midwest, rates are weakly positively correlated, while weak negative correlations exist in the south and Northeast. No clear relationship exists between the two outcomes. However, after race/ethnicity adjustment, homicide and suicide become aligned with moderate strength nationally, in every geographic region, and at every level of urbanization. Because the impact of race/ethnicity composition is so strong, the
geographic heterogeneity can completely obscure this important overlap.

Similarly, the relationship between suicide/homicide and ecological indicators of race/ethnicity (i.e. percent Black) also changes in many cases. For example, the correlation between age-adjusted suicide rates and percent NHW is .154. The standard interpretation of this would be that NHW communities have higher suicide rates, which follows logically from the fact that NHW people have suicide rates two to three times higher than other groups. However, given the propensity for NHW suicide, we would expect a much higher correlation of .964. So, after race/ethnicity adjustment, the correlation between suicide rates and percent NHW is -.199. This means that once accommodating for the elevated rates among the NHW population, NHW-dominated communities actually have suicide rates slightly lower than expected. The difference between rate calculation methods is the difference between identifying vulnerability or resilience. The opposite may also be true; the relationship between percent American Indian-Alaska Native (AIAN) and suicide rates remains high and largely unchanged between the two conditions. This confirms the impact of context, not composition, in high AIAN communities. This information is important for designing effective and realistic interventions.

The findings of this research underscore how critical it is to specify data correctly for our questions. Without race/ethnicity adjustment, researchers are likely to conflate characteristics associated with white communities with suicide and characteristics associated with Black communities with homicide. Thus, the overarching roots of lethal violence remain obscured by the confounding effect of race/ethnicity.

Objective 3: Create a Protocol for Diagnosing Compositional Effects in Health Data

To create a measure of the utility of various rate-adjustment techniques, I created a
simulation protocol based on the same indirect adjustment techniques used to investigate Objectives 1 and 2. For this demonstration, rates were created for age, race/ethnicity, and gender adjustment and compared to the observed crude rates of cancer and suicide. The type of simulated rate that best predicts the crude rates signifies the most prominent compositional distortion in the data. Furthermore, the correlation coefficients between the simulated rates and crude rates provide a measure of how much variance rate-adjustment will remove.

The results confirm that age-adjustment is the most appropriate rate adjustment technique for cancer, as hypothesized. Cancer is largely degenerative, so a population’s age structure will greatly influence the presentation of cancer. In this data set, age alone can explain 52.59 percent of the variance in cancer rates at the county level. Removing this variance allows researchers to compare other factors contributing to increased cancer rates from place to place. This experiment both shows how critical age-adjustment is to cancer data, but also provides a measure of compositional distortion to both justify the decision to adjust and compare to other data sets across time and space.

The results for suicide are quite different. Despite age-adjustment’s position as a “must have” for health geography research, age composition explains less than one percent of the variance in suicide rates. This simulation protocol provides the quantitative proof that age-adjustment is not necessary in this data set. Without this measure, other researchers and reviewers may be uncomfortable with the omission of age-adjustment and insist on it, despite contributing nothing but potential small numbers issues. Race/ethnicity is the best fit model for suicide in the simulation model, but it only explains three percent of the variance. Evidence from objectives 1 and 2 show why a researcher may want to go ahead and use race/ethnicity
adjustment in some circumstances. Depending on the research question it may not be necessary. However, this simulation protocol reveals these potential problems before analysis begins, to ensure better and clearly justified decisions about the data we have and the chosen analytical approach.

**Broader Impacts**

Racial/ethnic minorities consistently have worse mental health outcomes and less access and usage of specialty mental healthcare (Kim et al. 2016). This has been documented in nearly every corner of the behavioral health discipline including psychosis treatment (Heun-Johnson et al. 2021), substance abuse treatment (Sahker et al. 2020), autism services (Eilenberg et al. 2019), and sleep disorders (Johnson et al. 2019). However, this does not translate into the suicide statistics, which tend to be dominated by NHW. This project explored methods for incorporating these two observations into an analysis designed to untangle some of these contradictions. The results imply the need to revisit some theories and assumptions of the past.

The most durable assumption about the geography of suicide in the western world is that it is lowest in the cities and highest in rural areas, and this is portrayed as a linear relationship. However, the results of this analysis show a different pattern. The low rates in inner city areas are partially a product of high proportions of minority residents living in these areas. Once race/ethnicity is accounted for, suburban areas have the lowest rates of suicide. Therefore, the idea that suicidal behavior is driven by “white despair” (like Stein et al. 2017) is called into question when both the highest risk area (rural) and lowest risk area (suburban) are dominated by NHW residents. Other authors have been vocal opponents of the white despair theories, arguing that the theoretical basis is inappropriate and variable selection and analysis
may be biased towards confirming white despair hypotheses (Beseran et al. 2022; Diez Roux 2017). However, to my knowledge this is the first quantitative evidence supporting these counter arguments.

Related to the “white despair” theories, traditional analyses may inappropriately deem minorities as particularly resilient. Suicide is culturally patterned and is not the only outcome of severe psychological distress. Minority communities should not be sidelined because their distress takes other forms. These results show how a different approach to suicide data can reveal places where minority communities are struggling compared to their own norms, not compared to the NHW majority. The resilient minority idea may also get a boost from the misinterpretation of multivariate models confounded by the influence of race and ethnicity. Low suicide rates often correlate with high poverty, low levels of education, and high unemployment. Without explicitly dissecting the role of race/ethnicity, the interpretation of these numbers can become quite dangerous. By separating context from composition, the methods used in this paper can aid in making these relationships clearer and interpretation less fraught with contradictions.

Finally, explicitly interacting with the role of race/ethnicity in building a healthcare system to provide mental health services, can draw much needed attention to the specific needs of minority communities. For example, the race/ethnicity adjusted location-allocation model of Texas placed a site in the center of majority-Hispanic South Texas that was not flagged prior to race/ethnicity adjustment. The cultural and linguistic needs of this area are quite different from the site selected pre-adjustment and indicate a need to strengthen Spanish-language services. This is critical since people with limited English proficiency are less than half
as likely to access mental health services in the United States (Sentell, Shumway, and Snowden 2007). In some cases, provider density is not the issue at all. A study of urban neighborhoods showed that even though Black and Hispanic residents were more likely to live in neighborhoods with high provider density, they were less likely to actually use those services (Cook et al. 2016). The authors conclude that the services simply are not appropriate or welcoming to these groups. They write, “Low rates of initiation in neighborhoods with a high density of specialists suggest that interventions to increase mental health care specialists, without a focus on treating racial/ethnic minorities, may not reduce access disparities (Cook et al. 2016, p. 404).” High rates of poor mental health where provider density is high would not make sense without the lens of race/ethnicity.

Countries around the world are undertaking the immense project of addressing mental health issues at the population level. In the United States, calls for mental healthcare to assist in the opiate crisis, increasing rates of suicide among active-duty military, mass shootings, and other social ills are as of now primarily answered by band-aid solutions like crisis call centers. Building a truly effective, welcoming, and inclusive approach requires a multi-dimensional understanding of who needs help, where they need it, and what kind of services are appropriate. This work must be done with an eye on the role of race/ethnicity to avoid perpetuating structural violence against groups that already suffer from disadvantages in this area. Adding race/ethnicity adjustment as an option in our models and analyses provides an effective tool for double checking that no one is left behind.

References


