County Characteristics and Opioid Mortality Rates in the United States

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ABSTRACT

County Characteristics and Opioid Mortality Rates in the United States

by

Baksun Sung, Doctor of Philosophy

Utah State University, 2023

Major Professor: Dr. Erin Hofmann
Co-Major Professor: Dr. Gabriele Ciciurkaite
Department: Sociology and Anthropology

Socioeconomic disparities in opioid overdose deaths persist in the United States and do so across different regions. While such disparities in opioid overdose deaths are well documented, little is known about the association between social factors beyond income and education and these deaths. In this dissertation, I examine how opioid mortality trends are affected by opioid types, race, and region; how social vulnerability contributes to synthetic opioid mortality gaps across different counties; and how occupational and industrial composition contribute to changing synthetic opioid mortality rates over time, within an individual county. Specifically, using the Centers for Disease Control and Prevention’s Wide-Ranging Online Data for Epidemiologic Research, Multiple Cause of Death, 1999–2020, Centers for Disease Control and Prevention Social Vulnerability Index, and the American Community Survey—and employing moderation and longitudinal analysis—I analyze opioid mortality trends by opioid types, race, and region and investigate the effect of social vulnerability and occupational and industrial
composition on synthetic opioid mortality rates in the United States at the regional and county levels. In Chapter 1, I observe that first, synthetic opioid is a major contributor to overdose mortality in the United States more recently. Second, blacks are the most susceptible racial group to the epidemic caused by synthetic opioids. Third, the Eastern United States is the most vulnerable to the current epidemic. In Chapter 2, I observe that first, social vulnerability due to minority status and language skill is negatively associated with higher synthetic opioid mortality rates, but its protective role against this mortality rate is reducing over time, and it is not working well in the Midwest and Northeast. Second, social vulnerability due to socioeconomic status is a leading contributor to the synthetic epidemic in the Midwest. In Chapter 3, I demonstrate that first, primary industries and the wholesale trade industry are main contributors to the synthetic opioid epidemic in the Midwest and Northeast. Second, professional, scientific, and management, and administrative and waste management services industries are also contributors to the synthetic epidemic across the United States.

(173 pages)
PUBLIC ABSTRACT

County Characteristics and Opioid Mortality Rates in the United States

Baksun Sung

Opioid overdose deaths are not equally distributed across the United States. While some areas have a less severe problem with opioid abuse, others face serious challenges, which are affected by various social factors. To address that question, in Chapter 1, I investigate how opioid mortality trends differ according to opioid types, race, and region to identify susceptible populations and areas. In Chapter 1, I contend that synthetic opioid is a main trigger for the current opioid epidemic and that the epidemic is concentrated among blacks and in the Eastern United States. Next, the following studies examine how varying social vulnerabilities contribute to synthetic opioid mortality among counties; and how different kinds of occupational and industrial composition contribute to changing synthetic opioid mortality rates over time in a specific county. In Chapter 2, I look at how this social vulnerability, which is due to minority status and language, is associated with a decrease in mortality rates. However, this effect is lowered over time, and it is weakest in the Midwest and Northeast. Also, the adverse effect of low socioeconomic status significantly contributes to the synthetic opioid epidemic in the Midwest. In Chapter 3, I contend that primary industries and the wholesale trade industry have helped increase synthetic opioid mortality rates in the Midwest and Northeast. Additionally, professional, scientific, and management, and administrative and waste
management services industries have aided in the increase in deaths caused by synthetic opioid throughout the United States.
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INTRODUCTION

Opioid overdose is a serious social problem in the United States. Prescription opioid abuse incurs $78.5 billion in costs yearly, which is primarily fueled by health care costs, legal programs, and lost productivity (NCDAS, 2021). An even more substantial problem is the increasing number of deaths from opioid overdose, for which mortality rates have consistently increased over the last decade (NIDA, 2021a; CDC, 2021). Approximately 50,000 people in the United States die of opioid overdose annually, which accounts for nearly 72% of total drug overdose deaths in 2020 (NCDAS, 2021). Opioid overdose is thus a leading cause of death for those between 25 and 64 years of age (Dezfulian et al., 2021). Furthermore, it is a significant contributing factor to decreased average life expectancy in the United States (Dowell et al., 2017). Opioid use disorder falls under the broader definition of substance use disorder. Therefore, it is necessary to explain the concept of substance use disorder before expounding on opioid overdose.

Substance Use Disorder (SUD)

Substance use disorder (SUD) refers to mental illness, which influences a person’s brain and behavior, resulting in one’s incapacity to control one’s substance use behaviors (NIH, 2021). Approximately 50% of people who have an SUD in their lifetime will also have a co-occurring mental illness, such as an anxiety disorder, depression, attention-deficit hyperactivity disorder (ADHD), bipolar disorder, a personality disorder, or schizophrenia (NIH, 2021). According to American Addiction Centers, 19.7 million people (12 years and older) in the United States suffered from an SUD in 2017 (AAC,
In addition, substance abuse and addiction generated $740 billion in costs, including costs related to healthcare, criminal justice, and reduced productivity in the same year (AAC, 2022a). Substance use disorders pertain to various substances, such as alcohol, marijuana (cannabis), hallucinogens (phencyclidine), inhalants, opioids, sedatives (benzodiazepines), and stimulants (cocaine, methamphetamine) (AAC, 2022b). Nearly 6 million people (12 years and older) in the United States suffered from opioid use disorder in 2019, which was notably the highest count among all SUDs. What is more, a history of SUD is linked to an increased risk for prescription opioid misuse (Morasco et al., 2013). Patients who have chronic pain in addition to a history of SUD are more likely to obtain opioids from multiple sources (Reid et al., 2002), borrow them from other patients (Morasco & Dobscha, 2008), request an opioid prescription refill quickly and often (Morasco & Dobscha, 2008), take opioids to alter their mood (Barry et al., 2011), and take higher doses (Breckenridge & Clark, 2003; Morasco et al., 2011; Weisner et al., 2009) than those without a history of SUD. Prescription opioid misuse that is caused by SUD is also associated with illegal opioid misuse. This is the case because prescription opioids are normally the first opioids that people take before shifting to using of illegal opioids (e.g., heroin and illegally manufactured synthetic opioids) (Cicero et al., 2017).

The History of the Opioid Epidemic

Opioids have long blurred the boundary between illegal and legal drugs (Netherland & Hansen, 2017). There are two types of opioids: prescription and non-prescription. The former is defined as prescription medications, which are primarily used as painkillers; these include codeine, morphine, hydromorphone, and fentanyl (JHM, 2022; Leeds,
These must be prescribed by licensed physicians (Leeds, Grenville & Lanark District Health Unit, 2022). The latter are illegal opioids, which are unlawfully manufactured and can be far more deadly than prescribed medications (Leeds, Grenville & Lanark District Health Unit, 2022). Examples of non-prescription opioids include heroin and illegally manufactured synthetic opioids (e.g., unauthorized fentanyl) (JHM, 2022; Leeds, Grenville & Lanark District Health Unit, 2022).

Originally, morphine (an early form of opioid) was used to treat injured soldiers during the American Civil War (1861–1865), and it was also used to relieve menstrual pain among women during the Victorian Age (1837–1901) (Musto, 1999; Courtwright, 2001). In 1895, the German pharmaceutical company, Bayer, had developed heroin as an alternative medicine that treated respiratory diseases, such as cough suppressants (Hosztafi, 2001). Bayer advertised its product, heroin, claiming that it is more effective and less addictive than morphine (Hosztafi, 2001). This was not true, however; heroin was an extremely addictive drug, just like morphine (Hosztafi, 2001). As a result, both morphine and heroin were banned across the United States by the passing of the Harrison Act in 1914, in response to drug addiction problems (Netherland & Hansen, 2017).

Opioid misuse has re-emerged in the United States since the early 1990s (Netherland & Hansen, 2017). Between the 1990s and 2000s, opioid overdose deaths were mainly related to prescription opioids (Madras, 2017; Paulozzi et al., 2006) and caused by aggressive opioid marketing targeted to physicians and a change in the clinical treatment of chronic pain (Kolodny et al., 2015; Manchikanti et al., 2012). For example, the opioid manufacturer, Purdue, utilized false advertisement to promote its opioid product,
OxyContin, in the early 1990s (Netherland & Hansen, 2017). Specifically, Purdue marketed OxyContin with ads that asserted not only that its product is less addictive than other opioids but also that it had been proved by neuroscience (Netherland & Hansen, 2017; Cicero & Surratt, 2012). In fact, however, OxyContin was indeed highly addictive opioid, and many people thus became addicted to it (Netherland & Hansen, 2017; Cicero and Surratt, 2012). More recently, the causes leading to opioid overdose deaths are divided according to various opioid types. Specifically, heroin-induced deaths have been observed since the mid-2000s (Hedegaard et al., 2015; Jones et al., 2015; O’Donnell et al., 2017; Rudd et al., 2016, Rudd et al., 2014) and unlawfully manufactured synthetic opioids (e.g., illegal fentanyl) overdose deaths have been observed since 2014 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018).

**Racial Disparities in Opioid Mortality Rates**

During the 1990s and 2000s, overdose deaths caused by prescription opioids were concentrated among whites living in suburban and rural areas (Paulozzi et al., 2006; Paulozzi & Xi, 2008; Rudd et al., 2016; Alexander et al., 2018; Netherland & Hansen, 2017). During this same time, pharmaceutical companies—particularly those characterized by aggressive opioid marketing—encouraged physicians to prescribe increasingly more opioids, something that resulted in overprescribing opioids and an increase in opioid overdose deaths (Paulozzi et al., 2006; Rudd et al., 2016a; Van Zee, 2009). Provider bias was a main cause of the racial disparities seen in opioid prescribing at the time (Manchikanti et al., 2012; Okunseri et al., 2014; Pletcher et al., 2008; Todd et al., 1993). Provider bias, in this context, means that physicians tended to prescribe
opioids for pain remedy unequally across groups (Keister et al., 2021). In terms of race, whites were likelier to receive opioids than other racial groups, such as blacks and Hispanics (Tomayo-Sarver et al., 2003; Goyal et al., 2015; Green et al., 2003; Pines & Hollander, 2008). Furthermore, the subjective appraisal of pain has led to provider bias (Spencer & Grace, 2016). For example, physicians often (and wrongly) presume that whites have a lower pain threshold and that they are less likely to engage in illegal opioid use than their black counterparts (Lara-Millán, 2014; Sabin & Greenwald, 2012; Burgess et al., 2006; Hoffman et al., 2016). As a result, provider bias created the conditions for overprescribing opioids and the increase in overdose deaths among whites during the 1990s and 2000s (Lippold & Ali, 2020).

However, in the mid-2000s, deaths caused by opioid overdoses started to affect all racial groups due to heroin (Hedegaard et al., 2015; Jones et al., 2015; O’Donnell et al., 2017; Rudd et al., 2016, Rudd et al., 2014). This is because heroin is illegally manufactured and distributed such that anyone can purchase heroin on the black market. What is more, as the US government’s regulation of prescription opioids has grown, opioid use has transitioned from prescription opioids to heroin since 2010 (Compton et al., 2016; Dart et al., 2015; Jones, 2013; Jones et al., 2015; Lankenau et al., 2012; Muhuri et al., 2013; Rudd et al., 2014; Unick et al., 2014). Additionally, synthetic opioid overdose deaths have begun emerging since 2013 (Lippold & Ali, 2020). The use of unlawfully manufactured synthetic opioids, like illegal fentanyl, has spread quickly among all racial groups in the United States (Daniulaityte et al., 2017; Gladden et al., 2016; Jones et al., 2018; Lippold et al., 2019; O’Donnell et al., 2017; Peterson et al., 2016; Seth et al., 2018a; Shiels et al., 2018). Illegal opioids like heroin and illegal fentanyl, use is the most
frequent among blacks (Furr-Holden et al., 2021; Hoopsick et al., 2021). As a result, opioid mortality rates for this demographic have mirrored that of whites recently, even though the latter still have the highest opioid mortality rates across all racial groups in the United States (Alexander et al., 2018; KFF, 2021).

Socio-economic Disparities in Opioid Mortality Rates

The opioid epidemic is not only affected by supply chains for both prescription and illegal opioids, but also by various social factors (Altekruse et al., 2020). Educational attainment, income, and occupational level are considered important social factors (Braveman et al., 2011). Social disadvantages, such as low education and income levels and low-paying jobs have a positive correlation with ill health (Braveman et al., 2011). This is largely because social disadvantages limit social and economic opportunities and generate vulnerability, such as labor market exclusion, illegal occupations (e.g., drug trafficking, stealing), material deficiency (e.g., food insecurity, poor housing), low income, low educational attainment, and incarceration (Draanen et al., 2020). Social disadvantages are also positively correlated with substance abuse. Specifically, low-income households (Galea et al., 2006; Lanier et al., 2012; Silva et al., 2012), low educational attainment (less than high school) (Galea et al., 2006; Ho, 2017; Lanier et al., 2012; Silva et al., 2012), homelessness (Fischer et al., 2004), and incarceration (Green et al., 2012; Stewart et al., 2004) are positively associated with substance abuse deaths. In terms of opioid-related studies, low income (Cerdá et al., 2013; Feng et al., 2016; Marshall et al., 2017; Meiman et al., 2015; Ochoa et al., 2005; Visconti et al., 2015; Zlotorzynska et al., 2014) and low levels of educational attainment (Cropsey et al., 2013;
Cheng et al., 2013; Marshall et al., 2017; Patrick et al., 2016; Paulozzi et al., 2009; Siegler et al., 2014) are also positively associated with opioid overdose.

In addition, social disadvantages affect not only substance abuse deaths at the individual level but also at the macro-level. Regarding macro-level studies, poor regional characteristics, including regions with high levels of social anarchy, low socioeconomic areas, and drug diversion are positively correlated with substance abuse deaths (Krebs et al., 2016; Lanier et al., 2012; Otterstatter et al., 2016; Rintoul et al., 2010; Xiang et al., 2012; Zlotorzynska et al., 2014) and opioid-related deaths (Flores et al., 2020; Bernhardt & King, 2022). Some possible mechanisms that have been suggested include high levels of social anarchy lead both to lower standards of social efficacy (e.g., community supervision, social trust) (Sampson et al., 1999; Sampson & Raudenbush, 2001) and to informal social control (e.g., social norm) (Desmond & Kimbro, 2015; Desmond & Shollenberger, 2015; Huang et al., 2016; Muarcus et al., 2015). For example, a shortage of community supervision and the weakening of social norms are positively associated with high rates of crime and social alienation (Sampson & Raudenbush, 2001), both of which may contribute to the higher prevalence of opioid misuse (Flores et al., 2020). Additionally, high-poverty areas may be more susceptible to the introduction of illegally manufactured opioids into their communities (NASEM, 2017). What is more, people in such areas may be likelier to engage in illegal opioid use because those with low SES tend to purchase cheaper illegal opioids on the black market, due to economic difficulties, even when they have a prescription for opioids (NASEM, 2017; Monnat, 2019; Pear et al., 2019; Althoff et al., 2020; Butcher, 2021).
One’s occupation itself is yet an important predictor of opioid mortality because drug-related deaths rates vary according to different types of occupations (Monnat, 2018).

In terms of individual-level studies, one study based on Massachusetts found that construction workers and those employed in the fishing industry have higher opioid overdose death rates than other workers in Massachusetts (Hawkins et al., 2019). In addition, blue collar employees in Massachusetts, such as those in construction, agriculture, fishing, and forestry were associated with an increase in deaths due to despair (e.g., opioid overdose, suicide) (Hawkins et al., 2020). Among healthcare workers in Massachusetts, including medical assistants, nurses, psychiatrists, home health aides, and health technologists, have the highest death rate from deaths of despair (e.g., opioid overdose, suicides, alcohol-related liver diseases) (Sahith & Devan, 2021). Other individual-level studies have also found that construction workers are more vulnerable to injuries, which means that they are more likely to engage in prescription opioid overdose (Dale et al., 2020; Dong et al., 2020a; Dong et al., 2020b).

As for macro-level studies, opioid mortality rates (overall) are higher in counties characterized by high poverty rates and higher percentages of blue-collar and service workers (Monnat et al., 2019). Mortality rates for illegal opioids (e.g., heroin and illegally manufactured synthetic opioids) are higher in urban counties with low poverty rates and a higher percentage of professional workers (Monnat et al., 2019).

The Significance of the Problems of and Gaps in the Literature

Despite much public health investment, opioid mortality rates consistently increase in the United States (Schell et al., 2021). This opioid epidemic not only increases
healthcare costs (NCDAS, 2021) but also decreases the average life expectancy (Dowell et al., 2017). In addition, the production, distribution, marketing, and consumption of illegal opioids are largely based on criminal activities, drug trafficking, and an underground economy (Alexander et al., 2018), all of which have serious negative effects on public health and society. Therefore, it is necessary to examine the various social factors that affect opioid mortality rates.

Although the research examined above addresses some social aspects pertaining to the increasing opioid mortality rates in the United States, nonetheless, there are still gaps and obscurities in the established literature. Given that many studies are based mainly on income and education, this means that they overlooked social factors beyond how income and education affect opioid mortality rates in the United States.

According to individual-level studies, for example, low-income (Galea et al., 2006; Lanier et al., 2012; Silva et al., 2012; Cerdá et al., 2013; Feng et al., 2016; Marshall et al., 2017; Meiman et al., 2015; Ochoa et al., 2005; Visconti et al., 2015; Zlotorzynska et al., 2014) and low educational attainment (Galea et al., 2006; Ho, 2017; Lanier et al., 2012; Silva et al., 2012; Cropsey et al., 2013; Cheng et al., 2013; Marshall et al., 2017; Patrick et al., 2016; Paulozzi et al., 2009; Siegler et al., 2014) are positively associated with substance abuse deaths and opioid overdose. According to macro-level studies, poor regional circumstances, such as low socioeconomic areas and drug diversion, have a positive correlation with substance abuse deaths (Krebs et al., 2016; Lanier et al., 2012; Otterstatter et al., 2016; Rintoul et al., 2010; Xiang et al., 2012; Zlotorzynska et al., 2014) and opioid-related deaths (Flores et al., 2020; Bernhardt & King, 2022). Despite some individual-level studies having examined more diverse social factors beyond income and
education, such as homelessness (Fischer et al., 2004), housing insecurity (Wagner et al., 2010), and incarceration (Green et al., 2012; Stewart et al., 2004), little is known about the association between these social factors and the opioid mortality rate or substance abuse deaths in macro-level studies. Additionally, the opioid epidemic-related theory, like death of despair, also has limitations.

The death of despair theory provides a valuable contextual framework for identifying socioeconomic disparities in opioid overdose deaths (Altekruse et al., 2020). According to this theory, since the 1970s, income inequality and economic uncertainty have led to an increase in death rates among middle-aged white people. As manufacturing declined, many middle-aged working-class with lower education felt hopeless about the future given the dearth of high-paying jobs (Case & Deaton, 2015). As a result, they engaged in behaviors like drugs and suicide, which is referred to as “deaths of despair” (Case & Deaton, 2015). Therefore, death of despair theory is also based mainly on considering income and educational levels (Case & Deaton, 2015, 2017). In addition, Case & Deaton (2015, 2017) focused mainly on working-class, middle-aged American whites, which means that they did not discuss how the opioid epidemic affects ethnic minorities in the United States. However, the demographics of opioid mortality rates are both complicated and changing; for instance, rates among black Americans are now analogous to white Americans, even though the latter still have the highest rates across all racial groups in the United States (Alexander et al., 2018; KFF, 2021).

To overcome these limitations, scholars are paying attention to community characteristics, including a wide range of social variables that may be related to the different levels of opioid overdose deaths across regions. For these reasons, this study
will examine how opioid mortality rates are affected by social vulnerabilities, thus filling a critical gap in the academic literature. Social vulnerability refers to the susceptibility of social groups to latent harms from hazards (Blaikie et al., 1994; Hewitt, 1977) and their capacity to manage the impact of social and natural hazards (Wisner et al., 2004). Most importantly, social vulnerability includes diverse social variables beyond socioeconomic status (Fatemi et al., 2017). In this regard, social vulnerability provides a more robust measures of the association between social factors and opioid overdose deaths.

In terms of accounting for occupation, most studies are on the individual-level (Hawkins et al., 2019; Hawkins et al., 2020; Sahith & Devan, 2021; Dale et al., 2020; Dong et al., 2020a; Dong et al., 2020b). However, such research has a limited ability to evaluate the effect of occupation and industry on opioid overdose mortality because individual-level studies ignore the effects of occupational and industrial structures at the community level. Occupational and industrial structures are closely associated with regional contexts, such as traffic networks, international ports, rural or metropolitan environment, and underground resources. Because of this, manufacturing jobs are concentrated in the Midwest and Southern states, while finance jobs are concentrated in Northeast megalopolises (Schill, 2008). In this regard, drug death rates vary by occupation and region (Monnat, 2018). Specifically, people in rural areas are more likely to be employed in manual labor jobs than their urban counterparts (McGranahan, 2003). Naturally, these workers, who are employed in physically-demanding jobs, such as agriculture, forestry, fishing, hunting, and mining, are vulnerable to injuries, disability, and chronic pain (Coben et al., 2004; Keyes et al., 2014). As such, Appalachia (West Virginia, Eastern Kentucky, Western Pennsylvania, Eastern Tennessee, Western Virginia,
Northwestern Maryland, and Western North Carolina) and the Ozarks (Southern Missouri, Northern Arkansas, and Eastern Oklahoma) have a higher prevalence of disability and chronic pain than the national average (Van Gundy, 2006). As a result, opioid overdose is frequent in Appalachia’s coal mining areas (Keyes et al., 2014, Quinones, 2015).

While most studies focus on individual-level differences in occupation and industry, one has assessed the impact of occupational and industrial composition at the county-level on opioid overdose mortality. Specifically, counties with high poverty rates and more blue-collar and service workers have higher opioid mortality rates (overall) than other counties (Monnat et al., 2019). Additionally, urban counties with low poverty rates and a higher concentration of professional workers suffer more illegal opioids mortality rates than other counties (Monnat et al., 2019).

However, Monnat et al. (2019) conducted a cross-sectional analysis, which indicates that they did not account for temporal changes in regional industrial composition and opioid mortality rates. Nor did Monnat et al. (2019) distinguish regions by industrial composition and opioid overdose deaths, despite regional disparities (e.g., Midwest/Northeast/South/West/Appalachia) in industrial composition (Bednarikova et al., 2021; Nolan et al., 2011) and opioid overdose deaths (Mattson et al., 2021; Ruhm, 2017).

**Why Use County-Level Data?**

This study analyzes county-level variation in opioid overdose mortality, and it is based on a body of academic literature that emphasizes the importance of county contexts on population health. According to such studies, county contexts are closely associated with population health (Cosby et al., 2019; Cardona et al., 2021; Walsemann et al., 2021).
For example, rural counties are likelier to spend less on healthcare and living environment than urban counties, thereby leading to poor contexts in rural counties (Cardona et al., 2021). As a result, all-cause deaths in rural counties were 1.2 times more than those in urban counties in 2016 (Cosby et al., 2019). What is more, rural-urban mortality disparities have increased by 75% between 2004 and 2016 due to high poverty rates in rural counties (Cosby et al., 2019). Therefore, one can postulate that county-level disparities in contexts could generate different patterns of opioid overdose deaths depending on the county.

Moreover, counties constitute an appropriate level to analyze because they reflect regional economic and social conditions (Lobao et al., 2007). County governments provide socio-cultural structures, which influence the population’s health and mortality status (Monnat et al., 2019). Additionally, these governments offer many social programs, which are funded by state governments (Lobao et al., 2007). Therefore, county contexts are closely associated with the opioid epidemic, which is affected by the judicial system, drug policies, and social programs (Monnat et al., 2019). Previous studies in fact provide supporting evidence for this. First, the constitution of the county’s healthcare system is associated with opioid misuse (Wright et al., 2014). Second, counties suffering from high unemployment and poverty rates, low levels of education, and population density tend to have an increased rate of opioid misuse (Spiller et al., 2009).

Given these consideration and limitations in the existing scholarship, this dissertation will examine the trends in opioid mortality by opioid types, race, and region. Additionally, this study analyzes how opioid mortality rates are affected by social vulnerabilities and occupational and industrial composition using county-level data,
thereby filling a critical gap in the academic literature. It can be summarized as research overview.

**Research Overview**

This dissertation is composed of three chapters:

*Chapter 1: Trends in Opioid Mortality by Opioid Types, Race, and Geographical Region in the United States*

Even though examining opioid mortality trends is useful to grasp the current opioid epidemic and to decide on a research direction, there have been few studies on the regional trends of opioid mortality. Therefore, the goal of this dissertation is to investigate opioid mortality trends, not only by opioid types and race, but also by region.

The results from Chapter 1 indicated that the major cause of the current epidemic is synthetic opioids. Therefore, Chapters 2 and 3 focused on synthetic opioid mortality rates.

*Chapter 2: Social Vulnerabilities and Synthetic Opioid-Related Mortality Rates in U.S. Counties.*

Social vulnerability covers a broad range of social factors, beyond simply considering socioeconomic status, something that has been widely addressed in epidemiological studies pertaining to the opioid epidemic. Although social vulnerability is more often analyzed at the macro-level (e.g., group and community) than the individual-level, few studies have yet to examine the effect
of social vulnerability on the opioid epidemic using macro-level methods. Furthermore, nor did these studies account for the effects of region and temporal changes, both of which influence the link between social vulnerability and opioid mortality rates. Therefore, this study’s purpose is to identify the link between social vulnerability and synthetic opioid mortality rates via county-level analysis and to identify how this link is affected by region and temporal changes.

Chapter 3: The Longitudinal Effect of County-Level Occupational and Industrial Composition on Synthetic Opioid-Related Mortality Rates

Although occupation and industry are two important predictors of substance abuse, few studies have addressed the effect of these factors on the opioid epidemic. In addition, despite occupation and industry in the United States having been greatly affected by structural factors (e.g., deindustrialization and regional economic conditions), few papers have conducted a macro-level analysis of these topics. Therefore, the objective of this study is to examine the effect of occupational and industrial composition on synthetic opioid mortality rates using county-level analysis. Moreover, the occupational and industrial composition of the counties, as well as synthetic opioid mortality rates, change over time. As such, this dissertation used a longitudinal methodology.
CHAPTER I
TRENDS IN OPIOID MORTALITY BY OPIOID TYPES, RACE, AND REGION IN
THE UNITED STATES

Introduction

The opioid epidemic has become a serious public health crisis in the United States, and the biggest problem is the increasing mortality rate. Opioid mortality rates have consistently grown over the past 20 years (NIDA, 2021a; CDC, 2021). Even worse, these rates are increasing sharply (CDC, 2021). Even in the midst of the COVID-19 pandemic, opioid mortality rates have increased in some regions by 30 percent in 2020, in comparison to 2019 (Wen & Sadeghi, 2020).

Additionally, the epidemic is an extremely complex issue; it is not limited only to certain types of opioids, groups, and region. Specifically, this epidemic among whites was regularly observed between the 1990s and 2000s, due to prescription opioid misuse (Madras, 2017; Paulozzi et al., 2006). However, the epidemic has spread quickly to other racial groups, such as blacks and Hispanics, with the emergence of illegal opioids (e.g., heroin and illegally manufactured synthetic opioids) (Hedegaard et al., 2015; Jones et al., 2015; O’Donnell et al., 2017; Rudd et al., 2016, Rudd et al., 2014; Mack et al., 2017; Colon-Berezin et al., 2019; Shiels et al., 2018). Alongside this trend, opioid overdose deaths have diffused from suburban and rural areas into metropolitan areas (Mack et al., 2017; Colon-Berezin et al., 2019; Shiels et al., 2018). Therefore, it is necessary to examine the trends in opioid mortality rates by opioid types, race, and region.
A considerable body of literature already exists, which analyzes trends in opioid mortality by opioid types, race, and region in the United States (Alexander et al., 2018; Buchanich et al., 2018; Calcaterra et al., 2013; Cordes, 2018; Hoopsick et al., 2021; Mattson et al., 2021; O’Donnell et al., 2017; Romeiser et al., 2019). Even though these previous studies provide valuable information, gaps and obscurities in the literature nonetheless remain. One limitation among existing studies is that they are based only on graph analysis (Alexander et al., 2018; Buchanich et al., 2018; Calcaterra et al., 2013; Dart et al., 2015; Hoopsick et al., 2021; O’Donnell et al., 2017; Rudd et al., 2016). While graph analysis can examine the overall trends of opioid overdose mortality rates across the United States, it is not ideal for examining the regional (county-level) trends of opioid overdose mortality rates. For example, even though prescription opioid mortality rates and heroin mortality rates have been flattening out since 2016 according to national trends (Hoopsick et al., 2021; Mattson et al., 2021), both rates may have in fact increased in certain areas. Furthermore, new patterns of the epidemic caused by illegally manufactured synthetic opioids might be concentrated in specific regions, which are influenced by local environment and drug trafficking networks. Given such complex patterns of this epidemic, it is thus crucial to identify which regions have higher opioid mortality rates and which are more vulnerable to new patterns of the epidemic. Therefore, it is necessary to evaluate regional trends using geo mapping analysis. Even though existing studies, which did use geo mapping, showed regional variation in opioid mortality trends, they were based only on certain states (e.g. New York and North Carolina) (Cordes, 2018; Romeiser et al., 2019) and on the state level (Mattson et al., 2021; Ruhm, 2017).
Specifically, Cordes (2018) claims that, in North Carolina, opioid mortality rates are higher in western counties than in eastern ones. This is because western counties are located in Appalachia, which have the highest rates of opioid misuse and overdose deaths in the United States (Cordes, 2018). Additionally, mortality rates from prescription opioids, synthetic opioids, and methadone are concentrated in western counties and heroine-related mortality rates are concentrated in urban counties (Cordes, 2018).

Romeiser et al. (2019) assert that, in New York state, northern counties have higher rates of prescription opioid mortality, but they also have a lower opioid prescription rate. On the other hand, western counties have lower prescription opioid mortality rates in tandem with high opioid prescription rates (Romeiser et al., 2019). Despite these studies having used county-level estimates of the opioid mortality trends, they are focused on certain states (New York and North Carolina) but did not consider other regions.

Notably, Mattson et al. (2021) examined which regions have higher opioid mortality rates across the United States. Specifically, they found that the Northeast has the highest synthetic opioid mortality rates, whereas the West has the lowest (Mattson et al., 2021). Ruhm (2017) evaluated which regions have higher heroin mortality rates across the United States. Specifically, such rates were underestimated in some states (e.g., Pennsylvania, Indiana, New Jersey, and Arizona), which means that heroin overdose is still contributing to the increase in opioid mortality rates (Ruhm, 2017). Although these two studies did examine opioid mortality trends across the United States, they are based only on state-level estimates (Mattson et al., 2021; Ruhm, 2017). In particular, state-level analysis has a limited capacity for assessing regional trends because of regional variations in opioid mortality rates in a state. For example, in North Carolina, western counties have
higher opioid mortality rates than their eastern counterparts because western counties in North Carolina are part of Appalachia, wherein the opioid epidemic is the most severe (Cordes, 2018).

Thus, the opioid epidemic is not simply one homogenous epidemic, but is comprised of multiple, co-occurring epidemics—particularly those characterized by various opioid types, diverse geographical, time-dependent, and socio-demographic characteristics. Therefore, this study seeks to examine the trends in opioid overdose mortality rates by opioid types, race, and region. This study differentiates itself, as well, by using both descriptive line graph analysis and geo mapping analysis (at the county-level) across the United States, thus filling some crucial gaps in the academic literature.

Given these considerations, this research project has three aims. First, to assess whether the increase in opioid mortality trends differs by opioid types and time. Second, to investigate whether racial differences in opioid mortality rates vary by opioid types and time. Third, to identify if regional differences in opioid mortality rates are differ by opioid types and time. By doing this, this study can therefore examine vulnerable populations and areas and determine which types of opioids increase death rates from overdose.

Methods

Data

Data were derived from Centers for Disease Control and Prevention’s Wide-ranging Online Data for Epidemiologic Research (CDC WONDER), Multiple Cause of Death,
1999–2020 (CDC, 2021). CDC WONDER data were not available for all U.S. counties due to suppression rules, thus counties with very few deaths are flagged as “no data”. The number of counties listed differs by year and opioid types; that data are summarized below in Table 1.

**Table 1**

*The Number of Counties by Year and Opioid Types*

<table>
<thead>
<tr>
<th>Year</th>
<th>Variables</th>
<th>Number of Counties/Total</th>
<th>Number of Excluded Counties</th>
<th>Mean Mortality Rate (per 100,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>1,408/3,141</td>
<td>1,733</td>
<td>10.722</td>
</tr>
<tr>
<td>2010–2014</td>
<td>Prescription</td>
<td>961/3,141</td>
<td>2,180</td>
<td>7.105</td>
</tr>
<tr>
<td></td>
<td>Opioids</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heroin</td>
<td>450/3,141</td>
<td>2,691</td>
<td>3.602</td>
</tr>
<tr>
<td></td>
<td>Synthetic Opioids</td>
<td>417/3,141</td>
<td>2,724</td>
<td>2.097</td>
</tr>
<tr>
<td>2015–2020</td>
<td>Overall</td>
<td>1,756/3,141</td>
<td>1,385</td>
<td>15.916</td>
</tr>
<tr>
<td></td>
<td>Prescription</td>
<td>1,169/3,141</td>
<td>1,972</td>
<td>6.157</td>
</tr>
<tr>
<td></td>
<td>Opioids</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heroin</td>
<td>895/3,141</td>
<td>2,246</td>
<td>5.718</td>
</tr>
<tr>
<td></td>
<td>Synthetic Opioids</td>
<td>1,292/3,141</td>
<td>1,849</td>
<td>11.569</td>
</tr>
</tbody>
</table>

The main measure of the analysis is the opioid mortality rates by opioid types, race, and region in the United States from 2010 to 2020. Using data from 2010 to 2020 is ideal for this study because the patterns of the epidemic have changed since 2010. Specifically, the causes of opioid mortality have been diversified alongside the emergence of illegal opioids mortality since 2010 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018). In tandem with this trend, the demographics have thus become
more complex and are shifting; for example, rates among blacks are now similar to those of whites (Alexander et al., 2018; KFF, 2021).

In this study, opioid overdose deaths have been categorized based on the following:
(1) International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (Geneva, Switzerland: World Health Organization; 2011 [ICD-10]) codes; and (2) the underlying cause of death codes: X40-44 (unintentional), X60-64 (suicide), X85 (homicide), or Y10-Y14 (undetermined intent). Furthermore, the type of opioid included was defined by the multiple cause of death codes: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids or commonly prescribed opioids), T40.3 (methadone), T40.4 (other synthetic narcotics, commonly fentanyl or its analogs), and T40.6 (other and unspecified narcotics) (CDC, 2021).

The ICD-10 codes that have been used are those quoted in earlier literature (Iwanicki et al., 2018; Milam et al., 2021; Romeiser et al., 2019; Seth et al., 2018b). Based on these codes, opioid types were then categorized into four subsets (overall, prescription opioids, heroin, and synthetic opioids). This classification was performed because opioid overdose deaths have been caused mainly by prescription opioids (Madras, 2017; Paulozzi et al., 2006), heroin (Hedegaard et al., 2015; Jones et al., 2015; O’Donnell et al., 2017; Rudd et al., 2016, Rudd et al., 2014), and synthetic opioids (Hoopsick et al., 2021; Jones et al., 2018; O’Donnell et al., 2017; Scholl et al., 2018).

Statistical Analysis

Line graph analyses are presented in Figures 1 through 6. A line graph is a chart, which is used to display quantitative data that change over time (Investopedia, 2021). As
for the line graph analysis was employed to examine overall trends of opioid mortality rates across the United States, according to opioid type (prescription opioids, heroin, synthetic opioids) and race (whites, blacks, Asians, Hispanics) from 2010 to 2020. Although opioid overdose deaths have spread among all racial groups, there are disparities in both the size of effect of overdose deaths by racial groups and opioid types (Buchanich et al., 2016; Hedegaard et al., 2019; Jalal et al., 2018; Mack et al., 2017; Monnat, 2018; Rigg et al., 2018; Scholl et al., 2018; Shiels et al., 2018). While line graph analysis is useful, it has limitations, namely, that it is difficult to identify regional trends (county-level) of opioid overdose mortality rates.

Second, geo mapping analyses are presented in Figures 7 through 14. Geo mapping is a technique that turns quantitative data into a geo map (eSpatial, 2022), thereby enabling researchers to examine regional trends by comparing output among regions (maptive, 2022). As such, geo mapping analysis can attenuate the limitations of line graph analysis. Furthermore, this analysis was divided into two major periods: (1) from 2010 to 2014, and (2) 2015 to 2020. This sub-division is helpful because the patterns of opioid mortality have been changing in tandem with the rapid increase in synthetic opioid mortality rates since 2014 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018).

All statistical analyses were processed by STATA (version 15.0, StataCorp LLC., College Station, TX). There was no need to obtain approval from the institutional review board to conduct this study because all datasets are secondary data that have no confidentiality issues.
Results

As shown in Figure 1, opioid overdose mortality rates increased steadily in the United States between 2010 and 2017. For a few years, opioid mortality rates remained steady at 14 to 15 deaths per 100,000 people, but in 2020 the mortality rate rose sharply to over 20 deaths per 100,000.

Figure 1

Opioid Overdose Mortality Rates (Total) in the United States (per 100,000 persons), 2010–2020
As shown in Figure 2, most of the increase in opioid overdose mortality is attributable to the dramatic rise of synthetic opioid use. Mortality rates related to prescription opioids have been fairly consistent since 2010, at around four deaths per 100,000 people. For heroin, the mortality rates increased steadily from 2010 to 2016, and then began to stabilize at around the same level as prescription opioid deaths. Notably, mortality due to synthetic opioids was negligible until 2014, but has risen sharply since then, reaching its peak at over 17 deaths per 100,000 people in 2020.

Figure 2

*Opioid Overdose Mortality Rates by Opioid Types in the United States (per 100,000 persons), 2010–2020*
As Figure 3 demonstrates, whites had much higher opioid mortality rates than other racial groups until 2017, but opioid mortality rates among blacks began increasing rapidly in 2015 and have now narrowed the gap on whites year to year. As a result, blacks now have the highest rates of all racial groups, starting in 2020. Even though other racial groups, such as Asians and Hispanics, have much lower rates than both whites and blacks, the opioid mortality rates among Hispanic have also been increasing since 2015; in fact, they have exceeded 10 deaths per 100,000 in 2020.

Figure 3

*Opioid Overdose Mortality Rates (Overall) by Race in the United States (per 100,000 persons), 2010–2020*
Figure 4 presents data, which show that whites have much higher prescription opioid mortality rates than other racial groups. However, prescription opioid mortality rates among this same demographic have been repeatedly gone up and down (between 4.8 and 6 deaths per 100,000 people) from 2010 to 2020. Among blacks, this rate increased steadily from 2010 to 2017. Looking at data from 2017 to 2019, the growth in this rate for this group stagnated at 2.8 to 2.9 deaths per 100,000 people, but in 2020 the mortality rate increased noticeably to 3.7 deaths per 100,000. Prescription opioid mortality rates among Asians and Hispanics have consistently remained “very low”, that is, between 0.45 and 1.76 per 100,000, between 2010 and 2020.
As shown in Figure 5, heroin mortality rates among whites grew between 2010 and 2016, at 1.14 to 5.7 deaths per 100,000, but this rate has decreased since 2016. Additionally, these trends continued until 2020 (5.7 deaths → 4.40 deaths per 100,000 people). Heroin mortality rates among blacks increased sharply from 2010 to 2017 (0.76 deaths → 5.0 deaths per 100,000 ), but these trends have stabilized at 5.0 to 5.1 deaths per 100,000 from 2017 to 2020. Although the growth in heroin mortality rates among Hispanics was much smaller than it was for both whites and blacks, it expanded from...
2010 to 2016, namely, from 0.87 to 2.6 deaths per 100,000 people. Nonetheless, these trends stalled out at 2.6 to 2.87 deaths per 100,000 from 2017 to 2020. For the Asian population, heroin mortality rates increased consistently from 2010 to 2017 (0.08 deaths → 0.6 deaths per 100,000), despite this demographic having the lowest heroin mortality rates across all racial groups. This growth trajectory for heroin mortality rates did decrease, albeit temporarily, from 2017 to 2018 (0.6 deaths → 0.4 deaths per 100,000). However, from 2019 to 2020, these rates returned to 0.6 deaths per 100,000 people.

Figure 5
Heroin Mortality Rates by Race in the United States (per 100,000 persons), 2010–2020
From 2010 to 2013, the increase in synthetic opioid mortality rates among whites stagnated at 1.34 to 1.35 deaths per 100,000 people. In contrast, the rates for synthetic opioid mortality rates swelled from 4.0 to 11.0 deaths per 100,000 people between 2015 and 2017. Even though such growth slowed between 2017 and 2019 (11.0 → 13.0 deaths per 100,000 people), the rates sharply increased again from 2019 to 2020 (13.0 → 19.0 deaths per 100,000 people). Synthetic opioid mortality rates among blacks maintained “very low”, that is between 0.36 and 0.40 per 100,000 people, from 2010 to 2013, but increased significantly between 2015 to 2019 (2.4 deaths → 14.0 deaths per 100,000 people). Such trends have strengthened among blacks between 2019 and 2020 (14.0 → 24.0 deaths per 100,000); in fact, they became higher than those among whites in 2020. For Hispanics, synthetic opioid mortality rates showed similar growth patterns, despite Hispanics having lower synthetic opioid mortality rates. Synthetic opioid mortality rates among Asians maintained “very low” from 2010 to 2015. However, they rose moderately from 0.5 to 1.1 deaths per 100,000 people between 2015 and 2019, before sharply increasing between 2019 and 2020 (1.1 → 2.6 deaths per 100,000).
Figure 6

*Synthetic Opioid Mortality Rates by Race in the United States (per 100,000 persons), 2010–2020*

Figure 7 through Figure 14 detail this study’s geo-mapping analysis, which was conducted on opioid mortality trends in the United States. Counties in Alaska and Hawaii were excluded because of a technical problem, namely that including counties in Alaska and Hawaii makes the mainland United States map too small. Therefore, I excluded these counties to ensure the data was bigger and easier to read.

Figure 7 presents the mainland United States Map of opioid overdose mortality rates (per 100,000) by county level, from 2010 to 2014. Figure 8 is another map of opioid the
same rates (per 100,000 persons) by county level, from 2015 to 2020. As shown in Figure 7 (2010–2014), the highest opioid overdose mortality rates were concentrated in counties in the West (Northern California, Utah, Nevada, New Mexico), the Midwest (Missouri, Ohio), Appalachia (West Virginia and Eastern Kentucky), and the South (Oklahoma and Tennessee). Per Figure 8 (2015–2020), the highest opioid overdose mortality rates are concentrated in counties in the West (Utah and New Mexico), the Midwest (Missouri; Chicago-Naperville-Elgin, IL-IN-WI MSA; Ohio; Michigan; Detroit-Warren-Dearborn, MI, MSA; and Wisconsin), Appalachia (West Virginia and Eastern Kentucky), the Northeast/New England, East Coast (Maryland, Delaware, Virginia, and New Jersey), and the South (North Carolina, Tennessee, and Florida). By comparing the rates of Figures 7 and 8, the mortality rates show a decrease between 2015 and 2020 among counties in the West. On the other hand, these same rates increased from 2015 to 2020 among counties in the Midwest, Appalachia, the East Coast (Maryland, Delaware, Virginia, and New Jersey), and the Northeast/New England.
Figure 7

Mainland United States Map of Opioid Overdose Mortality Rates (Overall) (per 100,000 persons) by County, 2010 to 2014

Figure 8

Mainland United States Map of Opioid Overdose Mortality Rates (Overall) (per 100,000 persons) by County, 2015 to 2020
In Figure 9, the mainland United States Map shows the prescription opioid mortality rates by county level, from 2010 to 2014. As for Figure 10, the data present the prescription opioid mortality rates, also by county level, but for the years 2015 to 2020. As shown in Figures 9 (2010–2014) and 10 (2015–2020), the highest rates are concentrated in Western counties (Northern California, Nevada, Utah, and New Mexico), Ohio, Appalachia (West Virginia and Eastern Kentucky), New York, Maine, the East Coast (Maryland, Delaware, and Virginia), and the South (Oklahoma, North Carolina, Tennessee, Louisiana, and Florida). When comparing the rates detailed in Figures 9 and 10, one sees they decreased during 2015 to 2020 among counties in Oklahoma, Northern California, New Mexico, and Arizona. On the other hand, prescription opioid mortality rates increased during 2015 to 2020 for counties in Utah, Maine, and Louisiana.
Figure 9

Mainland United States Map of Prescription Opioid Mortality Rates (per 100,000 persons) by County, 2010 to 2014

Figure 10

Mainland United States Map of Prescription Opioid Mortality Rates (per 100,000 persons) by County, 2015 to 2020
Figure 11 shows the mainland United States Map of heroin mortality rates (per 100,000 persons) by county level, 2010 to 2014, and Figure 12 shows the same rates for the years of 2015 to 2020. As shown in Figure 11 (2010–2014), the highest heroin mortality rates are concentrated in counties in New Mexico, and the Midwest (St. Louis, MO-IL MSA; Ohio; and Cincinnati, OH-KY-IN MSA). Figure 12 (2015-2020) presents the highest rates are in counties in New Mexico, the Midwest (Chicago-Naperville-Elgin, IL-IN-WI MSA; Ohio; Michigan; and Detroit-Warren-Dearborn, MI MSA), Appalachia (West Virginia and Eastern Kentucky), New York, the Northeast/New England, the East Coast (Maryland, Delaware, Virginia, and New Jersey), and the South (Western Nashville, TN; Louisiana; Birmingham–Hoover–Talladega, AL MSA; and North Carolina). Comparing the heroin mortality rates between Figures 11 and 12, demonstrates that the heroin mortality rates increased between 2015 and 2020 among counties in New Mexico, the Midwest (Ohio; Michigan; and Detroit-Warren-Dearborn, MI MSA), Appalachia (West Virginia and Eastern Kentucky), New York, the Northeast/New England, the East Coast (Maryland, Delaware, Virginia, and New Jersey), and the South (Western Nashville, TN; Louisiana, Birmingham–Hoover–Talladega, AL MSA; and North Carolina).
Figure 11

Mainland United States Map of Heroin Mortality Rates (per 100,000 persons) by County, 2010 to 2014

Figure 12

Mainland United States Map of Heroin Mortality Rates (per 100,000 persons) by County, 2015 to 2020
Below, Figure 13 is a map of mainland United States Map, which shows the synthetic opioid mortality rates by county level, from 2010 to 2014. The next map, Figure 14, details these same rates by county level, between 2015 and 2020. As shown in Figure 13 (2010–2014), the highest synthetic opioid mortality rates are concentrated in Appalachia (West Virginia); according to Figure 14 (2015–2020), the highest rates are in counties in the Midwest (Missouri; Wisconsin; Chicago-Naperville-Elgin, IL-IN-WI MSA; Eastern Indiana; Ohio; and Michigan, Detroit-Warren-Dearborn, MI MSA), Appalachia (West Virginia and Eastern Kentucky), Pennsylvania, New York, the Northeast/New England, the East Coast (Maryland, Delaware, Virginia, and New Jersey), the South (Alabama, Louisiana, North Carolina, South Carolina Tennessee, and Florida). Upon conducting a comparison of the synthetic opioid mortality rates of Figures 13 and 14, synthetic opioid mortality rates showed an increase during 2015 to 2020 among certain counties in the West (Northern New Mexico and Southeastern Colorado), the Midwest (Missouri; Wisconsin; Chicago-Naperville-Elgin, IL-IN-WI MSA; Eastern Indiana; Ohio; Michigan; and Detroit-Warren-Dearborn, MI MSA), Appalachia (West Virginia and Eastern Kentucky), Pennsylvania, New York, the Northeast/New England, the East Coast (Maryland, Delaware, Virginia, and New Jersey), and the South (Alabama, Louisiana, North Carolina, South Carolina Tennessee, and Florida).
Figure 13
Mainland United States Map of Synthetic Opioid Mortality Rates (per 100,000 persons) by County, 2010 to 2014

Figure 14
Mainland United States Map of Synthetic Opioid Mortality Rates (per 100,000 persons) by County, 2015 to 2020
The purpose of this study is to investigate the trends in opioid overdose mortality rates by opioid types, race, and region. To this end, this dissertation has three goals. First, it aims to examine if the rise in opioid overdose deaths varies by opioid types and time. Second, this research seeks to evaluate whether racial disparities in opioid overdose deaths vary by the same factors, that is, by opioid types and time. Third, this paper considers whether geographical disparities in opioid overdose deaths vary by opioid types and time.

Firstly, this study observed that opioid mortality rates have indeed consistently increased over the last decade. Even though these rates from all opioid types have grown, synthetic opioid mortality rates did so the most. Synthetic opioid mortality rates have been rapidly increasing since 2014, whereas heroin mortality rates and prescription opioid mortality rates have been flattening out since 2016. One new, and important, finding is that the growth in opioid mortality rates has become even more pronounced recently (2019–2020) because of the dramatic rise in the synthetic opioid mortality rate between 2019 and 2020. This is supported by two line graph (Figure 1 and Figure 2), which show that the increased opioid mortality rate between 2019 and 2020 in Figure 1 roughly corresponds to the spike in synthetic opioid mortality rate between 2019 and 2020 in Figure 2.

This study also found that mortality rates from synthetic opioids were about four times higher than those from prescription opioids and heroin in 2020. Generally, synthetic opioids (fentanyl) are 50 to 100 times stronger than prescription opioids
(morphine) (NIDA, 2021b) and 50 times more so than heroin (Baumann et al. 2018; Burns et al., 2018). The substantial degree of potency that synthetic opioids have may be behind the opioid mortality rates (Skolnick, 2022). As a result, more recently, approximately 80% of overdose deaths are caused by synthetics (Ahmad et al., 2021). Public authorities therefore need to focus on reducing synthetic opioid mortality rates.

Secondly, this study also observed that both whites and blacks are suffering from a much higher opioid mortality rate than other racial groups, such as Asians and Hispanics. Another revelatory finding is that blacks are more vulnerable to synthetic opioid mortality than whites; they have had a higher synthetic opioid mortality rate since 2019. As a result, blacks had the highest opioid mortality rates (overall) in 2020 across all racial groups in the United States. Thus, the rapid rise in opioid mortality rates among blacks is mainly caused by this spike in deaths related to synthetic opioids.

What is more, research has confirmed that synthetic opioids have the potential to cause a serious health threat due to their high potency (Baumann et al. 2018; Burns et al., 2018; NIDA, 2021b). Additionally, synthetics’ potency makes them much easier to transport and distribute compared to prescription opioids and heroin (Skolnick, 2022). This is the case because high potency drugs can be taken in smaller amounts to be effective. For instance, a 20g dose of synthetic opioids is equal to 1kg of heroin, which would actually facilitate the mass production of synthetics (Skolnick, 2022). Consequently, synthetics cost an estimated 5% to 10% that of heroin on the black market (Frank & Pollack, 2017; Mars et al., 2019). That data show that black people tend to buy inexpensive synthetics on the black market because of financial troubles they may be facing when they have a prescription for opioids (Monnat, 2019; Pear et al., 2019;
Althoff et al., 2020; Butcher, 2021). This social disadvantage may thus be what is leading to a substantial increase in synthetic opioid mortality rates among blacks. Therefore, the interpretation of these results must account for these complex issues (e.g., drug trafficking, social disadvantages, and race-related issues) in which the synthetic opioid epidemic is deeply rooted. What is more, public health authorities have underestimated the issue of opioid overdose deaths in blacks more broadly (SAMHSA, 2020a); they therefore must now recognize that blacks are the most vulnerable demographic to synthetic opioid epidemic.

Thirdly, from the collected data, this study observed that there are geographical differences among opioid mortality rates. The first observation is that, recently, both the overall opioid mortality rate and the synthetic opioid mortality rate specifically are higher among counties in Appalachia, the Midwest, and the Northeast than they are in the Western United States. Appalachia has long been a hotspot of the opioid epidemic (CDC, 2021) this region has a higher prevalence of disability and chronic pain than the national average (Van Gundy, 2006; McGranahan & Parker, 2021). In fact, rural mining communities, generally, have high physical disability rates (McGranahan & Parker, 2021). Physical disability has indeed been associated with opioid overdose because physical disability leads to chronic pain (McGranahan & Parker, 2021). For this reason, opioid overdose occurs often in Appalachian coal mining communities (Keyes et al., 2014, Quinones, 2015).

Economic problems might also be a factor in the opioid epidemic. Poverty caused by a high unemployment rate is associated with opioid overdose (Case & Deaton, 2015, 2017; Monnat, 2018), which means that a local economic downturn could lead to an
opioid epidemic. The Midwest has been substantially affected by de-industrialization ever since the 1970s, and it has been contributing to consistently high unemployment rates in the Midwest. As a result, low socioeconomic status and high poverty rates are concentrated in this area (Kiang et al., 2019). As the manufacturing industry became more decadent, many middle-aged, working-class people with lower education had anxiety about their futures because of the shortage of high-paying jobs (Case & Deaton, 2015). As a consequence, they became addicted to substances, which is known as “deaths of despair” (Case & Deaton, 2015). Even though the Northeast is economically better off than Appalachia and the Midwest (World Population Review, 2022), the financial crisis of the late 2000s also impacted the Northeast in a particularly intense way. The 2008 financial crisis ushered in reduced wages and a dearth of jobs in the Northeast. This downturn triggered the opioid epidemic in the Northeast after 2010 (McGranahan & Parker, 2021). Meanwhile, high-salary and technology-based jobs have become more concentrated in the Sunbelt, such as in the West and the Southwest (Lamphere, 1985; Iceland et al., 2013). Such a drastic economic imbalance among regions in the United States may, therefore, have led to regional differences in opioid mortality rates.

One notable fact is that synthetic opioid mortality rates have been rising recently (2015–2020), and at an alarming pace, in the Midwest, the Northeast, and the East Coast. As shown in Figures 13 and 14, the synthetic opioid epidemic was restricted to Appalachia between 2010 and 2014, but between 2015 and 2020, deaths related to synthetics have been spreading to the Midwest, the Northeast, and the East Coast between 2015 and 2020. This phenomenon is cannot be explained fully by regional
economic problems, which is why follow-up studies are needed to examine other causes of the synthetic opioid epidemic spreading in such a short time across these regions.

A second is that, as is shown in Figures 8 and 14, both opioid mortality rates and those that are related to synthetics specifically significantly increased between 2015 and 2020 in metropolitan counties in the Midwest and the Northeast, such as St. Louis, Chicago, Detroit, Boston, New York, Philadelphia, and Baltimore. Urban environments may in fact lead to a rise in synthetic opioid mortality rates in these areas. Specifically, there are significant regional disparities in income and living standards in the metropolitan areas of the Midwest and the Northeast, which leads to inner-city shantytowns (Wright & Montiel, 2007). This is more common among cities in the Northeast and the Midwest than among those in the West (Wright & Montiel, 2007). Consequently, open-air drug markets, which are controlled by drug-trafficking rings, are prevalent in inner-cities in these regions (Johnson et al., 2020). These urban environments may lead to higher rates of mortality from illegal opioid use among urban counties in the Midwest and the Northeast.

The importance of conducting a county-level analysis of opioid mortality, here, is clear. State-level analysis presents some barriers to examining regional trends in opioid mortality rates because it fails to account for the regional differences in rates within a state. For example, in North Carolina, western counties have higher opioid mortality rates than eastern counties because the former are adjacent to Appalachia, where people are experiencing the worst opioid epidemic in the United States (Cordes, 2018). Appalachia encompasses some parts of many states (i.e., West Virginia, eastern Kentucky, western Pennsylvania, eastern Tennessee, northwestern Maryland, western North Carolina). Thus,
it is challenging to examine regional trends via state-level analysis. Instead, subregions of Appalachia (county-level) are useful for examining regional trends. Furthermore, U.S. states have both rural and urban counties, which means that state-level analysis cannot assess rural–urban mortality disparities. For example, in Illinois, both the overall opioid mortality rates and those related to synthetics have recently increased in Chicago metropolitan counties. In contrast opioid mortality rates, generally, have remained low in rural counties of southern Illinois (Figure 7 vs. Figure 8; Figure 13 vs. Figure 14). A county-level analysis is thus ideal for examining rural–urban opioid mortality disparities.

The observations originating from this study should be considered in light of some limitations. First, it was impossible to account for all US counties because, in the CDC WONDER data, any counts (i.e., number of deaths) fewer than 10 are designed to be suppressed for confidentiality reasons, and this might produce less accurate results. This is the case because suppression shows no data for many counties in the Great Plains and Texas; as such real variation in opioid mortality rates in these areas may be masked—even though no data means a very small number of deaths. Another limitation is that this study used descriptive statistics; as such, neither predictions nor inferences have been provided. Nonetheless, this study was able to evaluate regions vulnerable to death from opioid overdose in Chapter 1. Specifically, the Midwest and the Northeast have much higher opioid mortality rates than other regions, such as the South and the West. Therefore, this study will next examine regional disparities as they pertain to the effect of social factors on opioid mortality rates, in Chapters 2 and 3, by means of inferential statistics. By so doing, I will attenuate the limitations of this study and strengthen the link among chapters.
Conclusion

Despite these limitations, this study analyzed the trends in opioid mortality by opioid types, race, and region in the United States. In summary, opioid mortality rates have been consistently increasing over the last 10 years, but the rate of increase has recently grown sharply (2019–2020). This spike in opioid mortality rates is caused mainly by synthetic opioid mortality. The high potency of synthetics is closely associated with a rapid increase in mortality rates (Skolnick, 2022). Therefore, synthetics are much more dangerous than other opioids (e.g., prescription opioids and heroin). In terms of race, whites and blacks are at greater risk of opioid overdose deaths than other racial groups (e.g., Asian and Hispanic). Even though both whites and blacks have high synthetic opioid mortality rates, the rates among blacks have been exceeding those among whites since 2019. As a consequence, the overall opioid mortality rates were the highest among blacks in 2020. This indicates that blacks are the most vulnerable population of the recent opioid epidemic in the United States. In terms of geographical analysis, opioid mortality rates vary by region; both opioid mortality rates (overall) and synthetic opioid mortality rates (specifically) are concentrated among counties in Appalachia, the Midwest, the Northeast, and the East Coast. On the other hand, counties in the West have a less severe problem with synthetic opioid mortality. These areas (e.g., Appalachia, Midwest, Northeast, and the East Coast) are the most vulnerable to the current epidemic because, recently, synthetics are leading to higher mortality rates than other opioids, such as prescription opioids and heroin. Local industrial structure,
economic downturns, and environments might lead to a serious opioid epidemic among counties in Appalachia, the Midwest, the Northeast, and the East Coast.

Based on results from Chapter 1, I will now turn to focusing on certain types of opioids (synthetic opioids) in subsequent chapters. This is vital to this study’s analysis because synthetic opioids have contributed to a rapid increase in opioid mortality rates recently.
CHAPTER II
SOCIAL VULNERABILITY AND SYNTHETIC OPIOID-RELATED MORTALITY RATES IN U.S. COUNTIES

Introduction

Over the last two decades, the United States has had a substantial increase in opioid overdose deaths (NIDA, 2021a; CDC, 2021). Since 2014, the emergence of synthetic opioids have led to a rapid increase in opioid mortality rates (Alexander et al., 2018; Hoopsick et al., 2021). Furthermore, the high potency of synthetic opioids has fueled a surge in such mortality rates (Skolnick, 2018, 2022). Consequently, lately, approximately 80% of opioid overdose deaths are due to synthetics opioids (Ahmad et al., 2021). Therefore, it is necessary to focus on synthetic opioids rather than other opioids (e.g., commonly prescribed opioids and heroin).

Social factors have been established already as important predictors of opioid-related deaths. Even though many studies have examined the association between social factors and opioid-related deaths, they were largely based on socioeconomic status, such as low income (Bernhardt & King, 2022; Cerdá et al., 2013; Feng et al., 2016; Flores et al., 2020; Marshall et al., 2017; Meiman et al., 2015; Ochoa et al., 2005; Visconti et al., 2015; Zlotorzynska et al., 2014), low educational levels (Bernhardt & King, 2022; Cropsey et al., 2013; Cheng et al., 2013; Flores et al., 2020; Marshall et al., 2017; Patrick et al., 2016; Paulozzi et al., 2009; Siegler et al., 2014), and blue-collar jobs (Dale et al., 2020; Dong et al., 2020a; Dong et al., 2020b; Hawkins et al., 2019; Monnat et al., 2019). Additionally, although deaths of despair theory provides a valuable theoretical
framework for investigating socioeconomic disparities in the opioid epidemic, it is essentially based on individual-level estimates of socioeconomic status and the opioid epidemic (Case & Deaton, 2015, 2017). However, individual-level studies have limitations when it comes to analyzing the opioid epidemic because patterns of opioid overdose deaths vary by region (Monnat et al., 2019; Gawande, 2020). For example, according to the results of this study, which have been detailed in Chapter 1, synthetic opioids-related deaths prevail in certain regions (e.g., Appalachia, the Midwest, the Northeast, and the East Coast). Therefore, it is necessary to examine other social factors beyond socioeconomic status and synthetic opioid mortality rates by using macro-level data to fill in these gaps in the academic corpus.

Social vulnerability is a term used to encompass social, economic, and demographic contexts, and it encompasses both socioeconomic status and a variety of other factors (Cutter, 1996; Wisner et al., 2004; Yarnal, 2007). Thus, a social vulnerability is a superordinate concept to that of socioeconomic status; as such, that the term ‘social vulnerability’ can help compensate for the limitations of previous studies. What is more, social vulnerability is influenced by geographical characteristics, which determine not only a community’s capacity to manage hazards but also exposure to them (Kim & Bostwick, 2020). In fact, social vulnerability is more commonly associated with a group or community rather than with individuals. However, little is known about the association between social vulnerability and opioid mortality rates in macro-level studies. Even though one macro-level study (Sawyer et al., 2021) has examined this association, gaps and inadequacies remain. This is because the research conducted by Sawyer et al. (2021)
is based on only one specific state (Indiana), meaning it is impossible to identify national trends.

According to the outcomes, which were presented in Chapter 1, synthetic opioid mortality rates also vary by region. Specifically, such rates are greater in the Midwest and the Northeast. The former was heavily reliant on the a thriving manufacturing industry during the 1960s. During this time, manufacturing provided high-paying jobs for less-skilled and less-educated Americans in the region (Kollmeyer, 2018). Given that the Midwest has been experiencing de-industrialization since the 1970s, these areas are now known as the ‘Rust Belt’ because they have lost much of their manufacturing-based economy. Employment restructuring caused by de-industrialization has resulted in a reduction in high-paying jobs (Bailey et al., 2014). As a result, many people living in the Rust Belt of the Midwestern United States have lost hope for the future and have become dependent on drugs (Case & Deaton, 2015). This is also the case for the Northeast. The name ‘Rust Belt’ covers numerous regions in the Northeast (High, 2003); as such, people living within the Rust Belt have had similar experiences, such as drug abuse. For example, counties in the Northeast, where there are limited job opportunities for young adults, have been more affected by opioid epidemic (McGranahan & Parker, 2021).

In considering the results from Chapter 1, synthetic opioid mortality rates also vary by year. In fact, there were steep increases in synthetic opioid mortality rates every year. The annual rate of change in synthetic opioid mortality has also been reported in previous studies, which demonstrated that synthetic opioid mortality rates have been rapidly increasing since 2014 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018) and have thus contributed to the rapid increase in opioid mortality
rates (Alexander et al., 2018; Hoopsick et al., 2021). Unlike other opioids, synthetics lead to an abnormal jump in mortality rates every year.

Therefore, it is necessary to consider how factors like regions and temporal change (yearly change) affect the link between social vulnerability and synthetic opioid mortality rates. To this end, this study has two research questions:

*Research Question 1:* What is the effect of social vulnerability on synthetic opioid mortality rates in U.S. counties?

*Research Question 2:* Do region and year moderate the association between social vulnerability and synthetic opioid mortality rates in U.S. counties?

**Background**

*Social Vulnerability*

Social vulnerability is defined as the vulnerability groups have to possible loss from hazards (Blaikie et al., 1994; Hewitt, 1977), as well as certain group characteristics with regard to its ability to handle the consequences of social and natural hazards (Wisner et al., 2004). In conceptual terms, social vulnerability is comprised of a mix of social, cultural, economic, political, and institutional factors that create socio-demographic disparities in vulnerability (Spielman et al., 2020). For example, even though Hurricane Katrina hit parts of the Gulf Coast and parts of the southern United States in 2005, the damage incurred differed by socio-demographic demographic and region. Specifically, elderly population, groups without vehicles, minority populations with limited English skills, and low-lying areas (e.g., most parts of New Orleans) were particularly vulnerable
to damage from the hurricane (Flanagan et al., 2011). In this regard, policy-makers emphasized social vulnerability when they created policies (Spielman et al., 2020). Social vulnerability includes a vast range of variables beyond socioeconomic status, which indicates that such vulnerability can be gauged by socioeconomic status (Cutter & Finch, 2008; Holand & Lujala, 2013; Lixin et al., 2014), disability (Chakraborty et al., 2005), minority status (Flanagan et al., 2011), age groups (Martins et al., 2012; Chen et al., 2013), race and ethnicity (Emrich & Cutter, 2011; Li et al., 2010), housing status (Wood et al., 2010; Armas & Gavris, 2013), family structures (Schmidtlein et al., 2008), social security (e.g., percentage of social welfare recipients and percentage of pensioners) (Holand et al., 2011), and public health conditions (Morrow, 1999; Ge et al., 2013).

Socioeconomic status is indeed one of the most important indicators for vulnerable populations (Cutter & Finch, 2008). This is because economically disadvantaged people are more vulnerable to suffering damages related to hazards (Fatemi et al., 2017). Any negative effects from damages to property are more severe among economically disadvantaged households (De Oliveira Mendez, 2009). High levels of unemployment could also increase vulnerability amid a catastrophic situation (Adger, 1999; Burton, 2010; Roshti, 2010). Poverty is a trigger for social vulnerability due to its close relationship with material goods, which influence one’s capacity for managing the effects of disasters (Fatemi et al., 2017). The variables in this sector include both a higher percentage of unemployed people and a greater proportion of low income people, which raise the social vulnerability level (Holand & Lujala, 2013; Zhang & Huang, 2013).

Race and ethnicity are considered key indicators of social vulnerability because social and economic conditions differ by racial and ethnic groups. For example,
Hispanics and blacks face higher rates of social disadvantages (e.g., high poverty rates, unemployment rates, and working-poor rates) than whites (BLS, 2018; KFF, 2019). Therefore, socially vulnerable populations are concentrated in the Deep South and in the lower Mississippi Valley region, where a large black population lives (Cutter & Finch, 2008) and the Mexico–United States border area of Texas, where many Hispanics live (Cutter & Finch, 2008). The variables in this category contain a percentage of Hispanics, Asian, and other minorities (Cutter & Finch, 2008; Emrich & Cutter, 2011; Holand & Lujala, 2013; Li et al., 2010).

Disability is another crucial indicator of a vulnerable group, largely because people with physical or mental disabilities are more susceptible to disasters (Morrow, 1999). For example, disabled people living in group quarters (e.g., psychiatric hospitals and nursing homes) are vulnerable to emergency situations like a building catching on fire and earthquakes (Fatemi et al., 2017). Emergency planning and proper training would be helpful in decreasing a group’s vulnerability to potential mortality and harm stemming from disasters (Fatemi et al., 2017). The variables in this category include a percentage of families with disabled members and a percentage of households with members living with a long-term illness (Lee, 2014; Vincent & Cull, 2010).

Public health conditions are likewise regarded as a core indicator of vulnerable populations. This is because access to, or the availability of, healthcare is a determinant of health within a population (Morrow, 1999). Therefore, improving the accessibility of healthcare resources decreases vulnerability to the burden of diseases and to potential damages caused by disasters (Fatemi et al., 2017). The variables in this section include
the number of hospital beds per 1,000 residents, the number of physicians per 10,000 people, and distance to healthcare services (Ge et al., 2013; Holand & Lujala, 2013).

Social vulnerability is considered a latent variable, which means that social vulnerability is inherent in all groups and regions; therefore, it is difficult to see social vulnerability directly (Spielman et al., 2020). Considering social vulnerability as a latent variable indicates that social vulnerability can only be gauged numerically because indirectly-observable variables (social vulnerability) must be assessed indirectly by statistical methods (Spielman et al., 2020). The typical examples of such numeric measures is the Social Vulnerability Index (SoVI) and the Centers for Disease Control and Prevention’s Social Vulnerability Index (CDC’s SVI) (Spielman et al., 2020; ATSDR, 2021). First, the SoVI was established by Cutter et al. (2003) in an effort to examine hazard case studies (Spielman et al., 2020). The SoVI was made using latent variable procedure, such as principle component analysis (PCA) (King, 1966; Rees, 1970). Second, the CDC’s SVI was constructed by the United States Center for Disease Control (CDC), Agency for Toxic Substances and Disease Registry (ATSDR) to investigate vulnerable populations, which need more support to ameliorate the efficacy of disaster readiness and prompt restoration (Flanagan, et al., 2011). These numerical measures of social vulnerability (e.g. SoVI and CDC’s SVI) are often used not only in research, but also within government bodies (Spielman et al., 2020). Policy-makers tend to use such information for quantifying social vulnerability for data analysis (Beccari, 2016; Birkmann, 2007; Dunning & Durden, 2013; Fekete, 2012).

Previous studies have reported that socially vulnerable populations tend to be more vulnerable to health inequalities related to diseases prevalence and clinical outcomes
(Downie et al., 2011; Langabeer et al., 2019; Cheung et al., 2002; Gordon et al., 2006; Alter et al., 1999; Iezzoni et al., 2008; Chirikos et al., 2008). This means that opioid overdose mortality is likely to differ according to social vulnerability levels. In fact, social vulnerability is one of the most important indicators in epidemiological models (Anderez et al., 2020; Fang et al., 2022). Typical examples include the Susceptible-Infected-Removed (SIR) model and the Susceptible-Exposed-Infectious-Removed (SEIR) model (Anderez et al., 2020; Fang et al., 2022). The basic concept is that socially vulnerable populations are more susceptible to disease and ill health (Anderez et al., 2020; Grimm et al., 2021). Some empirical studies provide evidence that, firstly, counties with high levels of social vulnerability have greater rates of HIV or HCV infections (Van Handel et al., 2016; Wesner et al., 2020). Secondly, counties with a high degree of social vulnerability have higher rates of COVID-19 mortality (Carroll & Prentice, 2021; Kim & Bostwick, 2020; Sung, 2021). Thirdly, counties with a lot of social vulnerability also have higher rates of worse surgical outcomes (Diaz et al., 2021).

The SIR and SEIR models have also been applied to opioid research (Fang & Feng, 2020; Yang et al., 2020). This is because drug abuse and epidemics have many things in common, such as once a person is addicted to a drugs or infected with a disease, it is difficult to cure (Fang & Feng, 2020). What is more, people infected with a disease may be treated and then be re-infected, which is analogous to relapsing in terms of drug abuse (Fang & Feng, 2020). Specifically, Fang & Feng. (2020) developed an SEIR-based SUC model to examine the patterns and characteristics of the proliferation of opioid overdose among counties in Kentucky, Ohio, Pennsylvania, Virginia, and West Virginia. This model focuses on becoming a vulnerable population, which takes into account various
social vulnerabilities (Fang & Feng, 2020). Furthermore, Fang & Feng. (2020) account for the probabilities of opioid overdose differing by both region and year, which are affected by regional characteristics and change in opioid mortality rates by year. Based on this model, then, this study formulated its own research framework, which is summarized in Figure 1.

Figure 1
Research Framework

![Research Framework Diagram]

Regional Characteristics

Social Vulnerability

SEIR-Based SUC Model With Opioid Addiction and Mortality in U.S. Counties (e.g. Fang & Feng, 2020)

Change in Synthetic Opioid Mortality Rates by Year

Synthetic Opioid Mortality Rates in U.S. Counties
This research framework is guided by the outcomes identified in Chapter 1, which reported that the trends in synthetic opioid mortality rates in U.S. counties are different by region and year. This framework indicates that counties with high social vulnerability levels are likely to have higher synthetic opioid mortality rates than those with a lower degree of social vulnerability. Even though high social vulnerability is positively associated with higher synthetic opioid mortality rates, this positive association is nonetheless affected by regional characteristics and annual changes.

Economically distressed regions are vulnerable to an opioid epidemic (Case & Deaton, 2015; Jonas et al., 2012). For example, the Rust Belt, wherein the manufacturing industry has declined quite substantially, is among the U.S. regions most substantially affected by the opioid epidemic (Reinl, 2017). Finally, it should be noted that the Midwest is the heartland of the Rust Belt (High, 2003; Jablonsky, 2018; Varga, 2014). Therefore, my hypotheses are the following:

*Hypothesis 1a:* Counties with higher social vulnerability due to socio-economic conditions will have greater synthetic opioid mortality rates.

*Hypothesis 1b:* The region will moderate the positive association between social vulnerability due to socio-economic conditions and synthetic opioid mortality rates, such that it will be stronger in the Midwest relative to other regions.

Physical disability is closely linked to the opioid epidemic because it leads to chronic pain (McGranahan & Parker, 2021). Therefore, regions with a high rate of physical disability (e.g., rural mining counties) tend to have greater rates of opioid overdose (Keyes et al., 2014, Quinones, 2015). This lead to the second hypothesis:
Hypothesis 2: Counties with higher social vulnerability due to disability will have greater synthetic opioid mortality rates.

Minority communities (e.g., black and Hispanic communities) are experiencing a sharp increase in opioid-related mortality rates (Drake et al., 2020; James & Jordan, 2021). In addition, such rates among blacks have already outstripped those among whites in some states (James & Jordan, 2021). Social vulnerability due to minority status and language skills is concentrated in regions in which many immigrants and foreigners live, such as urban counties in the West (e.g., Los Angeles, San Francisco) (Barr & Wanat, 2005; Sohn & Harada, 2004; Zheng & Woo, 2017) and the Northeast (e.g., New York) (Gany et al., 2006), and counties that border Mexico (the Southwest) (Ko et al., 2021; Martinez, 2008). Therefore, the next set of hypotheses is:

Hypothesis 3a: Counties with higher social vulnerability due to minority status language skills will have greater synthetic opioid mortality rates.

Hypothesis 3b: The region will moderate the positive association between social vulnerability due to minority status and language skills and synthetic opioid mortality rates, such that it will be stronger in the Northeast and West, relative to other regions.

Regions with many mobile homes, a high number of households without a vehicle, and a significant number of homes that heat with coal are positively associated with greater opioid mortality rates (Gavali et al., 2021). Furthermore, regions with a lot of homeless people tend to have higher rate of lethal opioid overdose (Nesoff et al., 2022). Given these considerations, a fourth hypothesis will be tested:

Hypothesis 4: Counties with higher social vulnerability due to housing type and transportation will have greater synthetic opioid mortality rates.
Given that synthetic opioid mortality rates have increased annually since 2014 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018), the following hypothesis will also be examined:

**Hypothesis 5:** The year will moderate the positive or negative association between social vulnerability and synthetic opioid mortality rates. Specifically, the adverse effect of social vulnerability on synthetic opioid mortality rate will have increased as the year progressed; in contrast, the protective effect of social vulnerability against synthetic opioid mortality rates will have decreased as the year has progressed.

The reason why I expect that region only will moderate the effect of two social vulnerability variables (socioeconomic and minority status and language) on synthetic opioid mortality rates is because only these two variables are compatible with four U.S. census regions (Midwest/Northeast/South/West).

On the other hand, other social vulnerability variables (disability and housing type and transportation) are incompatible with these same four U.S. census regions. In terms of social vulnerability due to disability, the high rates of physical disability are concentrated in rural mining counties (e.g., the Appalachian and Ozark mountains) (Van Gundy, 2006), where they cover some parts of many U.S. regions (Midwest/South/Northeast). Therefore, the region cannot moderate the link between social vulnerability due to disability and synthetic opioid mortality rates. Additionally, social disability due to housing type and transportation is equally distributed throughout the United States. These include: (1) mobile home communities that are concentrated outside metropolitan areas across the United States (Flanagan et al., 2011); (2) multi-unit housing that is likewise concentrated in metropolitan areas (Cutter et al. 2003); and (3) a
low rate of car ownership, again concentrated in metropolitan areas, and especially among inner city poverty-stricken populations (Pucher & Renne 2004). Hence, the region cannot moderate the association between social vulnerability due to housing type and transportation and synthetic opioid mortality rates.

**Methods**

**Data**

This study focuses on analyzing synthetic opioid mortality rates, with pre-existing, cross-sectional social vulnerability in U.S. counties, in the following years: 2014, 2016, and 2018. According to the results discussed in Chapter 1, recently, opioid overdose deaths are caused mainly by synthetic opioid mortality. Specifically, mortality rates from synthetics were approximately four times higher than those from prescription opioids and heroin in 2020. Therefore, this study chose to restrict itself to evaluating synthetic opioid mortality. The reason for analyzing data from 2014 to 2018 is because synthetic opioid mortality rates have sharply increased since 2014 (Alexander et al., 2018; Hoopsick et al., 2021). Furthermore, aggregated cross-sectional data (2014, 2016, 2018) will also be employed in this study. By so doing, this study can examine changes in trends over time using repeated (multi-year) cross-sectional data. This is because opioid mortality rates have consistently increased over the last decade (CDC, 2021), meaning that per-year, cross-sectional data are limited in terms of examining the association between social vulnerability and opioid mortality rates.

*Dependent Variable*
To analyze the link between social vulnerability and synthetic opioid mortality rates, the dependent variable (i.e., synthetic opioid mortality rates in U.S. counties per 100,000 persons) \((N=922)\) was extracted from 2014, 2016, 2018 Centers for Disease Control and Prevention’s Wide-ranging Online Data for Epidemiologic Research (CDC WONDER), and Multiple Cause of Death, 1999–2020 (CDC, 2021). This study could not include all U.S. counties \((N=3,141)\) because of suppression data in CDC WONDER. Therefore, 2,219 counties were excluded, which meaning that only 922 counties were examined in this study.

Synthetic opioid overdose deaths were classified using International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (Geneva, Switzerland: World Health Organization; 2011 [ICD-10]) codes; underlying cause of death codes: X40-44 (unintentional), X60-64 (suicide), X85 (homicide), or Y10-Y14 (undetermined intent); and the opioid type was designated by the multiple cause of death codes: T40.4 (other synthetic narcotics, commonly fentanyl or its analogs) (CDC, 2021). Additionally, the ICD-10 codes were classified using the previous studies (Iwanicki et al., 2018; Milam et al., 2021; Romeiser et al., 2019; Seth et al., 2018b). The dependent variable (synthetic opioid mortality rates) was log-transformed to attain a more normal distribution.

**Independent Variables**

Independent variables were extracted from the 2014, 2016, and 2018 CDC’s Social Vulnerability Index (CDC’s SVI) (ATSDR, 2021). Specifically, four social vulnerability variables (socioeconomic, household composition and disability, minority status and
language, housing type and transportation) and the overall social vulnerability ranking variable were extracted from the 2014, 2016, and 2018 CDC’s Social Vulnerability Index (CDC’s SVI) (ATSDR, 2021).

CDC’s SVI has classified 15 different social factors into four broader themes (percentile ranking): (1) socioeconomic status (below poverty level, unemployed, income, and no high school diploma); (2) household composition and disability (aged 65 or older, aged 17 or younger, over age 5 with a disability, and single-parent households); (3) minority status and language (all persons except non-Hispanic whites and individuals who speak English “less than well”); and (4) housing type and transportation (multi-unit structures, mobile homes, crowding, no vehicle, and group quarters) (ATSDR, 2021). Percentile ranking values were categorized on a scale from 0 to 1, with higher values displaying higher vulnerability (ATSDR, 2021).

Even though both CDC’s Social Vulnerability Index (CDC’s SVI) and its Social Vulnerability Index (SoVI) provide geographic units for social vulnerability (Spielman et al., 2020), there are some distinctions between CDC’s SVI and SoVI. Specifically, the CDC’s SVI is superior for describing a socioeconomic related social vulnerability, whereas SoVI concentrates on elderly-age-related social vulnerability (Tarling, 2017). This current study is more likely to be associated with socio-economic related social vulnerability than with elderly-age-related social vulnerability; therefore, CDC’s SVI is the most suitable for this study.

*Sensitivity Analysis*
Sensitivity tests were conducted to check for potential bias caused by missing data, using three-year average synthetic opioid mortality rates (2014 by 2013–2015; 2016 by 2015–2017; and 2018 by 2017–2019). The results are similar to those of the original analysis. (See Table 1 in Appendix A.)

**The Moderating Role of Region and Year**

A moderating variable influences the association between the independent and dependent variables (Hayes, 2013). The moderation effect can be applied to both region and year, as discussed in the hypotheses. Therefore, it is necessary to enter both into the models as moderating variables. First, region was given as numeric variables by state (e.g., Alabama (1) ~ Wyoming (56)) (ACS, 2021). Grouping variables were thus created for the region variable based on four census regions (the South (1), the West (2), the Northeast (3), and the Midwest (4)) (USCB, 2021a). Second, year variable was created as 2014, 2016, 2018 to examine time-related interactions. By so doing, trend changes could be examined over time.

**Control Variables**

Two control variables (the percentage of male and population size) were extracted from the 2014, 2016, and 2018 American Community Survey at the county level. First, men are more likely than women to be influenced by synthetic opioid-related deaths (Pal, 2020). Within this trend, regions with a higher percentage of males (e.g., mining areas) (Botha & Cronjé, 2015) have greater opioid mortality rates (Keyes et al., 2014, Quinones, 2015). Second, large population size is positively associated with increased opioid
mortality rates (McGranahan & Parker, 2021; Spiller et al., 2009). This means that both the percentage of males and the population size influence the correlation between social vulnerability and synthetic opioid mortality rates. For these reasons, these two control variables were entered into the models to adjust for potential confounding factors.

Statistical Analysis

Ordinary least squares (OLS) regression models were used to examine the association between social vulnerability and synthetic opioid mortality rates because dependent variables are continuous. Additionally, two types of interaction terms were employed to examine the moderating effects of region and year on the link between social vulnerability and synthetic opioid mortality rates. There are three OLS regression models. Model 1 included both independent and control variables. As for model 2, this was comprised of independent variables, an interaction term (Year × Social Vulnerability), and control variables. Model 3 included independent variables, and interaction term (Region × Social Vulnerability), and control variables. Each model includes one interaction term to reduce model complexity. This is helpful because a complex model with multiple interaction terms can lead to multicollinearity problems, which means that a simplified model with one interaction term can relieve this problem (Shieh, 2010).

Each statistical analysis was performed using STATA (version 15.0, StataCorp LLC., College Station, TX). This study does not require IRB review because it is not associated with human subjects or private information.
Results

Tables 1 and 2 present the descriptive statistics. The average synthetic opioid mortality rate per 100,000 persons (logged) in the sampled 922 U.S. counties is 2.339.

There were relatively low social vulnerabilities due to socio-economic (0.368) and household composition and disability (0.329) among the 922 U.S. counties. Notably, however, there were relatively high social vulnerabilities due to minority status and language (0.646) and housing type and transportation (0.560) among the sampled counties. What is more, the average percentile ranking values of the overall tract summary among the 922 counties is 0.447, and did not exceed 0.5. This indicates that, on average, overall social vulnerability is not very high among the sampled counties.

Two moderating variables (year and region) were calculated as percentages. They were also categorized into more than two groups, and the mean of synthetic opioid mortality rates by year and region were calculated using ANOVA. The average percentages of years for the 922 counties are: (1) 2014 (13.99%); (2) 2016 (35.47%); and (3) 2018 (50.54%). The mean of synthetic opioid mortality rates by year in these counties are: (1) 2014 (1.072); (2) 2016 (2.357); and (3) 2018 (2.677). These results suggest that there was a significant amount of data created in 2018; also, as the years passed, synthetic opioid mortality rates continued to rise in these counties. Next, the average percentage of regions in the 922 sampled counties are: (1) South (40.35%); (2) West (4.34%); (3) Northeast (35.79%); and (4) Midwest (19.52%). The mean of synthetic opioid mortality rates by region in the 922 U.S. counties are: (1) South (2.320); (2) West (0.655); (3) Northeast (2.469); and (4) Midwest (2.516). These outcomes indicate that this study has the greatest amount of data for the South and the Northeast. In contrast, it has the least
amount for the West. This is mainly because the South and Northeast have a high number of counties. Noticeably, each county in the West covers a vast area; naturally, this meant a small number of counties in the West. Furthermore, the Midwest and Northeast have higher synthetic opioid mortality rates than do the South and the West. The former has remarkably low mortality rates compared to other regions, meaning that Western counties were likelier to be suppressed in the CDC WONDER data due to a low number of reported deaths.

Table 1


<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synthetic Opioid Mortality Rates per 100,000 persons (logged)</td>
<td>2.339 ±0.977</td>
<td>-1.439</td>
<td>4.645</td>
<td></td>
</tr>
<tr>
<td>Socio-economic</td>
<td>0.368 ±0.222</td>
<td>0.001</td>
<td>0.976</td>
<td></td>
</tr>
<tr>
<td>Household Composition &amp; Disability</td>
<td>0.329 ±0.243</td>
<td>0.000</td>
<td>0.984</td>
<td></td>
</tr>
<tr>
<td>Minority Status &amp; Language</td>
<td>0.646 ±0.258</td>
<td>0.015</td>
<td>0.998</td>
<td></td>
</tr>
<tr>
<td>Housing Type &amp; Transportation</td>
<td>0.560 ±0.258</td>
<td>0.005</td>
<td>0.994</td>
<td></td>
</tr>
<tr>
<td>The Overall Tract Summary Ranking</td>
<td>0.447 ±0.238</td>
<td>0.007</td>
<td>0.996</td>
<td></td>
</tr>
<tr>
<td>% of Male</td>
<td>48.983 ±0.916</td>
<td>46.300</td>
<td>55.500</td>
<td></td>
</tr>
</tbody>
</table>

SD = Standard Deviation
Table 2


<table>
<thead>
<tr>
<th>Variables</th>
<th>N (%)</th>
<th>Mean Synthetic Opioids Mortality Rate</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Year</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>129</td>
<td>1.072</td>
<td>±0.931</td>
</tr>
<tr>
<td>2016</td>
<td>327</td>
<td>2.357</td>
<td>±0.815</td>
</tr>
<tr>
<td>2018</td>
<td>466</td>
<td>2.677</td>
<td>±0.793</td>
</tr>
<tr>
<td><strong>Region</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>372</td>
<td>2.320</td>
<td>±0.961</td>
</tr>
<tr>
<td>West</td>
<td>40</td>
<td>0.655</td>
<td>±0.769</td>
</tr>
<tr>
<td>Northeast</td>
<td>330</td>
<td>2.469</td>
<td>±0.863</td>
</tr>
<tr>
<td>Midwest</td>
<td>180</td>
<td>2.516</td>
<td>±0.898</td>
</tr>
</tbody>
</table>

Table 3 shows the results from the ordinary least squares (OLS) regression models for independent variables and synthetic opioid mortality rates.

First, counties with higher percentile ranking values of minority status and language was negatively associated with higher synthetic opioid mortality rates. Next, counties had higher synthetic opioid mortality rates in 2016 and 2018 than in 2014. Third, counties in the West have lower synthetic opioid mortality rates than counties in the South. Finally, counties in the Northeast and the Midwest have higher synthetic opioid mortality rates than those in the South.

*Year × Social Vulnerability*

The interaction term for Year × Minority & Language in 2018 was significant. Specifically, the year of 2018 facilitated a positive association between social...
vulnerability (minority and language) and synthetic opioid mortality rates. This suggests that counties with higher social vulnerability due to minority status and language in 2018 have higher synthetic opioid mortality rates than those in 2014.

*Region × Social Vulnerability*

Noticeably, the Midwest facilitated a positive link between social vulnerability (socioeconomic) and synthetic opioid mortality rates. Such outcomes suggest that the Midwest counties with higher social vulnerability due to socio-economic conditions have greater synthetic opioid mortality rates than those in the South. As shown in Figure 2, only the Midwest counties show this strong positive relationship between social vulnerability (socio-economic) and synthetic opioid mortality rates.
Furthermore, the Midwest and Northeast both facilitated a positive association between social vulnerability (minority and language) and synthetic opioid mortality rates. As such, the data indicate that the Midwest and Northeast counties with higher social vulnerability due to minority and language have greater synthetic opioid mortality rates than those in the South. As shown in Figure 3, the slope for the regression line decreased in the Northeast and the Midwest, compared to the South, suggesting that the negative association between social vulnerability (minority status and language) and synthetic opioid mortality rates is moderated by region.
opioid mortality rates decreased in the Midwest and Northeast. Additionally, the minimum percentile ranking value of minority status and language in the West is more than 0.5, which means that the West has more ethnic minorities and people who have a language barrier.

**Figure 3**

*Moderating Effect of Region on the Association Between Social Vulnerability (Minority Status & Language Barrier) and Synthetic Opioid Mortality Rates*
Table 3

*Ordinary Least Squares (OLS) Regression Models of Social Vulnerability and Synthetic Opioid Mortality Rates, 2014, 2016, 2018*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 (N=922)</th>
<th>Model 2 (N=922)</th>
<th>Model 3 (N=922)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Coef. [Standard Error]</td>
<td>Coef. [Standard Error]</td>
<td>Coef. [Standard Error]</td>
</tr>
<tr>
<td>Independent Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic</td>
<td>0.017 [0.466]</td>
<td>-0.888 [1.464]</td>
<td>-0.921 [0.785]</td>
</tr>
<tr>
<td>Household Composition &amp; Disability</td>
<td>-0.284 [0.239]</td>
<td>-0.201 [0.692]</td>
<td>0.657 [0.362]</td>
</tr>
<tr>
<td>Minority Status &amp; Language</td>
<td>-0.807*** [0.237]</td>
<td>-2.314** [0.712]</td>
<td>-1.723*** [0.401]</td>
</tr>
<tr>
<td>Housing Type &amp; Transportation</td>
<td>-0.040 [0.253]</td>
<td>-0.134 [0.746]</td>
<td>0.051 [0.435]</td>
</tr>
<tr>
<td>The Overall Tract Summary Ranking</td>
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<td>1.270 [2.316]</td>
<td>1.458 [1.297]</td>
</tr>
<tr>
<td>Year</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2014 Year</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>2016 Year</td>
<td>0.879*** [0.071]</td>
<td>-0.048 [0.554]</td>
<td>0.909*** [0.069]</td>
</tr>
<tr>
<td>2018 Year</td>
<td>1.129*** [0.069]</td>
<td>-0.293 [0.533]</td>
<td>1.176*** [0.068]</td>
</tr>
<tr>
<td>Region</td>
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</tr>
<tr>
<td>South</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>West</td>
<td>-0.706*** [0.119]</td>
<td>-0.645*** [0.118]</td>
<td>-2.442 [1.343]</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.183** [0.053]</td>
<td>0.181** [0.053]</td>
<td>-0.604 [0.369]</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.144* [0.065]</td>
<td>0.142* [0.064]</td>
<td>-0.959* [0.426]</td>
</tr>
<tr>
<td>Year * Social Vulnerability</td>
<td>Reference</td>
<td></td>
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<td>-----------------------------</td>
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<td></td>
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<tr>
<td></td>
<td>Year * Socioeconomic</td>
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<tr>
<td></td>
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<td>Reference</td>
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<td>&amp; Disability</td>
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<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>2016</td>
<td>-0.330</td>
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<td></td>
<td></td>
<td>[0.792]</td>
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<tr>
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<td></td>
<td></td>
<td>[0.757]</td>
<td></td>
</tr>
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<td></td>
<td>Year * Minority Status &amp; Language</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>1.197</td>
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<tr>
<td></td>
<td></td>
<td>[0.796]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2018</td>
<td>1.859*</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>[0.767]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Year * Housing Type &amp; Transportation</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>-0.105</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td>[0.818]</td>
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</tr>
<tr>
<td></td>
<td>Year * The Overall Tract Summary Ranking</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>-0.348</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>[2.635]</td>
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<tr>
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<td>Reference</td>
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<td></td>
</tr>
<tr>
<td>------------------------------</td>
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<td>South</td>
<td>Reference</td>
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<td>West</td>
<td>0.575</td>
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<td>-0.442</td>
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<tr>
<td>Midwest</td>
<td>3.840**</td>
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<td>South</td>
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<tr>
<td>Midwest</td>
<td>-0.174</td>
<td>[0.624]</td>
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<td>Region * Minority Status &amp; Language</td>
<td>Reference</td>
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<tr>
<td>South</td>
<td>Reference</td>
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<tr>
<td>West</td>
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<td>Northeast</td>
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<td>Midwest</td>
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<td>Region * Housing Type &amp; Transportation</td>
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<td>South</td>
<td>Reference</td>
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<tr>
<td>West</td>
<td>-1.150</td>
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<td>Region</td>
<td>Summary Ranking</td>
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<td>--------</td>
<td>----------------</td>
<td>-----------</td>
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<tr>
<td>Northeast</td>
<td>-0.218</td>
<td>[0.589]</td>
<td></td>
</tr>
<tr>
<td>Midwest</td>
<td>-1.228</td>
<td>[0.689]</td>
<td></td>
</tr>
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</table>

**Control Variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Male</td>
<td>-0.098***</td>
<td>[0.026]</td>
</tr>
<tr>
<td>Population(logged)</td>
<td>-0.326***</td>
<td>[0.035]</td>
</tr>
<tr>
<td>Constant</td>
<td>10.660***</td>
<td>[1.428]</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.567</td>
<td>0.585</td>
</tr>
</tbody>
</table>

* P<0.05, ** P<0.01, *** P<0.001
Discussion

The aim of this study is to investigate the relationship between social vulnerability and synthetic opioid mortality rates, and to assess how this relationship varies by region and time in U.S. counties.

The Effect of Minority Status and Language Barrier

Minority status and language barrier are negatively associated with higher synthetic opioid mortality rates. Thus, counties with a higher percentage of minorities are less vulnerable to synthetic opioid mortality than are counties with a higher percentage of native-born residents. This finding was inconsistent with hypotheses 3a and 3b, namely that: (1) counties with higher social vulnerability because of minority status and language will display greater synthetic opioid mortality rates (hypothesis 3a); and (2) the region will facilitate a positive relationship between social vulnerability due to minority status and language and synthetic opioid mortality rates, such that this moderation effect will be maximized in the Northeast and West when compared to other regions (hypothesis 3b). This may be because social vulnerability due to minority status and language barrier includes the Asian population, and they have very low death rates from synthetic opioids. This is supported by the results presented in Chapter 1, which reported that synthetic opioid mortality rates among Asians have remained “very low” between 2010 to 2020.

However, the protective effects of minority status and language barrier against synthetic opioid mortality is actually decreasing over time. This finding was consistent with the hypothesis 5, namely, that the year will moderate the negative relationship
between social vulnerability and synthetic opioid mortality rates. This may be the case because there has been a dramatic increase in synthetic opioid mortality rates annually since 2014 (Hoopsick et al., 2021; Jones et al., 2018; O'Donnell et al., 2017; Scholl et al., 2018).

Furthermore, the protective effect of minority status and language barrier against synthetic opioid mortality is weaker in the Midwest and Northeast. Therefore, even though counties with a higher percentage of minorities have lower synthetic opioid mortality rates than those with higher percentage of those who are native-born, it is necessary to develop tailored interventions that consider regional contexts to account for synthetic opioid mortality in counties with a higher percentage of minorities.

Social Vulnerability and Synthetic Opioid Mortality Rates

Social vulnerability variables are not significantly associated with synthetic opioid mortality rates, except for minority status and language barrier. As a result, the following two research hypotheses were rejected: (1) counties with higher socioeconomic vulnerability will show greater synthetic opioid mortality rates \((hypothesis \ 1a)\); and (2) counties with higher social vulnerability because of disability will display greater synthetic opioid mortality rates \((hypothesis \ 2)\). These seem to be associated with low percentile ranking scores. Social vulnerabilities was computed as a percentile ranking score, and were ranked from 0 to 1 (ATSDR, 2021). The problem was that, in general, social vulnerability scores were low (socio-economic: 0.368, household composition & disability: 0.329; overall: 0.447) in the 922 sampled counties. This may have produced
insignificant results. On the other hand, on average, minority status and language had a high social vulnerability score (0.646) and produced significant results in all models.

Although social vulnerability due to housing type and transportation resulted in a relatively high score (0.560), it also failed to produce a statistically significant result. This finding was inconsistent with hypothesis 4, which stated that counties with higher social vulnerability because of housing status and means of transportation will show greater synthetic opioid mortality rates. This may be the case because social vulnerability due to these factors does not include homelessness—something that is considered a significant and influential factor of the opioid epidemic (SAMHSA, 2020b). The mechanisms through which homelessness contributes to the opioid epidemic have been demonstrated to be that some people became addicted to opioids after they were no longer homeless, whereas others became homeless due to an opioid overdose (SAMHSA, 2020b). For these reasons, throughout the whole United States—from rural to metropolitan areas—regions with the largest homeless population are hotbeds of the epidemic (SAMHSA, 2020b).

Nevertheless, statistical models produced some instructive results through interaction terms (moderation).

The Moderating Effect of Region

The Midwest served as a moderator in the link between social vulnerability (socio-economic) and synthetic opioid mortality rates. Specifically, the Midwest promoted the influence of social vulnerability (socio-economic) on synthetic opioid mortality rates. As such, the adverse effects of social vulnerability due to socio-economic conditions were
maximized in the Midwest. This finding was consistent with hypothesis 1b, which expected that the region would facilitate the positive association between socio-economic vulnerability and synthetic opioid mortality rates; specifically, the adverse effect of the latter on the former would be stronger in the Midwest when compared to other regions.

This same region has experienced a serious economic downturn, which has been caused by deindustrialization ever since the 1970s. In addition, opioids are treated as a form of currency in regions with such serious and long-term economic difficulties, like the Midwest after the emergence of opioids (Jonas et al., 2012). In response, and specifically to decrease synthetic opioid mortality rates, local midwestern governments should account for various social vulnerabilities due to socio-economic status (e.g., poverty, high unemployment, low income, less than a high school education).

The results of this study must be taken into account alongside some limitations. First, it was not feasible to include all US counties because of the suppression rule (i.e., counties with fewer than 10 deaths are excluded) in CDC WONDER data. This rule means that there were no data displayed for numerous counties. For this reason, the subset of counties with available data over-represents wealthy and privileged counties, which may in turn result in lower social vulnerability scores and insignificant results. Second, the temporal causal relationship between independent and dependent variables could not be identified because of the cross-sectional design. Finally, the CDC’s SVI was incompatible with synthetic opioid mortality rates. As a result, many social vulnerability variables failed to produce a statistically significant outcome. Therefore, follow-up studies would benefit from using the other sources of SVI to examine more fully the effect of social vulnerability on synthetic opioid mortality rates.
Concluding Remarks

Despite many social vulnerability variables not providing statistically significant results, this study offers valuable information. One important finding is that the association between social vulnerability and synthetic opioid mortality rates is affected by regional characteristics. This means that social vulnerability is not equally distributed across the United States, thereby leading to regional differences among synthetic opioid mortality rates. For example, the positive link between social vulnerability due to socio-economic conditions and synthetic opioid mortality rates is stronger in the Midwest than in other regions (e.g., Northeast/South/West). As such, regional economic depression plays a significant role in the increasing of synthetic opioid mortality rates in the Midwest.

Most importantly, CDC’s SVI has a limited capacity to explain the current synthetic opioid epidemic. This is because CDC’s SVI has produced many insignificant results regarding synthetic opioid mortality, even though CDC’s SVI has been associated with many other health issues, such as HIV and HCV infections (Van Handel et al., 2016; Wesner et al., 2020), COVID-19 mortality (Carroll & Prentice, 2021; Sung, 2021), and worse surgical outcomes (Diaz et al., 2021). In consideration of the social and health implications of the synthetic opioid epidemic, public health authorities need to develop a new Social Vulnerability Index that specializes in opioid research, thereby facilitating vital research on the effect that social vulnerability has on synthetic opioid mortality rates.
CHAPTER III
THE LONGITUDINAL EFFECT OF COUNTY-LEVEL OCCUPATIONAL AND INDUSTRIAL COMPOSITION ON SYNTHETIC OPIOID-RELATED MORTALITY RATES

Introduction

Regional occupational and industrial composition can be demonstrated as influential factors of the opioid epidemic. Drug-related mortality rates differ according to occupation (Monnat, 2018) and, furthermore, the types of occupation and industry vary regionally. Specifically, rural areas tend to have a higher proportion of manual labor jobs compared to urban areas (McGranahan, 2003). People who are employed in manual labor (e.g., agriculture, forestry, fishing, hunting, and mining) are susceptible to injury, physical disability, and chronic pain (Coben et al., 2004; Keyes et al., 2014). Naturally, as such, rural mining areas, like Appalachia and the Ozarks, have a higher frequency of physical disability and chronic pain than the national average (Van Gundy, 2006), thereby contributing to higher rates of overdose (Keyes et al., 2014, Quinones, 2015). Despite the importance of this topic, there have been few studies on the effect of occupation and industry on opioid mortality rates in macro-level studies (i.e., those that consider the county-level). There is one county-level study (Monnat et al., 2019), which investigated the effect of occupational and industrial composition of these counties on opioid mortality rates. Monnat et al. reported that, first, opioid mortality rates are concentrated among counties with high economic hardship and more blue-collar and service workers. Second, mortality rates stemming from illegal opioids are concentrated among urban
counties with low economic hardship and more professional employees (Monnat et al., 2019). Finally, patterns of opioid mortality vary by region, indicating that mortality from a specific type of opioid is concentrated in certain regions, namely: (1) prescription opioid mortality rates are higher in southern Appalachia, eastern Oklahoma, and parts of the Southwest; (2) heroin mortality rates are greater in New York, the Midwest, central North Carolina, and the Southwestern and Northwestern United States; and (3) synthetic opioid mortality rates are stronger in New England, central Appalachia, and central New Mexico.

Even though this study (Monnat et al., 2019) provides useful information, there still seem to be some important gaps and questions to address. Specifically, the study conducted by Monnat et al. (2019) was based on cross-sectional research (i.e., data collected at an one point in time). However, regional industrial structures change over time because economic advancement is closely related to variations in the structure of economic behaviors (Alcorta et al., 2013). In addition, opioid mortality rates are also greatly affected by temporal changes (Hoopsick et al., 2021; Mattson et al., 2021). This means that a cross-sectional study (Monnat et al., 2019) has a limited capacity to examine the effect that county-level occupational and industrial composition has on opioid mortality rates. What is more, these compositions differ by region (Bednarikova et al., 2021; Nolan et al., 2011). There are also wide regional variations across regions (e.g., Midwest/Northeast/South/West/Appalachia) regarding opioid mortality rates (Mattson et al., 2021; Ruhm, 2017). However, Monnat et al. (2019) do not differentiate regions by industrial structure or opioid mortality rates. In this viewpoint, this study has two research questions to fill these gaps:
Research Question 1: What are the longitudinal effects of occupational and industrial composition on synthetic opioid mortality rates in U.S. counties?

Research Question 2: Are there regional differences (e.g. Midwest/Northeast vs. South/West) in the longitudinal effect of occupational and industrial composition on synthetic opioid mortality rates?

There is also a third wave of the opioid epidemic, which has been caused by the emergence of synthetic opioids in 2014 (Alexander et al., 2018; Hoopsick et al., 2021). The United States is, in fact, currently experiencing this third wave. Therefore, this study has decided to concentrate on synthetic opioid mortality rates.

Background

Occupation, Industry, and Region

Occupation and industry greatly influence a region. This is the case, essentially, because regional economies have been established by occupation and industry (Barbour & Markusen, 2007; Harrington, 1999). Therefore, regional economies are often conditioned by their main industry or industries. For example, fluctuating prices for grain tremendously influence agricultural counties, just as the shale-gas boom has had on mining counties (USDA, 2015). In this regard, much importance is given to regional occupational and industrial structures in terms of economic development, local development planning, and policies among local governments (Nolan et al., 2011). What is more, occupation and industry are configured into regional clusters; thus, interrelated businesses are concentrated within a certain region (Bednarikova et al., 2021; Nolan et al.,
For this reason, regional industry clusters generate distinctive occupational characteristics from region to region (Bednarikova et al., 2021; Nolan et al., 2011). Thus, the conditions of occupational and industrial structures are naturally affected by varying regional economic, social, and working conditions (Cainelli and Iacobucci, 2016; Neffke et al., 2018), which can lead to regional differences in health outcomes.

Developed countries, including the United States, have decreased health-harming factors (e.g., extremely toxic industrial substances and work-related injuries) in occupations and industries (BLS, 2021a; Creely et al., 2007). However, there were still a plethora of work-related injuries and illnesses in the United States in 2020 (4,764 deaths, 2.7 million injuries and illnesses) (BLS, 2021b; BLS, 2021c). The essential problem is that work-related injuries and illnesses are concentrated in certain types of occupations and industries (e.g., transportation/material-moving occupations and construction/extraction jobs) (BLS, 2021b). This means that manual labor has a negative impact on health outcomes, both regionally and individually. For this reason, occupation and industry have been conceptualized in health-related empirical studies. In terms of individual-level studies, workers in manual labor, such as in agriculture (Orrenius & Zavodny, 2009; Xiao et al., 2013), construction (Arcury et al., 2012; Dong et al., 2009; Grzywacz et al., 2007), and manufacturing (Quandt et al., 2006), have a higher prevalence of employment-related injuries. Generally, occupation-related health problems were conceptualized as deriving from a mixture of individual-level factors (e.g., age, education, and gender) and occupation-related ones (e.g., working hours, physical and psychological desire, and industry) (Berdahl, 2008; Wilkins & Mackenzie, 2007). Therefore, there has been relatively less concern with examining macro-level effects in
the occupational health field. However, macro-level effects have become more important in the field because they provide insight into regional differences in occupational health, which enable tailored intervention strategies based on regional contexts (Schuurman et al., 2008). Regional differences in occupational health can happen among regions with different socio-demographic characteristics (e.g., socioeconomic status) or different types of occupations and industries (Diez-Roux, 1998). Regional differences in occupational health can also occur because of environmental factors (Boyle & Willms, 1999).

Specifically, the enforcement of the occupational health and safety act has varied state-by-state in the United States, which has led to regional disparities in occupational health. For example, levying a fine decreased work-related accidents in states with strong federal Occupational Safety and Health Agency (OSHA) enforcement (Gray & Scholz, 1993). States that focused on state-oriented OSHA programs were more likely to reduce work-related mortalities compared to those that placed attention on federal-oriented OSHA programs (Bradbury, 2006). Additionally, regional contexts like economic and social conditions can lead to regional disparities in occupational health outcomes. For example, economically depressed regions, such as the Rust Belt, tend to have a higher prevalence of work-related injuries (Lopez, 2004) and lower life expectancy (Woolf & Schoomaker, 2019).

Occupation and industry have also been conceptualized in terms of substance abuse studies. Substance abuse, like heavy drinking, is associated with occupation-related mechanisms, such as social networks (Ahern et al., 2008) and job-related stress that differ by occupation (Barrett, 2002; Bennett et al., 2000; Frone, 1999; MacDonald & Shields, 2001). As a result, according to individual-level studies, workers in service, sales, and
agriculture have higher rates of heavy drinking than professional employees (Diala et al., 2004; Jarman et al., 2007; Matano et al., 2002). Barnes & Brown (2013) reported that workers in installation, construction, and sales are prone to higher heavy drinking rates than what is the case for professional workers. According to multi-level analysis (a combination of individual- and macro-level), students living in rural mining counties are likelier to use alcohol and tobacco than those living in rural, non-mining counties (Gay et al., 2018). According to macro-level studies, counties that are characterized by higher levels of poverty and a higher proportion of blue-collar and service jobs have higher overall opioid mortality rates (Monnat et al., 2019). Second, drug-related mortality rates are greater in counties dependent on the mining industry (Monnat, 2018).

Structural-level analysis is ideal for explaining the effect of occupation and industry on substance abuse much more so than individual-level analysis. This is because structural factors, such as labor market insecurity and industrial structure, are closely associated with substance abuse triggers like mental illnesses, injuries, and chronic pain (Montez et al., 2017; Sherman, 2009; Solar & Irwin, 2010). For example, the workers who perform hard manual labor in primary industries (e.g., agriculture, forestry, fishing, hunting, and mining) are susceptible to injuries, disability, and chronic pain (Coben et al., 2004; Keyes et al., 2014). For this reason, coal mining areas of the Southern United States, such as Appalachia and the Ozarks have a higher percentage of disability and chronic pain than others (Van Gundy, 2006), thereby leading to a higher rate of opioid overdose (Keyes et al., 2014, Quinones, 2015). Myriad coal mines are located in the Western United States; in addition, the coal mining industry has become more prosperous in the West than in the Eastern United States (Metcalf & Wang, 2019). In terms of
agriculture industries, environmental stress factors like exacting work, weather hazards, and financial burdens have also contributed to an increase in opioid overdose (Choi, 2020; Shaw et al., 2020). Counties in the Western United States (e.g., California’s Central Valley, Eastern Oregon, and Eastern Washington) have the highest proportion (e.g., people in workforce 10.7+) of agriculture industries in the United States (DATA USA, 2022a). Thus, the following hypotheses have been developed:

**Hypothesis 1:** In the South and the West, increasing the percentage of primary industry occupations or primary industries in a county will be associated with greater county-level synthetic opioid mortality rates.

Second, Rust Belt counties (e.g., Midwest and Northeast counties) dependent on secondary industries (e.g., manufacturing and production) have experienced serious economic downturn, including deindustrialization, high unemployment, and low wages, over the last few decades, which lead to higher drug-related death rates (Keyes et al., 2014; McLean, 2016). The following hypothesis is thus proposed:

**Hypothesis 2:** In the Midwest and the Northeast, increasing the percentage of secondary industry occupations or secondary industries in a county will be associated with greater county-level synthetic opioid mortality rates.

In addition, this phenomenon is not limited to secondary industries like manufacturing and production in Rust Belt counties (e.g., Midwest and Northeast counties). This is the case because regional economies are determined by main industry. Therefore, the demise of a region’s main industry (secondary industries) also negatively influences consumer industries in Rust Belt counties due to a decrease in purchasing power. In such areas, furthermore, high-wage manufacturing jobs have been replaced by
low-wage service jobs, again, due to deindustrialization (Cheremukhin, 2014; Massey & Hirst, 1998). As a result, low-wage service jobs in this region are closely associated with higher rates of opioid overdose death (Ikeler, 2021). In light of this literature review, this study hypothesizes that:

**Hypothesis 3:** In the Midwest and Northeast, increasing the percentage of consumer industries (e.g., sales and service occupations) in a county will be associated with higher county-level synthetic opioid mortality rates.

Drug distributors are responsible for the U.S. opioid epidemic because they engage in diversion of opioids in cooperation with drug trafficking networks; nor do they report suspicious orders of restricted drugs placed by their customers (Haffajee & Mello, 2017; Inciardi et al., 2007). Drug trafficking networks operate mainly in the Midwest and Northeast (DEA, 2019; Stamm, 2020). For this reason, legal actions have been filed against numerous pharmaceutical distribution centers, which are located in the Midwest and Northeast, in states like Michigan, Ohio, and New York (Haffajee & Mello, 2017). Based on this evidence, the following hypothesis has been drafted:

**Hypothesis 4:** In the Midwest and Northeast, increasing the percentage of distribution industries (e.g., wholesale trade and retail trade industries) in a county will be associated with higher county-level synthetic opioid mortality rates.

Counties, which are characterized by attributes like being urban, having less poverty, and employing more professional workers, have higher mortality rates from illegal opioids (Monnat et al., 2019). Even though the synthetic opioid epidemic is thought to have originated in the eastern parts of the United States (Pardo et al., 2019; Zoorob, 2019), synthetic opioid epidemic has already spread to the Western and Southwestern
United States according to some news articles (Greenson, 2020; Healy, 2019). Consequently, recently (2017–2019), synthetic opioid mortality rates have sharply increased, especially among metropolitan areas in the Southern and Western United States, such as Dallas-Fort Worth, TX (Denton, Johnson, Parker, and Tarrant counties), Harris County, TX (Houston), Denver County, CO (Denver), King County, WA (Seattle), and Los Angeles County (Los Angeles), CA (Shover et al., 2020). Based on these previous studies, the next hypothesize states that:

**Hypothesis 5:** In the South and West, increasing the percentage of professional, scientific, and management, and administrative and waste management services industries in a county will be associated with higher county-level synthetic opioid mortality rates.

**Methods**

**Data**

This study is designed to examine the effect of county-level occupational and industrial composition on synthetic opioid mortality rates using a longitudinal design. Drawing on data from the Centers for Disease Control and Prevention’s Wide-Ranging Online Data for Epidemiologic Research (CDC WONDER), Multiple Cause of Death (2014-2018) and the American Community Survey (2014-2018), this study created an aggregate time-series dataset (balanced panel dataset) for longitudinal analysis. A balanced panel is a dataset in which each panel element is detected every year (Baltagi, 2008). However, panel data are generally unbalanced because of a dearth of observations
collected in specific years (Baltagi & Liu, 2020). Even though unbalanced panel data can be used in longitudinal analyses (e.g., fixed/random effects models), they inflate error terms that may produce biased inference (Baltagi, 2008). Therefore, a balanced panel dataset was generated.

Synthetic opioid mortality rates have started to increase since 2014 (Alexander et al., 2018; Hoopsick et al., 2021), so that I used data from 2014 to 2018.

**Dependent Variable**

To investigate the longitudinal effect of county-level occupational and industrial composition on synthetic opioid mortality rates, a dependent variable (synthetic opioid mortality rates) \(N=1,653\) was gleaned from CDC WONDER, Multiple Cause of Death, 1999–2020 (CDC, 2021). Synthetic opioid mortality rates were also sorted, depending on International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (Geneva, Switzerland: World Health Organization; 2011 [ICD-10]) codes; underlying cause of death codes: X40-44 (unintentional), X60-64(suicide), X85 (homicide), or Y10-Y14 (undetermined intent). Additionally, the opioid type was defined by the multiple cause of death codes: T40.4 (other synthetic narcotics, commonly fentanyl or its analogs) (CDC, 2021). The categorization of ICD-10 codes was derived from previous studies (Iwanicki et al., 2018; Milam et al., 2021; Romeiser et al., 2019; Seth et al., 2018b). The dependent variable (synthetic opioid mortality rates in U.S. counties per 100,000 persons) was changed into a logged variable to reduce skewing.

**Independent Variables**
Nine Independent variables (occupations and industry) were obtained from the American Community Survey (2014–2018) because it provides occupation and industry variables at the county-level (ACS, 2021). Industry refers to the kind of activity conducted at a worksite; occupation refers to the type of work performed to make a living (USCB, 2021b). The American Community Survey (ACS) provides valuable information about changes in county-level occupational and industrial composition by year (ACS, 2021; USCB, 2021b).

The ACS provides data on five occupations (management, business, science, and the arts; service; sales and office work; natural resources, construction, and maintenance; production, transportation, and material-moving jobs) and 12 industries (agriculture, forestry, fishing and hunting, and mining; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing, and utilities; information; finance, and insurance, and real estate and rental and leasing industries; professional, scientific, and management, and administrative and waste management services; educational services, and health care and social assistance; arts, entertainment, and recreation, and accommodation and food services; public administration) (ACS, 2021). However, previous studies have reported that substance abuse problems (e.g., heavy drinking or opioid overdose deaths) are associated with certain occupational and industrial sections, such as service, sales, and manual labor (Diala et al., 2004; Jarman et al., 2007; Matano et al., 2002), secondary industries (Keyes et al., 2014; McLean, 2016), agricultural industries (Choi, 2020; Shaw et al., 2020), the mining industry (Monnat, 2018), distribution industries (e.g. wholesale trade and retail trade industries) (Haffajee & Mello, 2017; Inciardi et al., 2007), and professional employees (Monnat et al., 2019). Therefore,
this study included only 11 variables, namely, four occupations (% of service occupations; % of sales and office occupations; % of natural resources, construction and maintenance occupations; % of production, transportation, and material moving occupations) and seven industries (% of agriculture, forestry, fishing and hunting, and mining industries; % of construction industry; % of manufacturing industry; % of wholesale trade industry; % of retail trade industry; % of transportation and warehousing, and utilities industries; % of professional, scientific, and management, and administrative and waste management services industries).

Furthermore, six manual labor occupations and industries were merged into four composite variables to avoid messy models. This include: (1) percentage of primary industry occupations (% of natural resources, construction and maintenance occupations); (2) percentage of primary industries (% of agriculture, forestry, fishing and hunting, and mining industries + % of construction industry); (3) percentage of secondary industry occupations (% of production, transportation, and material moving occupations); and (4) percentage of secondary industries (% of manufacturing industry + % of transportation and warehousing, and utilities industries).

Hence, only nine independent variables were included: the four occupations (% of service occupations; % of sales and office occupations; % of primary industry occupations; % of secondary industry occupations) and five industries (% of primary industries; % of secondary industries; % of wholesale trade industry; % of retail trade industry; % of professional, scientific, and management, and administrative and waste management services industries).
Control Variables

Eight control variables (% of unemployed, % of poverty, household income, % of bachelor’s degree, % of white, % of black, % of male, and population size) were gleaned from the ACS (2014–2018) at the county level. This is because these eight variables can serve as latent confounders, which affect the association between independent (occupation and industry) and dependent (synthetic opioid mortality rates) variables. The data show that the counties struggling with high levels of unemployment, poverty, lower educational achievement, and high population density are more likely to have a greater prevalence of opioid misuse (Spiller et al., 2009). Furthermore, there are racial disparities among opioid mortality rates; opioid mortality rates are the strongest among whites and blacks (Alexander et al., 2018; KFF, 2021). Men are also more vulnerable to synthetic opioid-related mortality (Pal, 2020); thus, male-dominated regions (e.g., rural mining regions) (Botha & Cronjé, 2015) tend to have higher rates of opioid overdose deaths (Keyes et al., 2014, Quinones, 2015).

Statistical Analysis

The fixed-effects (FE) regression model was used to examine the longitudinal effect of county-level occupational and industrial composition on synthetic opioid mortality rates in the sampled U.S. counties (Table 3) because a dependent variable is a continuous variable. This can be summarized as follows (Figure 1):
The FE regression model is a statistical model in which the levels of independent variables (model parameters) are presumed to be fixed, whereas the dependent variable changes in compliance with the levels of independent variables (Allison, 2005; Salkind, 2010). In addition, in an FE regression model, the constant term is presumed to be fixed and to change according to the time series objects. On the other hand, the slope ($\beta_n$) is considered to be the equal by time series objects (Wooldridge, 2015). This differs from a random effects (RE) model in which some model parameters (e.g., unobserved differences($u_i$)) are treated as random variables (Allison, 2005). The Hausman & Taylor test is used primarily to choose between FE and RE models (Hausman & Taylor, 1981).
Specifically, if the null hypothesis is false \((p < 0.05)\), then a FE is appropriate. If the null hypothesis is true \((p > 0.05)\), then an RE is ideal (Hausman & Taylor, 1981). The results of the Hausman & Taylor test indicate that the null hypothesis is false \((p < 0.05)\) (Table 3), which means that an FE regression model is the most suitable for this study.

There are two FE regression models. The first pertains to the Midwest and Northeast; the second model shows the South and West. The reason why this model was divided into two regions is because counties in the Midwest and Northeast have higher synthetic opioid mortality rates than those in the South and West, according to Chapters 1 and 2. Therefore, it is necessary to compare the effect of county-level occupational and industrial composition on synthetic opioid mortality rates between the two regions.

All Statistical analyses were carried out by STATA (version 15.0, StataCorp LLC., College Station, TX). This study does not require acceptance from the institutional review board because it used secondary data, which do not contain personal information.

**Results**

Table 1 (Midwest/Northeast) and Table 2 (South/West) display the descriptive statistics. The Midwest and Northeast (880 counties) have higher synthetic opioid mortality rates (logged) than the South and West (773 counties) (2.521 vs 2.024). This is supported by a two-tailed t-test, which indicates that the result is statistically significant \((p\text{-value}: .000, \text{obtained t-value}: -10.34)\).

The occupational and industrial composition of the counties were calculated as percentages. In the Midwest and Northeast, there are high proportions of sales and office work (23.13%), service jobs (17.86%), and secondary industry occupations (13.78%).
Additionally, secondary industries (17.67%) constitute the largest industry in the Midwest and Northeast.

In the South and West, there are high proportion of sales and office work (23.92%) and service occupations (18.08%). Both secondary industries (13.82%) and retail trade (11.92%) are the largest industry, even though the South and West (13.82%) have a lower proportion of secondary industries than the Midwest and Northeast (17.67%). Instead, the South and West (11.82%) have a higher concentration of professional, scientific, and management, and administrative and waste management services industries than the Midwest and Northeast (9.82%).

One important feature is that there are high proportions of sales and office work jobs and service occupations throughout the United States, which means that consumer industries based on the domestic market lead the U.S. economy. Another important attribute is that secondary industries (e.g., manufacturing and production) are still the main industries in the Midwest and Northeast. In contrast, professional and scientific industries lead the economies in the South and West.
Table 1

*Descriptive Statistics of Occupational and Industrial Composition and Synthetic Opioid Mortality Rates of Counties in the Midwest and Northeast (N=880), 2014–2018*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synthetic Opioid Mortality Rates per 100,000 persons (logged)</td>
<td>2.521</td>
<td>±0.850</td>
<td>-0.747</td>
<td>4.425</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Service Occupations</td>
<td>17.86</td>
<td>±2.654</td>
<td>11.10</td>
<td>33.50</td>
</tr>
<tr>
<td>% of Sales and Office Occupations</td>
<td>23.13</td>
<td>±1.919</td>
<td>16.30</td>
<td>27.70</td>
</tr>
<tr>
<td>% of Primary Industry Occupations</td>
<td>8.211</td>
<td>±2.183</td>
<td>2.000</td>
<td>19.50</td>
</tr>
<tr>
<td>% of Secondary Industry Occupations</td>
<td>13.78</td>
<td>±5.008</td>
<td>3.800</td>
<td>31.60</td>
</tr>
<tr>
<td>% of Primary Industries</td>
<td>6.906</td>
<td>±2.177</td>
<td>1.800</td>
<td>19.70</td>
</tr>
<tr>
<td>% of Secondary Industries</td>
<td>17.67</td>
<td>±5.845</td>
<td>5.400</td>
<td>39.90</td>
</tr>
<tr>
<td>% of Wholesale Trade Industry</td>
<td>2.647</td>
<td>±0.656</td>
<td>0.600</td>
<td>4.900</td>
</tr>
<tr>
<td>% of Retail Trade Industry</td>
<td>11.59</td>
<td>±1.287</td>
<td>7.200</td>
<td>16.00</td>
</tr>
<tr>
<td>% of Professional, Scientific, and Management, and Administrative and Waste Management Services Industries</td>
<td>9.816</td>
<td>±2.826</td>
<td>3.300</td>
<td>20.50</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Unemployed</td>
<td>4.258</td>
<td>±1.209</td>
<td>1.800</td>
<td>9.900</td>
</tr>
<tr>
<td>% of Poverty</td>
<td>9.239</td>
<td>±3.857</td>
<td>2.300</td>
<td>28.30</td>
</tr>
<tr>
<td>Household Income(logged)</td>
<td>11.53</td>
<td>±1.004</td>
<td>9.011</td>
<td>14.49</td>
</tr>
<tr>
<td>% of Bachelor’s Degree</td>
<td>18.67</td>
<td>±5.523</td>
<td>6.600</td>
<td>36.80</td>
</tr>
<tr>
<td>% of White</td>
<td>82.57</td>
<td>±13.21</td>
<td>20.60</td>
<td>97.90</td>
</tr>
<tr>
<td>% of Black</td>
<td>8.687</td>
<td>±8.713</td>
<td>0.300</td>
<td>48.10</td>
</tr>
<tr>
<td>% of Male</td>
<td>49.05</td>
<td>±0.864</td>
<td>46.80</td>
<td>54.60</td>
</tr>
<tr>
<td>Population(logged)</td>
<td>12.47</td>
<td>±1.021</td>
<td>9.957</td>
<td>15.47</td>
</tr>
</tbody>
</table>

SD = Standard Deviation
Table 2

Descriptive Statistics of Occupational and Industrial Composition and Synthetic Opioid Mortality Rates of Counties in the South and West (N=773), 2014–2018

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Synthetic Opioid Mortality Rates per 100,000 persons (logged)</strong></td>
<td>2.024</td>
<td>±1.099</td>
<td>-1.626</td>
<td>4.822</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Service Occupations</td>
<td>18.08</td>
<td>±2.841</td>
<td>10.50</td>
<td>30.20</td>
</tr>
<tr>
<td>% of Sales and Office Occupations</td>
<td>23.92</td>
<td>±2.509</td>
<td>13.80</td>
<td>29.80</td>
</tr>
<tr>
<td>% of Primary Industry Occupations</td>
<td>9.011</td>
<td>±2.529</td>
<td>2.700</td>
<td>21.90</td>
</tr>
<tr>
<td>% of Secondary Industry Occupation</td>
<td>11.59</td>
<td>±4.016</td>
<td>2.600</td>
<td>28.30</td>
</tr>
<tr>
<td>% of Primary Industries</td>
<td>7.985</td>
<td>±2.637</td>
<td>2.700</td>
<td>23.20</td>
</tr>
<tr>
<td>% of Secondary Industries</td>
<td>13.82</td>
<td>±4.967</td>
<td>4.000</td>
<td>33.30</td>
</tr>
<tr>
<td>% of Wholesale Trade Industry</td>
<td>2.541</td>
<td>±0.756</td>
<td>0.500</td>
<td>5.400</td>
</tr>
<tr>
<td>% of Retail Trade Industry</td>
<td>11.92</td>
<td>±1.770</td>
<td>3.900</td>
<td>17.10</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Unemployed</td>
<td>4.335</td>
<td>±1.152</td>
<td>1.600</td>
<td>8.700</td>
</tr>
<tr>
<td>% of Poverty</td>
<td>10.41</td>
<td>±3.704</td>
<td>2.300</td>
<td>22.70</td>
</tr>
<tr>
<td>Household Income(logged)</td>
<td>11.70</td>
<td>±1.135</td>
<td>8.870</td>
<td>15.01</td>
</tr>
<tr>
<td>% of Bachelor’s Degree</td>
<td>19.15</td>
<td>±5.430</td>
<td>4.800</td>
<td>37.20</td>
</tr>
<tr>
<td>% of White</td>
<td>72.92</td>
<td>±15.90</td>
<td>18.00</td>
<td>98.60</td>
</tr>
<tr>
<td>% of Black</td>
<td>16.14</td>
<td>±14.32</td>
<td>0.300</td>
<td>71.90</td>
</tr>
<tr>
<td>% of Male</td>
<td>48.99</td>
<td>±1.015</td>
<td>46.30</td>
<td>55.70</td>
</tr>
</tbody>
</table>

SD = Standard Deviation
Table 3 displays the results of the FE regression models, in which all measured and unmeasured, time-invariant, and county characteristics are considered (Allison, 2005) for independent variables and synthetic opioid mortality rates from 2014 to 2018.

**Midwest/Northeast**

First, an increase in the percentage of primary industries in a given county has been associated with higher synthetic opioid mortality rates ($B=0.182$, $p<0.05$). Second, an increase in the percentage of wholesale trade industry in a given county has been associated with greater synthetic opioid mortality rates ($B=0.384$, $p<0.01$). Third, an increase in the percentage of professional, scientific, and management, and administrative and waste management services industries in a given county has been linked with higher synthetic opioid mortality rates ($B=0.241$, $p<0.01$).

**South/West**

Strengthening the percentage of professional, scientific, and management, and administrative and waste management services industries in a county has been connected with greater synthetic opioid mortality rates ($B=0.164$, $p<0.05$).
### Table 3

*Fixed Effects Regression Models of Occupational and Industrial Composition and Synthetic Opioid Mortality Rates of Counties, 2014–2018*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Midwest/Northeast ((N=880))</th>
<th>South/West ((N=773))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>Coef.</td>
</tr>
<tr>
<td></td>
<td>[Standard Error]</td>
<td>[Standard Error]</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Service Occupations</td>
<td>0.021</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>[0.057]</td>
<td>[0.058]</td>
</tr>
<tr>
<td>% of Sales and Office Occupations</td>
<td>-0.000</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>[0.048]</td>
<td>[0.046]</td>
</tr>
<tr>
<td>% of Primary Industry Occupations</td>
<td>-0.119</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>[0.091]</td>
<td>[0.086]</td>
</tr>
<tr>
<td>% of Secondary Industry Occupations</td>
<td>-0.179</td>
<td>-0.084</td>
</tr>
<tr>
<td></td>
<td>[0.056]</td>
<td>[0.055]</td>
</tr>
<tr>
<td>% of Primary Industries</td>
<td><strong>0.182</strong></td>
<td>-0.074</td>
</tr>
<tr>
<td></td>
<td>[*0.087]</td>
<td>[0.086]</td>
</tr>
<tr>
<td>% of Secondary Industries</td>
<td>0.084</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>[0.060]</td>
<td>[0.064]</td>
</tr>
<tr>
<td>% of Wholesale Trade Industry</td>
<td><strong>0.384</strong></td>
<td>-0.103</td>
</tr>
<tr>
<td></td>
<td>[*0.130]</td>
<td>[0.131]</td>
</tr>
<tr>
<td>% of Retail Trade Industry</td>
<td>0.080</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>[0.070]</td>
<td>[0.057]</td>
</tr>
<tr>
<td>% of Professional, Scientific, and Management, and Administrative and Waste Management Services Industries</td>
<td><strong>0.241</strong></td>
<td><strong>0.164</strong></td>
</tr>
<tr>
<td></td>
<td>[*0.074]</td>
<td>[*0.069]</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Unemployed</td>
<td>-0.775***</td>
<td>-0.548***</td>
</tr>
<tr>
<td></td>
<td>[0.051]</td>
<td>[0.051]</td>
</tr>
<tr>
<td>% of Poverty</td>
<td>0.085</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>[0.046]</td>
<td>[0.041]</td>
</tr>
<tr>
<td>Variable</td>
<td>Estimate 1</td>
<td>Estimate 2</td>
</tr>
<tr>
<td>---------------------------</td>
<td>------------</td>
<td>------------</td>
</tr>
<tr>
<td>Household Income (logged)</td>
<td>-8.817*</td>
<td>-4.236</td>
</tr>
<tr>
<td>% of Bachelor’s Degree</td>
<td>0.093</td>
<td>0.073</td>
</tr>
<tr>
<td>% of White</td>
<td>-0.063</td>
<td>-0.088*</td>
</tr>
<tr>
<td>% of Black</td>
<td>0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td>% of Male</td>
<td>0.114</td>
<td>0.228</td>
</tr>
<tr>
<td>Population (logged)</td>
<td>6.226</td>
<td>0.633</td>
</tr>
<tr>
<td>Constant</td>
<td>22.891</td>
<td>39.123</td>
</tr>
<tr>
<td>$u_i$ (Standard Deviation)</td>
<td>1.945</td>
<td>2.661</td>
</tr>
<tr>
<td>$\varepsilon_t$ (Standard Deviation)</td>
<td>0.409</td>
<td>0.398</td>
</tr>
<tr>
<td>$\rho$ (Fraction of variance due to $u_i$)</td>
<td>0.958</td>
<td>0.978</td>
</tr>
<tr>
<td>Hausman &amp; Taylor Test (Chi-Square)</td>
<td>206.66***</td>
<td>166.36***</td>
</tr>
</tbody>
</table>

* P<0.05, ** P<0.01 *** P<0.001
Discussion

The objective of this study is to investigate the effect that counties’ occupational and industrial structures have on synthetic opioid mortality rates, by means of a longitudinal methodology. Therefore, this study attempts to understand changes over time (2014–2018) regarding the burden of synthetic opioid mortality in occupational and industrial composition of the counties comprising the two U.S. regions (e.g., Midwest/Northeast vs. South/West).

The Effect of Primary Industries

In the Midwest and Northeast, an increase in the percentage of primary industries in a given county has been linked to a growth in synthetic opioid mortality rates in that county. This finding was inconsistent with hypothesis 1, which expected that, in the South and West, increasing the proportion of primary industry occupations or primary industries in a county would be linked with higher county-level synthetic opioid mortality rates. This is because hard manual labor jobs in primary industries are closely associated with work-related injuries, physical disability, and chronic pain (BLS, 2021b; Coben et al., 2004; Keyes et al., 2014)—all of which lead to opioid overdose and deaths. More importantly, this phenomenon was observed in only the Midwest and Northeast, and it may in fact be related to types of coal mining and deindustrialization. Specifically, Western coal mines (e.g., in Arizona, Montana, New Mexico, Uinta Basin, and Wyoming) are more productive than their Eastern counterparts (e.g., in Appalachia, Ohio, Pennsylvania, and New York) because those in the West are composed mainly of open-
pit coal mines (Metcalf & Wang, 2019). On the other hand, coal mines in the East consist largely of underground mines (Metcalf & Wang, 2019). For this reason, these mines are more vulnerable to workers’ accidents and injuries (Rahimi et al., 2022). This, in turn, leads to higher rates of opioid overdose death. In addition, this industry has been relocated from the Eastern United States to the West due to a lack of productivity in the East’s mines (Metcalf & Wang, 2019). As a result, the decline of the mining industry has contributed to high unemployment and economic difficulties in the Midwest and Northeast. This phenomenon has resulted in mental illnesses and opioid overdosing, outcomes which are termed “deaths of despair.” (Case & Deaton, 2015). As such, even though the Western United States has a higher concentration of primary industries than the East (e.g., the Midwest and Northeast), primary industries, such as mining, have triggered synthetic opioid mortality in only the Eastern United States (e.g., Midwest and Northeast). It is thus urgent that public health authorities focus on reducing synthetic opioid mortality rates by targeting counties with a higher percentage of primary industries in the Midwest and Northeast. These areas also need regional economic revival plans and bolstered occupational safety and health for manual laborers, if there is to be a decrease in synthetic opioid mortality rates.

On the other hand, primary industry occupations failed to produce a statistically significant result. This finding was inconsistent with hypothesis 1, which stated that, in the South and West, an increase in the proportion of primary industry occupations or primary industries in a given county would be associated with higher county-level synthetic opioid mortality rates. This may be the case because, compared to primary industries, primary industry occupations are highly concentrated in western parts of the
United States (DATA USA, 2022b)—precisely where the synthetic opioid mortality rates are lowest.

**Secondary Industries and Synthetic Opioid Mortality Rates**

Secondary industry occupations (production, transportation, and material moving occupations) and secondary industries (manufacturing industry + transportation and warehousing, and utilities industries) did not lead to statistically significant results. These findings were inconsistent with hypothesis 2, which expected that, in the Midwest and Northeast, increasing the proportion of secondary industry occupations or secondary industries in a given county would be linked to higher county-level synthetic opioid mortality rates. There are several reasons why these, in fact, occurred.

First, secondary industries include numerous occupations (BLS, 2022). Therefore, worksite environments differ greatly. Specifically, production, transportation, and material moving occupations include both manual labor jobs (e.g., delivery truck drivers, hand laborers and material movers, heavy and tractor-trailer truck drivers, material moving machine operators, and railroad workers) and non-manual labor positions (e.g., air traffic controllers, airline and commercial pilots, flight attendants) (BLS, 2022), which may lead to an insignificant relationship between secondary industry occupations and synthetic opioid mortality rates. Second, secondary industry (i.e., manufacturing) includes not only low-skilled, manual labor jobs (e.g. miscellaneous production workers; other assemblers and fabricators; machinists; industrial truck & tractor operators; packers & packagers, hand), but also high-skilled, non-manual occupations (e.g., other managers; industrial engineers, including health & safety; other engineering technologists; software
developers; aerospace engineers) (DATA USA, 2022c), which may lead to an insignificant relationship between secondary industries and synthetic opioid mortality rates. These results may reflect that governments in Rust Belt areas have been trying to achieve manufacturing industry transformation (dying smokestack industry → innovative technology-based industry) through industry–university collaboration since the 1980s (Atkinson, 1991; Jones, 1986). Some Rust Belt cities (e.g., Pittsburgh, PA and Chicago, IL) have indeed achieved such desired results (Planey, 2020; Armstrong, 2021). Secondary industries may thus be less vulnerable to the synthetic opioid epidemic than primary industries in the Midwest and Northeast.

*Consumer Industries and Synthetic Opioid Mortality Rates*

Consumer industries, such as sales and service occupations, failed to produce a statistically significant result. This finding was inconsistent with *hypothesis 3*, which expected that, in the Midwest and Northeast, increasing the proportion of consumer industries in a given county would be linked to higher county-level synthetic opioid mortality rates. This may be because the substance abuse status in consumer industries is likelier to be affected by individual-level factors like age, education, gender, psychosocial stress than by macro-level factors, including labor market insecurity and industrial structure. In this regard, the research covered in this study’s literature review are also based mainly on individual-level factors (Barnes & Brown, 2013; Diala et al., 2004; Jarman et al., 2007; Matano et al., 2002). There is, however, one macro-level study (Monnat et al., 2019) that demonstrated that counties with a higher percentage of service occupations have higher rates of overall opioid mortality.
The Effect of Wholesale Trade Industry

In the Midwest and Northeast, increasing the percentage of wholesale trade industry in a county has been associated with an increase in synthetic opioid mortality rates. This finding was consistent with hypothesis 4, which stated that, in the Midwest and Northeast, increasing the proportion of distribution industries (e.g., wholesale trade industry) would be linked to higher county-level synthetic opioid mortality rates.

Wholesale trade industry has been associated with the opioid epidemic because prescription opioids have been circulated by pharmaceutical wholesale distributors, which is closely linked with prescription opioid diversion in cooperation with drug trafficking networks (Inciardi et al., 2007). The same is true of synthetic opioids. The supply of illegally manufactured synthetic opioids is more likely to takes place through wholesale than retail (Ciccarone et al., 2017). What is more, drug trafficking networks operate mainly in the Midwest and Northeast (DEA, 2019; Stamm, 2020), which has resulted in that wholesale trade industry becoming the major contributor to the synthetic opioid epidemic in the Midwest and Northeast.

Professional, Scientific, and Management, and Administrative and Waste Management Services Industries

Across the United States, increasing the percentage of professional, scientific, and management, and administrative and waste management industries in a county has been associated with an increase in synthetic opioid mortality rates. This outcome was inconsistent with hypothesis 5, which postulated that, in the South and West, increasing
the proportion of professional, scientific, and management, and administrative and waste management industries would be linked to higher county-level synthetic opioid mortality rates.

This is paradoxical because, normally, high occupational grades like professional, white-collar jobs are negatively associated with opioid overdose deaths. This paradox is associated with job classification. Specifically, professional, scientific, and management, and administrative and waste management industries cover both high-wage positions (e.g., managers, software developers, lawyers, judges, accountants, auditors, management analyst, computer systems analysts, project management specialists, and marketing managers) and low-wage earners (e.g. landscaping and groundskeeping workers, janitors and cleaners, security guards, maids and housekeepers) (DATA USA, 2022d). Therefore, low-wage occupations in this sector may also have high rates of synthetic opioid mortality. Given that professional, scientific, and management, and administrative and waste management industries are concentrated in urban areas (Monnat et al., 2019) (Figure 2), this may mean that the synthetic opioid epidemic has spread to urban areas in the United States.
Public health authorities must therefore increase their efforts to decrease synthetic opioid mortality rates by targeting low-wage occupations in urban areas.

The outcomes of this research do also have some limitations. First, due to the suppression rule in CDC WONDER (counties with fewer than 10 deaths are eliminated), it was unfeasible to include all US counties. Therefore, suppressed data often exclude thinly-populated counties, and this may have produced an inaccurate inference. To address issues pertaining to this bias, a sensitivity analysis was conducted using three-year average synthetic opioid mortality rates (2014 by 2013–2015; 2016 by 2015–2017; 2018 by 2017–2019). According to these outcomes (see Appendix A), overall, the results
are identical to the original analysis, meaning that suppressed data did not generate biased inference. Second, because five-year longitudinal data (2014–2018) were used, this study was unable to consider fully the changes in occupational and industrial structures by region (long-period variation) and the influence of the COVID-19 pandemic (after Feb. 2020). Therefore, the interpretation of the results may be limited in scope.

Concluding Remarks

This study contributes to the established academic corpus by examining the effect that counties’ occupational and industrial composition have on synthetic opioid mortality rates, by means of longitudinal design (2014–2018). According to Chapter 1, synthetic mortality rates have been sharply increasing since 2014 and, furthermore, they have generated different values from year to year. Therefore, this study took into account temporal variations in synthetic opioid mortality rates that produced accurate results.

Through this study, it was confirmed that the occupational and industrial composition of a counties is a crucial indicator to address synthetic opioid epidemic. Most importantly, certain occupational and industrial clusters are more likely to be associated with the epidemic. Additionally, this situation is seen mainly in the Midwest and Northeast where the epidemic is at its worst. Specifically, both primary industries and the wholesale trade industry have contributed to the increase in synthetic opioid mortality rates, but only in the Midwest and Northeast. Regional characteristics of these regions, such as deindustrialization and drug distribution networks, may have produced significant results regarding the synthetic opioid mortality rates. It is therefore suggested that public health authorities should concentrate on occupations and industries in the
Midwest and Northeast when planning interventions for this epidemic. What is more, occupational and industrial classifications may lead to either an increase or a decrease in synthetic opioid mortality rates because each category covers numerous occupations, including both high-paying positions and low-paying jobs, or both non-manual labor occupations and those that involve manual labor. Therefore, occupational and industrial classifications should be considered when interpreting this study’s results.
CONCLUSION

The opioid epidemic is now considered the epicenter of the public health crisis in the United States. There are many deaths, annually, that are directly attributed to opioid overdose. There are also regional, racial, and socio-economic disparities among opioid mortality rates, which lead to wider health gaps between diverse racial and socio-economic groups. This dissertation examined trends in opioid mortality by opioid types, race, and region; it also investigated the county-level estimates an effect of social vulnerability and occupational and industrial composition on synthetic opioid mortality rates.

In Chapter 1, I discovered that, first, synthetic opioids were the leading contributor to recent opioid overdose deaths in the United States. As such, I contended that public authorities must concentrate on synthetic opioid problems. Second, mortality rates from every type of opioid are higher among whites and blacks. It is certainly, as well, that according to recent patterns of synthetic opioid mortality (2019–2020), blacks have higher synthetic opioid mortality rates than whites. However, public health authorities have yet to pay attention to this very serious problem among black population (SAMHSA, 2020a). Therefore, it is vital that public health authorities focus on reducing synthetic opioid mortality rates within the black population. Third, a severe synthetic opioid epidemic is highly concentrated in certain regions, namely, Appalachia, the Midwest, the Northeast, and East Coast, whereas the West has a more minor problem with synthetics. This suggests that the synthetic opioid epidemic tends to spread quickly to geographically-connected regions.
In Chapter 2, I also identified that social vulnerability due to minority and language skills contributed to a decrease in synthetic opioid mortality rates. This means that counties with a higher percentage of ethnic minorities with language barriers are less susceptible to deaths from synthetic opioid overdose. However, the protective role of these factors against synthetic opioid mortality is wearing off as the year progressed; they are also less effective in the Midwest and Northeast. This suggests that the synthetic opioid epidemic is worsening over time and is spreading to various ethnicity groups; it also indicates that the region is the main contributor to the differences in mortality rates related to synthetic opioids. In addition, this study demonstrated that the Midwest had a positive moderating effect on the association between social vulnerability due to socio-economic conditions and synthetic opioid mortality rates. This suggests that the negative effects of social vulnerability (socio-economic) on these mortality rates were strengthened in the Midwest. This study thus recommends that public health policies and programs focus on decreasing such rates should be aimed at improving the socio-economic conditions in the Midwest. Lastly, this study identified that many social vulnerability variables have produced non-significant results. This suggests that the CDC’s SVI has a weak relationship with synthetic opioid mortality rates. Follow-up research is therefore needed to examine the association between social vulnerability and synthetic opioid mortality rates, by means of using other SVI sources.

Chapter 3 details another important discovery, namely that primary industries were significant contributors of the increasing synthetic opioid mortality rates in the Midwest and Northeast. Generally, hard manual labors in primary industries are noticeable contributors to work-related injuries, physical disability, and chronic pain (BLS, 2021b;
Coben et al., 2004; Keyes et al., 2014), all of which result in deaths from opioid overdose. This phenomenon is more common in the Eastern United States (e.g., Midwest and Northeast) because coal mines are often underground, and places where accidents frequently occur (Rahimi et al., 2022). Moreover, primary industries, such as coal mining, in the Rust Belt have suffered greatly from deindustrialization. This has largely resulted from low productivity in the East’s coal mines (Metcalf & Wang, 2019), which has contributed to mental disorders and drug abuse (Case & Deaton, 2015). In this context, the synthetic opioid epidemic has been spreading quickly to the Midwest and Northeast since 2014; as a result, primary industries in these regions became a hot spot for the synthetic opioid epidemic. Second, I also found that the wholesale trade industry contributed to the increase in synthetic opioid mortality rates in the Midwest and Northeast. This industry has made significant contributions to the spread of the synthetic opioid epidemic because the distribution of illegally manufactured synthetic opioids has primarily been performed by wholesale trade (Ciccarone et al., 2017) in cooperation with drug trafficking networks (Inciardi et al., 2007). To make matters even worse, drug trafficking networks are based in the Midwest and Northeast (DEA, 2019; Stamm, 2020). As a result, this industry has become the single most contributing factor to the synthetic opioid epidemic in these regions. Lastly, I identified that professional, scientific, and management, and administrative and waste management services industries contributed to the increase in synthetic opioid mortality rates in the United States. This is a contradiction because, normally, professional occupations have lower synthetic opioid mortality rates than their manual labor counterparts. This suggests that occupational and industrial categorizations may influence the effect that a county’s occupational and
industrial composition has on synthetic opioid mortality rates. This is because each classification includes both high-paying and low-paying jobs, or both non-manual labor positions and those involving manual labor (DATA USA, 2022d). For example, professional, scientific, and management, and administrative and waste management industries include high-salary employment (e.g., managers, software developers, lawyers, judges, accountants, auditors, management analyst, computer systems analysts, project management specialists, marketing managers), but manual labor and low-salary occupations (e.g., landscaping and groundskeeping workers, janitors & building cleaners, security guards, maids and housekeepers) also account for approximately 20% percent of these industries (DATA USA, 2022d). This may result in higher synthetic opioid mortality rates. Therefore, further consideration needs to be given to the interpretation of occupational and industrial categorization.

On the basis of previous studies (Barnes & Brown, 2013; Case & Deaton, 2015; Diala et al., 2004; Fang & Feng, 2020; Fatemi et al., 2017; Flanagan, et al., 2011; Gay et al., 2018; Jarman et al., 2007; Matano et al., 2002; Monnat, 2018; Monnat et al., 2019; Spielman et al., 2020), these studies discovered growing evidence that various social factors—including social vulnerability and occupational and industrial composition—are contributing to increasing or decreasing synthetic opioid mortality rates in the United States. Therefore, this dissertation has provided innovative insights and discerning evidence as to how social factors, beyond simply income and education, influence synthetic opioid mortality rates. By examining a vast range of social variables, this study made crucial discoveries regarding important risk factors of synthetic opioid epidemic, which had not been identified in any of the previous studies. Additionally, this
dissertation has produced detailed evidence of the regional disparities among risk factors of the synthetic opioid epidemic. To achieve this, I divided regions into several parts and focused on specific areas. Notably, the adverse effects of risk factors for the synthetic opioid epidemic are stronger in certain regions, where the synthetic epidemic is the most serious. One important implication is that it is necessary to account for regional characteristics when planning specific public health interventions that address risk factors related to the synthetic opioid epidemic.
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APPENDICES
Appendix A. Results from the Sensitivity Analysis

Table 1 presents the results from the sensitivity analysis, which was performed to check for possible bias related to missing values through the three-year average death rate from synthetic opioids (2014 by 2013–2015; 2016 by 2015–2017; 2018 by 2017–2019).

Table 1

<table>
<thead>
<tr>
<th>Variables</th>
<th>2014 (N=387)</th>
<th>2016 (N=683)</th>
<th>2018 (N=924)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef. [Standard Error]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independent Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic</td>
<td>-0.541 [0.615]</td>
<td>-0.923 [0.531]</td>
<td>-0.213 [0.448]</td>
</tr>
<tr>
<td>Household Composition &amp; Disability</td>
<td>-0.118 [0.335]</td>
<td>-0.571 [0.293]</td>
<td>-0.335 [0.244]</td>
</tr>
<tr>
<td>Minority Status &amp; Language</td>
<td>-1.273*** [0.324]</td>
<td>-1.304*** [0.269]</td>
<td>-0.650** [0.230]</td>
</tr>
<tr>
<td>Housing Type &amp; Transportation</td>
<td>0.094 [0.371]</td>
<td>-0.597 [0.312]</td>
<td>-0.236 [0.266]</td>
</tr>
<tr>
<td>The Overall Tract Summary Ranking</td>
<td>0.750 [1.062]</td>
<td>2.109* [0.921]</td>
<td>1.011 [0.776]</td>
</tr>
<tr>
<td>Region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>West</td>
<td>-0.508*** [0.112]</td>
<td>-0.928*** [0.139]</td>
<td>-1.020*** [0.094]</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.018 [0.078]</td>
<td>0.165* [0.070]</td>
<td>0.237*** [0.063]</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.078 [0.089]</td>
<td>0.190* [0.082]</td>
<td>0.087 [0.072]</td>
</tr>
<tr>
<td>Control Variables</td>
<td>% of Male</td>
<td>Population(logged)</td>
<td>Constant</td>
</tr>
<tr>
<td>---------------------------</td>
<td>-----------</td>
<td>--------------------</td>
<td>----------</td>
</tr>
<tr>
<td></td>
<td>-0.109**</td>
<td>-0.081**</td>
<td>-0.068**</td>
</tr>
<tr>
<td></td>
<td>[0.034]</td>
<td>[0.028]</td>
<td>[0.022]</td>
</tr>
<tr>
<td></td>
<td>-0.335***</td>
<td>-0.204***</td>
<td>-0.144***</td>
</tr>
<tr>
<td></td>
<td>[0.049]</td>
<td>[0.041]</td>
<td>[0.033]</td>
</tr>
<tr>
<td>Population(logged)</td>
<td>11.309***</td>
<td>9.146***</td>
<td>7.666***</td>
</tr>
<tr>
<td></td>
<td>[1.908]</td>
<td>[1.566]</td>
<td>[1.230]</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.578</td>
<td>0.330</td>
<td>0.322</td>
</tr>
</tbody>
</table>

* P<0.05, ** P<0.01 *** P<0.001
INTRODUCTION

“My research interests are sociology of health, social determinants of health, socio-demographic disparities in health related to substance abuse (opioids, marijuana, tobacco, alcohol) and obesity. My approaches include secondary data analysis and quantitative research methods.”

EDUCATION

2023  Ph.D. Sociology, Utah State University, Logan, Utah
- Dissertation Title: “County Characteristics and Opioid Mortality Rates in the United States”

2015  M.P.H. Public Health, Indiana University, Bloomington, Indiana
- Master of Public Health in Behavioral, Social, and Community Health

2013  B.H.A. Health Administration, Yonsei University, South Korea

RESEARCH & TEACHING INTERESTS

Sociology of Health; Social Inequality; Population Health; Health Disparities; Substance Abuse; Opioids/Marijuana; Tobacco; Alcohol; Obesity; Gender; Race/Ethnicity; Occupation/Industry; Social Vulnerability; Demography; Secondary Data Analysis; Quantitative Research; Spatial Analysis; STATA

HONORS AND AWARDS

1. 2018  Doctoral Funding Package - $20,000 per year stipend with full tuition waiver and subsidized health plan.
2. 2019  Doctoral Funding Package - $20,000 per year stipend with full tuition waiver and subsidized health plan.
3. 2020  Doctoral Funding Package - $20,000 per year stipend with full tuition waiver and subsidized health plan.
4. 2021  Doctoral Funding Package - $20,000 per year stipend with full tuition waiver and subsidized health plan.
PEER REVIEWED PUBLICATIONS


PEER REVIEWED PEDAGOGICAL MATERIALS


PUBLISHED RESEARCH REPORTS


CONFERENCE PRESENTATIONS

Oral Presentation


Poster Presentation


GRANTS & FUNDING

Internal
2019  Graduate Student Travel Grant. *Utah State University Research and Graduate Studies* ($300)

2019  Graduate Student Travel Grant. *Utah State University Department of Sociology, Social Work, and Anthropology* ($500)

**COURSES AS TEACHING ASSISTANT**

*Spring 2022 (Lecturer)*  
SOC-3120-MO1 XL Social Statistics (Online), Utah State University

*Summer 2021 (Lecturer)*  
SOC-3120-MO1 XL Social Statistics (Online), Utah State University

*Spring 2021*  
SOC-3330-MO1 Medical Sociology, Dr. Gabriele Ciciurkaitė  Utah State University

*Fall 2020*  
SOC-3330-MO1 Medical Sociology, Dr. Gabriele Ciciurkaitė  Utah State University  
SOC-6010-001 Development of Sociological Theory, Dr. Gabriele Ciciurkaitė  Utah State University

*Spring 2020*  
SOC 3120-LB1XL Social Statistics, Dr. Mehmet Soyer  Utah State University

*Fall 2019*  
SOC 3120-001 Social Statistics, Dr. Mehmet Soyer  Utah State University  
SOC 3120-002 Social Statistics, Dr. Mehmet Soyer  Utah State University

*Spring 2019*  
SOC 3110  Social Inequality, Dr. So-Jung Lim  Utah State University

**RELATED PROFESSIONAL EXPERIENCE**

Research Assistant  *Utah State University*, Logan, Utah  
Aug 2018 - May 2022  - Conducted research on social inequality and substance abuse of vulnerable population

Editorial Board  *SAGE Publications Inc: Tobacco Use Insight*  
(https://journals.sagepub.com/editorial-board/tui)  
Jan 2019 - Present  - Reviewed and evaluated manuscripts
- Reviewed Papers


7. Manuscript ID (TUI-2020-0050): Acceptability of smokers of a cigarette tracker as wearable for smoking reduction. 18-Dec-2020


9. Manuscript ID (TUI-2021-0003): Perceptions of Vaping among Young Adults: Does Regulation Improve Health Outcomes?. 23-Feb-2021

10. Manuscript ID (TUI-2021-0011): Translation and examination of the reliability and validity of the Spanish version of the Smoking Self-Efficacy Questionnaire among Latino smokers?. 04-April-2021


Guest Reviewer

- Preventive Medicine

- Journal of Health Psychology


- Substance Abuse: Research and Treatment


- Journal of Public Health


- British Journal of Clinical Psychology


- Asia Pacific Journal of Public Health


- Social Problems

- Tobacco Induced Diseases


- Public Health Reports


SKILLS AND LANGUAGES

Program: Stata, SPSS, Excel
Language: English (Fluent), Korean (Native)

PROFESSIONAL MEMBERSHIPS

2019 - Present American Sociological Association (ASA)
   - Drugs and Society
2021 - 2021 Population Association of America (PAA)