Social and Economic Determinants of the Fatal Overdose Rate in Ohio

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Preface

List of Terms

ACS: American Community Survey

Appalachia: A region ranging from southern New York to northern Alabama that has been traditionally been associated with coal mining and poverty.

CDC: Center for Disease Control

Fentanyl: A synthetic opioid that is extremely strong relative to traditional opioids.

MAT: Medication-Assisted Treatment

Opioids: A class of powerful analgesic drugs that activate opioid receptors that are either derived from opium or synthesized.

OxyContin: Brand name version of oxycodone (an opioid)

Pill Mills: Physician-owned opioid distributors masquerading as pain management clinics. They are effectively semi-legal drug dealers.

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Abstract

The United States is currently suffering from a severe opioid addiction epidemic that kills more people than car crashes, HIV/AIDS, or gun violence. This thesis examines the impact of economic and demographic factors on the opioid overdose death rate in counties in Ohio. I find that while most indicators are fairly ambiguous, the disability rate among females aged 35 to 64 is positively correlated with the fatal overdose rate, whereas the same disability rate with males has a protective effect. Furthermore, medium density areas have the lowest rates. These findings are important for addressing the root causes of the epidemic, and can help target prevention and treatment resources towards those who would benefit from them the most.

Introduction

The current opioid epidemic is the worst drug epidemic in US history. While opioids are a legitimate medical treatment for acute pain, they are highly addictive and come with the risk of abuse, dependence, and fatal overdose.[1] Abuse of and dependence on opioids has serious consequences. Since 2016, drug overdoses have been the leading cause of accidental death in the United States.[2] Overdoses kill more people than gun violence, motor vehicle incidents, or the HIV/AIDS epidemic did at its peak.[3] In fact, the scourge of opioid overdoses is so severe that it has led to an increase in all-cause mortality for white Americans despite mortality decreasing for all other Americans and citizens of comparably developed countries.[4] Reducing the number of deaths due to opioids is essential to reversing this trend, increasing the labor supply, and improving outcomes for millions of Americans.

In this thesis, I will start by reviewing the literature. The literature review will open by defining rationality in the context of economics. I will follow this up by examining the different models of addiction and how they approach rationality, and what these models say about opioid addiction policy. I will then examine the history of the opioid epidemic. I will open this by defining opioids, then provide a brief timeline, and then discuss the first American opioid epidemic (which occurred shortly after the Chinese opioid epidemic). Next, I will discuss the factors that led to the current opioid epidemic, such as changes in physician attitudes towards opioids and the introduction of Oxycontin. I will then describe the transition from prescription painkillers to heroin and synthetic opioids, and how they became available across the United States. I will briefly discuss opioid addiction treatment and naloxone, and then give a quick rundown on the state of Ohio. I end the literature review by classifying explanations as either supply side or demand side. In my data and methods chapter, I explain my model, provide summary statistics and visualizations of my data, describe my data sources, and then finally explain my choice of statistical methods. In my results chapter, I run ordinary least squares regressions, and then briefly describe the results. Finally, I provide a conclusion and a copy of some of the code I used to produce this thesis.

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[1] Aliprantis and Schweitzer, "Opioids and the Labor Market."

[2] Maguire, "The Opioid Crisis in Appalachia."

[3] Quinones, *Dreamland*; Ciccarone, "Fentanyl in the US Heroin Supply"; Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes."

[4] Case and Deaton, "Mortality and Morbidity in the 21st Century."

Chapter 1

Literature Review

1.1 Rationality

1.1.1 Definition of Rationality

While there is significant evidence that consumers are not "rational", the economics discipline is founded upon the theory of consumer rationality[1]. According to traditional economic theory, individuals making consumption decisions engage in economizing behavior, meaning that they "choose the options that best advance their personal desires and goals at the least possible cost."[2] This is a form of rational decision-making. Economists abstract away personal desires and goals by viewing them through the lines of utility, which measures the benefit an individual derives from making any particular choice. Utility differs from person to person because each individual has different preferences, making rational decisions inconsistent between individuals. Furthermore, making rational choices does not necessarily mean making the correct choices. People sometimes derive more utility from doing something "wrong", like eating junk food, than doing something "right", like eating sufficient vegetables[3].

For the theory of consumer rationality to work, consumers must make choices based on a set of consistent preferences that are complete, reflexive, and transitive. Completeness means that given any two goods X and Y, either X is preferred to Y, Y is preferred to X, or X and Y are preferred equally. Reflexivity means that consumers are indifferent between two identical instances of the same good. For example, reflexivity would be violated if a consumer preferred one dime to another. Transitivity means that if a consumer prefers X to Y, and prefers Y to Z, then they must prefer X to Z.[4]

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[1] Arcidiacono, "Consumer Rationality in a Multidisciplinary Perspective."
[2] Gwartney, *Microeconomics*, 11.
[3] Gwartney, *Microeconomics*.
[4] Black, Hashimzade, and Myles, "Consumer Rationality."

1.1.2 Addiction and Rationality

Health economists study addiction using three types of models. Imperfectly rational models of addiction give consumers two incompatible yet internally consistent utility functions. For example, a consumer might have both a farsighted utility function used for making long-term decisions, such as buying a house, and a short-term utility function for making marginal decisions, such as choosing to use heroin to stave off withdrawal.[5] This model does a good job of explaining how heroin addicts living on the street can simultaneously express impressive plans for the future while injecting leftover drops of heroin from a dirty cotton using a used needle.[6] Myopic irrational models describe addicts' utility functions as exclusively shortsighted by using some combination of heavy discounting of future consequences and future consequences being unknown. For example, an addict may not care about long-term health consequences, and even if they do no individual substance user knows what consequences they will face in the future. Finally, there are theories of rational addiction, as exemplified by Becker and Murphy's work.[7]

1.1.3 A Theory of Rational Addiction

While "addictions would seem to be the antithesis of rational behavior", Becker and Murphy's *A Theory of Rational Addiction* attempts to bridge the gap between homo economus and homo sapiens.[8] According to the authors, "a good is potentially addictive if increases in past consumption raise current consumption."[9] This property is referred to as adjacent complementarity. Adjacent complementarity can also be described as an increase in consumption today increasing the marginal utility of consumption in the future. The level of adjacent complementarity of a good determines the addictiveness of that good.[10] Given that opioid dependence has been known to occur after only a week of continuous use, and that opioid cravings are so extreme that long-term addicts are unable to "appreciate the intensity of craving when they are not currently experiencing it", opioids are extremely addictive under this definition.[11] This is supported by the medical literature, which finds that heroin is significantly more addictive than any other substance.[12]

Harmful addictions usually feature tolerance and reinforcement. Tolerance means that current consumption is less satisfying when past consumption is greater, while reinforcement means that greater current consumption increases future consumption.[13] Opioid tolerance makes any given level of consumption less satisfying because it decreases the duration and intensity of euphoria, sedation, and analgesia that opioids

[5] Culyer, *The Dictionary of Health Economics.*
[6] Bourgois and Schonberg, *Righteous Dopefiend.*
[7] Culyer, *The Dictionary of Health Economics.*
[8] "A Theory of Rational Addiction."
[9] Becker and Murphy, 675.
[10] Becker and Murphy, "A Theory of Rational Addiction."
[11] Meier, *Pain Killer*; Badger et al., "Altered States," 685.
[12] Nutt et al., "Development of a Rational Scale to Assess the Harm of Drugs of Potential Misuse."
[13] Becker and Murphy, "A Theory of Rational Addiction."

induce, which encourages users to increase their consumption over time.[14] From a clinical perspective, opioid tolerance occurs through three mechanisms: changes in the body's metabolism of the drug, changes in the body's receptors for a drug, and changes in the brain's response to the stimulus from the drug.[15] The most famous reinforcement mechanism for opioids is withdrawal. Withdrawal is a common term for the symptoms that chronic opioid users feel when they discontinue use.[16] These symptoms are deeply unpleasant, and the "fear of withdrawal has been considered to be one of the major forces behind persistent drug abuse in addicts."[17]

Jonathan Gruber and Botond Koszegi expanded on Becker and Murphy's theory of rational addiction in their article "Is Addiction"Rational"? Theory and Evidence". While Gruber and Koszegi agree with the majority of the traditional theory of rational addiction, they make consumer preferences time-inconsistent. This means that users of addictive substances do not fully factor in the cost of future addiction when making the decision to consume an addictive substance. While time consistency in preferences is an assumption of the rational consumer model, psychological experiments support Gruber and Koszegi's claim that consumers do not have truly time consistent preferences.[18] Anecdotally, this is reflected in the number of substance users who express a desire to quit while continuing to consume.[19] Under this modified theory of rational addiction, in addition to the externalities of substance use, there is an "internality": users consume more of a harmful substance than they would choose to if the substance did not have addictive properties. These internalities can dwarf the externalities of a substance in size, meaning that corrective policies that only factor in externalities can be significantly smaller than would be optimal[20] [[21]].

1.1.4 Policy Implications of Addiction Models

Each model of addiction suggests somewhat different policies. Under the imperfectly rational model, policymakers should try to help addicts and potential future addicts use their far-sighted utility function when considering substance use. In contrast, the myopic model suggests maximizing the price of addictive substances, since under the model addicts do not have a long-view utility function to appeal to, and therefore minimizing access is the only feasible approach. When using the theory of rational addiction, policymakers should select policies that either prevent initial addiction (e.g. high prices on addictive goods) or help addicted individuals escape the reinforcement trap (e.g. inpatient treatment, detoxes, and medication-assisted treatment) are

[14] Collett, "Opioid Tolerance"; Morgan and Christie, "Analysis of Opioid Efficacy, Tolerance, Addiction and Dependence from Cell Culture to Human."

[15] Collett, "Opioid Tolerance."

[16] Collett; Morgan and Christie, "Analysis of Opioid Efficacy, Tolerance, Addiction and Dependence from Cell Culture to Human."

[17] Collett, "Opioid Tolerance," 62.

[18] Kahneman, *Thinking, Fast and Slow.*

[19] Bourgois and Schonberg, *Righteous Dopefiend*; Gruber and Koszegi, "Is Addiction "Rational"?"

[20] This section uses the terms "male" and "female" to indicate that the dataset only captures biological sex at birth, and not gender identity.

[21] Gruber and Koszegi, "Is Addiction "Rational"?"; Gruber, "Smoking's 'Internalities'."

effective, since the model imagines addicts as rational decision makers that derive excessive utility from substance use. While Gruber and Koszegi's modification of the theory of rational addiction does not change the policy implications, it suggests that much larger interventions are needed (e.g. much higher price increases), since the internalities of addiction are often just as large, if not larger, than the externalities, and the original model does not consider internalities.

1.2 History of the Opioid Epidemic

1.2.1 What are Opioids?

Opioids are a group of powerful analgesic drugs.[22] They both alleviate pain and create intense euphoria, and are considered highly addictive.[23] Opioids generate these effects via activating opioid receptors.[24] Opium–the original opioid–is processed liquid from opium poppies, and has been used for pleasure, pain alleviation, and controlling dysentery for thousands of years. In the early 1800s, opium was first purified into morphine, which was later transformed into heroin in the 1870s. More opium derivatives, as well as fully synthetic opioids, were developed in the 1900s. Today, the family of opioids includes heroin, morphine, Fentanyl, oxycodone, hydrocodone, buprenorphine, and methadone. Unfortunately, these new stronger opioids increased the risk of overdose, which is when a high dose of opioids causes respiratory failure among other things. While opioids are highly addictive and considered dangerous, they remain uniquely effective at treating severe pain.[25]

1.2.2 America's First Opioid Epidemic

Opium and its derivatives have been consumed in the United States since the nation's founding.[26] During the American Civil War, injured soldiers were given morphine to treat their pain.[27] At the time, morphine was relatively new, and was considered almost a miraculous panacea. While some physicians noticed and warned others about the dangers of morphine as early as the late 1860s, it was prescribed heavily by doctors until approximately 1900 due to demand from patients and inadequate medical education.[28] By 1895, approximately 0.5% of Americans were addicted to morphine and other opioids, with addiction being more prevalent among middle and upper class whites, especially white women.[29] Eventually, a combination of medi-

[22]Kastin, *Handbook of Biologically Active Peptides*.

[23]Macy, *Dopesick*; Quinones, *Dreamland*.

[24]Kastin, *Handbook of Biologically Active Peptides*.

[25]Brummett and Cohen, *Managing Pain*; Rastegar and Fingerhood, *The American Society of Addiction Medicine Handbook of Addiction Medicine*.

[26]Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[27]Arablouei and Abdelfatah, "A History of Opioids in America."

[28]Arablouei and Abdelfatah; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[29]Trickey, "Inside the Story of America's 19th-Century Opiate Addiction"; White, *Slaying the Dragon*.

cal education, changing social norms, and regulation convinced doctors to cut back their opioid prescriptions, ending the epidemic.[30] Afterwards, opioid usage became associated with poor people of color–specifically opium with Chinese immigrants and heroin with African Americans–setting the stage for the demonization of opioids that lasted until quite recently.[31]

There are many similarities between the current opioid epidemic and the one that ended 120 years ago. Both epidemics were driven by iatrogenic addiction, meaning that users first started with opioids that were legitimately prescribed to them by a physician.[32] Both epidemics primarily affected wealthier white Americans.[33] In both cases, doctors were incentivized to acquiesce to demands for opioids from wealthier patients, despite evidence suggesting that it was not a proper or safe treatment.[34] Both epidemics were worsened by new supposedly non-addictive opioids–morphine and heroin in the 19th century and OxyContin in the 21st.[35] Finally, in both epidemics, addiction was treated as a medical issue, which is in sharp contrast to how opioid addiction was treated during the era in which it primarily affected impoverished people of color.[36]

1.2.3 Changes in Pain Treatment

The current opioid epidemic was ushered in by changing physician attitudes towards pain alleviation. After the first American opioid epidemic, physicians had an extremely negative outlook on opioids. They were rarely prescribed, even to terminally ill patients in hospitals.[37] During this time period, chronic pain was considered out of scope for most physicians. Patients went to specialized multidisciplinary pain centers, where they received a variety of non-opioid treatments before opioids were even considered. If doctors elected to prescribe opioids, they used low strength pills that were combined with less addictive painkillers, such as acetaminophen, which made them difficult to abuse. By the 1980s, the last physicians who had dealt with widespread iatrogrenic addiction had died off, and stigma towards opioids began to fade.[38]

The change in physicians' attitudes towards opioids was accelerated by several factors. Insurance companies seeking to cut costs reduced payments to or stopped reimbursing entirely providers of multidisciplinary pain care due to its relatively high sticker price compared to medication-based treatment. More generally, insurance companies pressured doctors to spend less time with patients, and there is no better

[30] Ciccarone, "Fentanyl in the US Heroin Supply"; Quinones, *Dreamland*; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[31] Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[32] Meier, *Pain Killer*; Musto, "Iatrogenic Addiction"; Quinones, *Dreamland*; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[33] Quinones, *Dreamland*; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[34] Meier, *Pain Killer*; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[35] Ciccarone, "Fentanyl in the US Heroin Supply"; Quinones, *Dreamland*; Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[36] Trickey, "Inside the Story of America's 19th-Century Opiate Addiction."

[37] Quinones, *Dreamland*.

[38] Meier, *Pain Killer*; Quinones, *Dreamland*.

way to quickly end a visit than breaking out a prescription pad.[39] Simultaneously, hospitals began prioritizing patient satisfaction, creating an incentive structure that rewarded handing out opioid prescriptions to anyone who demanded them, including suspected addicts.[40] Finally, the introduction and marketing of OxyContin further quelled fears of iatrogenic addiction and made opioids prescriptions seem as routine as antibiotics or statins.[41] By 1995, physician attitudes toward pain had shifted so much that pain became the fifth vital sign, leading to changes in treatment guidelines that encouraged opioid prescriptions for non-cancer chronic pain.[42]

1.2.4 The Introduction of OxyContin

OxyContin is a prescription opioid painkiller brought to market by Purdue Pharmaceuticals in 1996.[43] It is made from oxycodone, a derivative of opium, and can rival morphine in strength.[44] OxyContin was unlike previous prescription painkillers in several aspects. In contrast to previous medications such as Vicodin, OxyContin was not blended with additional substances such as acetaminophen, which made it much easier to snort and inject. Furthermore, it was available in up to 160 milligram doses, whereas previous painkillers were capped at five to ten milligrams.[45] Finally, OxyContin featured a time-delay release mechanism, which the FDA allowed Purdue to market as an abuse deterrent, leading to the perception that OxyContin was non-addictive despite a complete lack of clinical studies demonstrating that this was the case.[46]

More specifically, OxyContin's original label stated "Delayed absorption as provided by OxyContin tablets, is believed to reduce the abuse liability of a drug."[47] In addition to encouraging more prescriptions from physicians, this label quelled the concerns of pharmacists seeing a huge uptake in opioid prescriptions in the late 1990s. Furthermore, Purdue Pharmaceuticals sponsored continuing medical education for physicians that minimized the risk of opioid addiction. The seminars lauded a supposed study by Porter and Jick, claiming that it demonstrated that less than one percent of patients could become addicted to opioids.[48] In reality, the "study" was

[39] Meier, *Pain Killer*; Quinones, *Dreamland*; Van Zee, "The Promotion and Marketing of OxyContin."

[40] Quinones, *Dreamland*.

[41] Meier, *Pain Killer*; Quinones, *Dreamland*; Van Zee, "The Promotion and Marketing of OxyContin."

[42] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes"; Meier, *Pain Killer*; Quinones, *Dreamland*.

[43] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes"; Meier, *Pain Killer*; Quinones, *Dreamland*.

[44] Meier, *Pain Killer*; Quinones, *Dreamland*.

[45] Quinones, *Dreamland*.

[46] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes"; Esch, "How One Sentence Helped Set Off the Opioid Crisis"; Meier, *Pain Killer*; Quinones, *Dreamland*; Van Zee, "The Promotion and Marketing of OxyContin."

[47] Esch, "How One Sentence Helped Set Off the Opioid Crisis"; Quinones, *Dreamland*, 27.

[48] In reality, the only thing that Porter and Jick's letter demonstrated was that opioid dependence can occur after a brief period of use even when used exclusively under medical supervision while in

a brief letter that simply provided summary statistics on opioid use from a database that only covered inpatient care, but the gambit was effective at encouraging wanton prescribing of OxyContin.[49] By the turn of the century, however, some activists, physicians, and pharmacists had noticed a major rise in opioid addictions in their communities, and began to warn others.[50]

Warning signs of the current opioid crisis first arose in Appalachia, where physicians such as Dr. Art Van Zee observed a huge rise in opioid addictions following the introduction of OxyContin.[51] Communities that had previously only faced alcoholism suddenly had large number of opioid addicts, who were usually much younger–high school students in inpatient rehabilitation was not unheard of. Anecdotally, Dr. Art Van Zee noticed addicts seeking OxyContin by name within one month of it arriving in local pharmacies.[52] Addicts were not the only ones to notice the Purdue's blockbuster drug—it was the first drug the DEA targeted for monitoring by brand name.[53] By the early 2000s, there was an organized coalition based in Appalachia seeking to reformulate or recall OxyContin. The movement failed, however, due to clever legal and political maneuvering by Purdue.[54]

Despite the warnings, opioid prescriptions continued to rise throughout the 2000s and early 2010s, as can be seen om figure 1.1.[55] In total, there was a 356% increase in prescriptions from 1999 to 2015.[56] In fact, some communities received more prescription painkillers than there were people who could use them, which highlights the high level of diversion of prescription opioids for non-medical use during this period.[57] While many doctors treated OxyContin and similar prescription painkillers as routine pharmaceuticals, their impact on patients was more similar to heroin than statins. Approximately one in every 550 patients started on opioid therapy dies from an opioid-related cause, with most deaths occurring within three years of the initial prescription.[58] Furthermore, prescription painkillers often lead to heroin use; approximately 75% of heroin users first misused prescription opioids.[59] OxyContin's

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hospital.

[49] Haney and Hsu, "Doctor Who Wrote 1980 Letter on Painkillers Regrets That It Fed the Opioid Crisis"; Meier, *Pain Killer*; Porter and Jick, "Addiction Rare in Patients Treated with Narcotics"; Quinones, *Dreamland*; Van Zee, "The Promotion and Marketing of OxyContin"; Zhang, "The One-Paragraph Letter from 1980 That Fueled the Opioid Crisis."

[50] Meier, *Pain Killer*.

[51] Meier; Van Zee, "The Promotion and Marketing of OxyContin"; Quinones, *Dreamland*.

[52] Meier, *Pain Killer*.

[53] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes."

[54] Meier, *Pain Killer*.

[55] Macy, *Dopesick*; Meier, *Pain Killer*; Quinones, *Dreamland*.

[56] Krueger, "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate."

[57] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes"; Quinones, *Dreamland*.

[58] Frieden and Houry, "Reducing the Risks of Relief the CDC Opioid-Prescribing Guideline"; Krueger, "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate."

[59] O'Donnell, Gladden, and Seth, "Trends in Deaths Involving Heroin and Synthetic Opioids Excluding Methadone, and Law Enforcement Drug Product Reports, by Census Region United States,

devastation would continue unrestrained until its reformulation in the early 2010s.[60]

1.2.5 OxyContin Reformulation

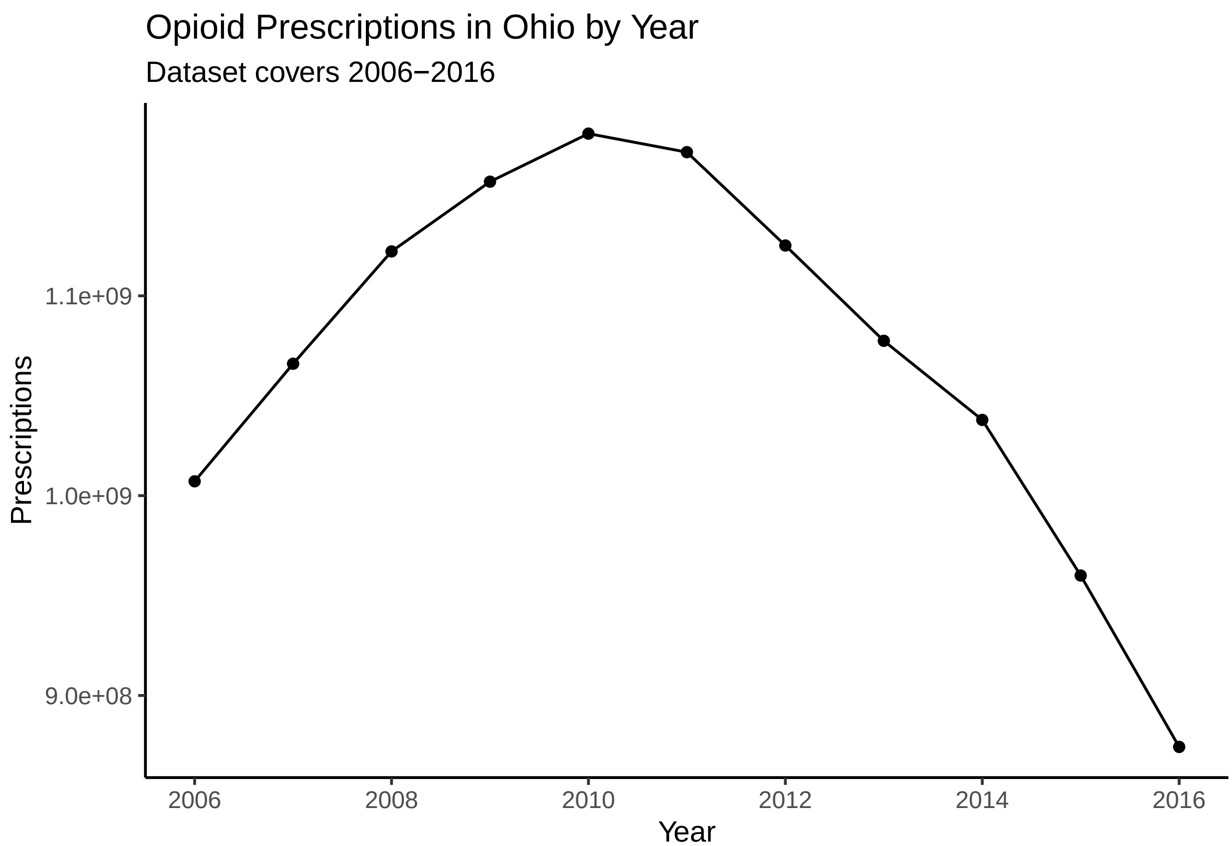

Figure 1.1: Opioid prescribing rate in Ohio from 2006 to 2016

In 2010, OxyContin was reformulated. The reformulation made it difficult to grind up and snort or inject, which made it less useful for recreational use.[61] As shown in figure 1.1, opioid prescriptions in Ohio began to fall the year OxyContin was reformulated. Medical studies find that the formulation decreased recreational OxyContin abuse between 30 and 50 percent, and decreased overdoses by up to two-thirds.[62] This led to the first decrease in prescription opioid and overdose deaths since 1990. Unfortunately, this decrease coincided with an unprecedented rise in heroin overdoses and deaths, as shown in figure 1.2.[63] This is likely because the reformulation made

20062015.”

[60]Quinones, *Dreamland*.

[61]Alpert, Powell, and Pacula, “Supply-Side Drug Policy in the Presence of Substitutes”; Macy, *Dopesick*; Quinones, *Dreamland*.

[62]Cicero, Ellis, and Surratt, “Effect of Abuse-Deterrent Formulation of OxyContin”; Coplan et al., “The Effect of an Abuse-Deterrent Opioid Formulation (OxyContin) on Opioid Abuse-Related Outcomes in the Postmarketing Setting.”

[63]Alpert, Powell, and Pacula, “Supply-Side Drug Policy in the Presence of Substitutes.”

OxyContin an inferior good compared to heroin, and other changes in prescription painkiller supply made heroin relatively cheaper.

1.2.6 The Introduction of Black Tar Heroin

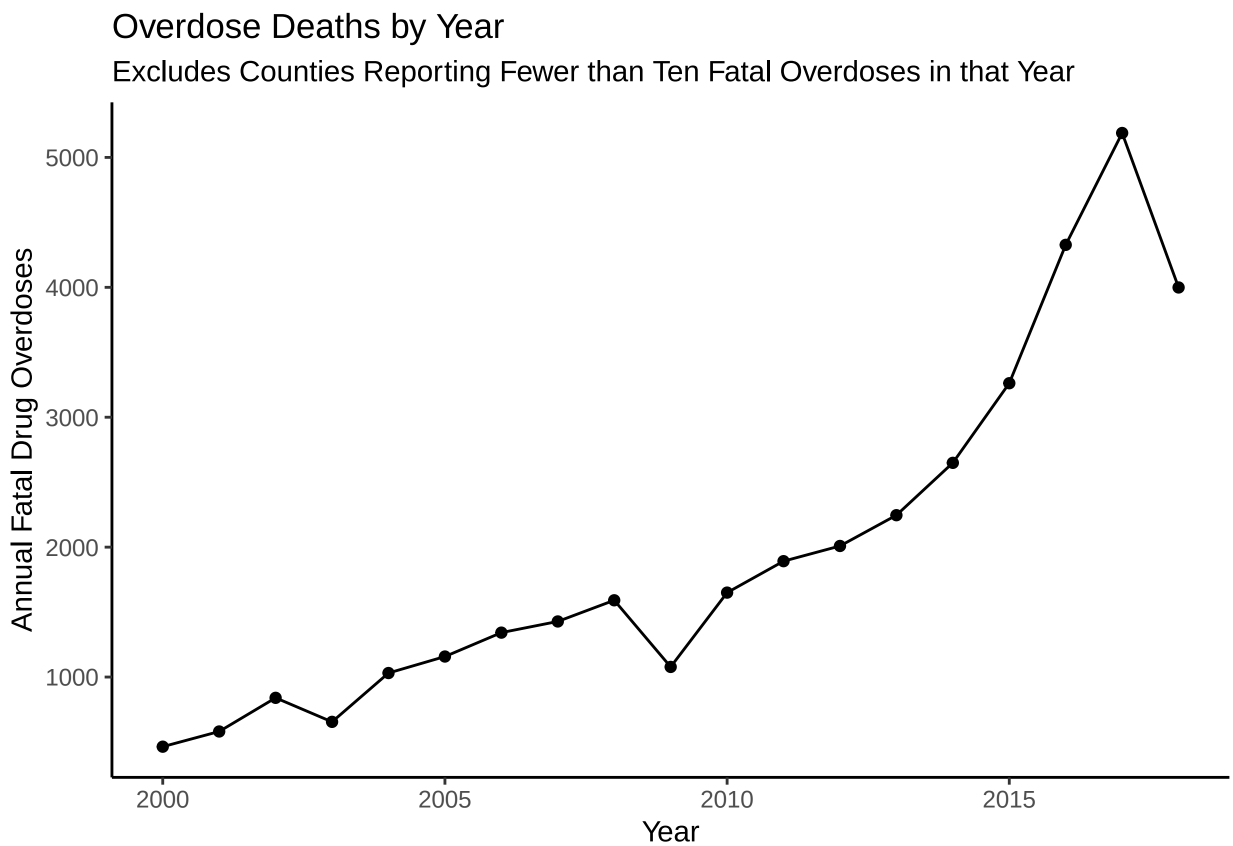

Figure 1.2: Annual fatal drug overdoses in Ohio counties included in sample

Prior to the 1980s, the US heroin market was dominated by white powder heroin trafficked from Asia into the US through New York City. This heroin was heavily adulterated, expensive, and almost exclusively available in impoverished neighborhoods of major metropolitan areas in the Northeast. In the early 1980s, however, black tar heroin started to trickle into Los Angeles from the Mexican state of Nayarit. The "Xalisco Boys"–young men from the town of Xalisco in Nayarit–would migrate to the US with a small quantity of heroin, sell it, and return home. Unlike traditional heroin markets, which operated out of abandoned buildings in major cities, the Xalisco Boys delivered heroin to suburban buyers after arranging purchases through a network of pagers and phones. This led to a demographic shift in heroin consumption, which had been predominantly consumed by poor urban blacks, towards middle and upper class whites. Further differentiating them from traditional heroin distributors, the

Xalisco Boys eschewed violence and operated in small, independent cells, which minimized police attention and kept them off the radar for almost two decades. By the 1990s, the Xalisco Boys began to expand to small and medium sized cities without a preexisting heroin market across the United States.[64]

By the 2000s, relatively large heroin markets supplied exclusively with Nayarit black tar existed in cities such as Portland, Columbus, Salt Lake City, Charleston, and Denver, where there had previously been almost no demand. While police in each individual city were aware of the markets, they were not considered a priority, and were not aggressively targeted by the DEA until after the spike in heroin overdose deaths.[65] While it is difficult to accurately quantify the size of black markets, it is safe to say that heroin sales exploded after the reformulation of OxyContin and the increase in monitoring and regulation of opioid prescriptions.[66] This is because illegal drug prices increase the further they are sold from distribution centers, and a decrease in prices is almost guaranteed to lead to an increase in sales.

1.2.7 Regulatory Changes

In response to the opioid epidemic, some states enacted regulations to attempt to reduce the supply of prescription opioids on the gray and black market. For example, states such as Ohio and Kentucky instituted prescription monitoring programs. These programs identified doctor shoppers[67] as well as physicians prescribing opioids and other medications of concern in very high quantities or to an abnormally high percentage of their patients. Furthermore, some states began targeting pill mills[68].[69] These laws were effective at reducing opioid overdose deaths–both from prescription opioids and heroin–by approximately 2000 a year.[70] These laws increased the cost of acquiring prescription painkillers, which limited their use among both already addicted individuals and new users. Unfortunately, the benefits of these laws were limited by their state-specific scope, as some states like Florida became a haven for pill mills and other prescription diversion tactics, which created a steady supply of painkillers for

[64] Quinones, *Dreamland*.

[65] Quinones.

[66] Alpert, Powell, and Pacula, "Supply-Side Drug Policy in the Presence of Substitutes"; Macy, *Dopesick*; Quinones, *Dreamland*.

[67] Doctor shoppers are individuals who go to multiple doctors seeking specific highly divertable medications

[68] Pill mills are essentially physician-owned opioid distributors masquerading as pain management clinics. According to Quinones, dead giveaways include: high fees payable only in cash, large queues in rural areas, and open drug use around the clinic. While these clinics were often shut down, they were quickly replaced until regulations made them difficult to open at all, and the physicians operating them usually faced license suspensions at most unless they were caught working with organized criminal operations or having inappropriate relationships with doctor-shopping patients Quinones, *Dreamland*.

[69] Macy, *Dopesick*; Popovici et al., "The Effect of State Laws Designed to Prevent Nonmedical Prescription Opioid Use on Overdose Deaths and Treatment"; Quinones, *Dreamland*.

[70] Popovici et al., "The Effect of State Laws Designed to Prevent Nonmedical Prescription Opioid Use on Overdose Deaths and Treatment."

the black market elsewhere.[71] Furthermore, the introduction of extremely strong–and therefore extremely dangerous–synthetic opioids into the black market opioid supply chain undid these efforts by more than an order of magnitude.

1.2.8 The Introduction of Fentanyl

Synthetic opioids such as Fentanyl entered the US black market supply chain in the 2010s.[72] These substances are much stronger than conventional opioids like heroin and OxyContin; Fentanyl is 50 to 100 times as powerful as morphine.[73] Drug dealers and distributors blend synthetic opioids into heroin, or press them into fake pills, because the synthetics are approximately 95% cheaper than heroin.[74] While most opioid addicts dislike the synthetic opioids, they are unable to identify its presence in their drugs without relatively expensive testing kits, which minimizes the risk to drug distributors who chose to cut their product to maximize profit.[75] When synthetic opioids are introduced to a black market, overdose deaths increase.[76] Figure 1.2 shows that there was a massive increase in overdose deaths in Ohio in the 2010s, when prescription painkillers were replaced by heroin and then synthetic opioids.

The introduction of synthetic opioids such as Fentanyl into the black market increases overdose deaths for several reasons. For one, the extreme potency of synthetic opioids means that even tiny amounts of heterogeneity in the final product sold in the street can cause a fatal overdose.[77] Furthermore, its introduction lowers the price of street opioids, causing both greater consumption by current users and higher numbers of new users.[78] Since Fentanyl is a substitute for other opioids, this price decrease increases consumption among all opioid addicts, including those who previously only used prescription painkillers. In addition, non-opioid recreational drugs are sometimes contaminated with Fentanyl and other synthetic opioids, causing fatal opioid overdose in non-opioid users.[79] Furthermore, Fentanyl overdoses can kill in as little as two minutes, whereas traditional opioids like heroin take 20 to 30 minutes, which

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[71] Quinones, *Dreamland*.

[72] Macy, *Dopesick*; Quinones, *Dreamland*.

[73] CDC, "Fentanyl."

[74] Frank and Pollack, "Addressing the Fentanyl Threat to Public Health"; Hempstead and Yildirim, "Supply-Side Response to Declining Heroin Purity."

[75] Carroll et al., "Exposure to Fentanyl-Contaminated Heroin and Overdose Risk Among Illicit Opioid Users in Rhode Island"; Socias and Wood, "Epidemic of Deaths from Fentanyl Overdose."

[76] Hempstead and Yildirim, "Supply-Side Response to Declining Heroin Purity"; O'Donnell, Gladden, and Seth, "Trends in Deaths Involving Heroin and Synthetic Opioids Excluding Methadone, and Law Enforcement Drug Product Reports, by Census Region United States, 20062015"; Socias and Wood, "Epidemic of Deaths from Fentanyl Overdose."

[77] Ciccarone, "Fentanyl in the US Heroin Supply"; Hempstead and Yildirim, "Supply-Side Response to Declining Heroin Purity"; Marshall et al., "Epidemiology of Fentanyl-Involved Drug Overdose Deaths"; O'Donnell, Gladden, and Seth, "Trends in Deaths Involving Heroin and Synthetic Opioids Excluding Methadone, and Law Enforcement Drug Product Reports, by Census Region United States, 20062015"; Socias and Wood, "Epidemic of Deaths from Fentanyl Overdose."

[78] Frank and Pollack, "Addressing the Fentanyl Threat to Public Health."

[79] Fairbairn, Coffin, and Walley, "Naloxone for Heroin, Prescription Opioid, and Illicitly Made Fentanyl Overdoses"; Frank and Pollack, "Addressing the Fentanyl Threat to Public Health."

dramatically reduces the opportunity window for bystanders and emergency medical services to provide naloxone.[80] Finally, opioids contaminated with Fentanyl dramatically increase the risk of overdose in recreational users, increasing the pool of people liable to overdose from exclusively dependent users.[81]

1.2.9 Naloxone

Opioid overdoses can be treated with naloxone.[82] Access to naloxone is key to reducing opioid overdose deaths. Community-level naloxone distribution to people who inject drugs began in Chicago in 1996, and has slowly diffused across the country since then. Large decreases in overdose deaths have been observed in cities after the introduction of naloxone; opioid overdose deaths decreased 95% in the 10 years following San Francisco's decision to supply naloxone.[83] Given that naloxone has such a major impact on overdose deaths, access to naloxone is important to understanding the variation in opioid overdose deaths per capita across the United States.

1.2.10 Medication-Assisted Treatment: The Gold Standard of Opioid Recovery

Medication-assisted treatment, or maintenance therapy, is the gold standard for treating opioid addiction. While opioids are considered dangerous substances, barring overdose, the primary medical concerns of chronic use are all related to how it is used[84] Rastegar and Fingerhood[85]]. Since "long-term abstinence after detoxification is the exception rather than the rule", the most effective way to treat individuals with an opioid addiction is to provide them with a long-term maintenance dose of opioids to minimize cravings and withdrawal coupled with counseling services.[86] Maintenance opioids include methadone and buprenorphine, and are much longer lasting than recreational opioids like heroin.[87]

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[80] Fairbairn, Coffin, and Walley, "Naloxone for Heroin, Prescription Opioid, and Illicitly Made Fentanyl Overdoses."

[81] Socias and Wood, "Epidemic of Deaths from Fentanyl Overdose."

[82] Rastegar and Fingerhood, *The American Society of Addiction Medicine Handbook of Addiction Medicine*.

[83] Fairbairn, Coffin, and Walley, "Naloxone for Heroin, Prescription Opioid, and Illicitly Made Fentanyl Overdoses."

[84] For example, street users of heroin often suffer from abscesses from improper injections, HIV and other blood-borne diseases from sharing and reusing needles, and systemic infections. None of these conditions are directly caused by opioid use, and all are greatly exacerbated by homelessness and other poor living conditions Bourgois and Schonberg, *Righteous Dopefiend*; Rastegar and Fingerhood, *The American Society of Addiction Medicine Handbook of Addiction Medicine*.

[85] *The American Society of Addiction Medicine Handbook of Addiction Medicine*.

[86] Rastegar and Fingerhood, 155.

[87] Rastegar and Fingerhood, *The American Society of Addiction Medicine Handbook of Addiction Medicine*.

1.2.11 Economy and History of Ohio

Figure 1.3: Map of Ohio with counties labeled

Cuyahoga County, which contains Cleveland, was traditionally the only part of Ohio to have an active heroin market.[88] This helps explain the high rate of heroin usage in Cuyahoga County. While Cleveland was historically a major city–fifth in the nation by population at one point–today it exemplifies “deindustrialization, population decline, and entrenched poverty.”[89] This phenomena is not limited to Cleveland proper. Between 1985 and 2010, manufacturing employment fell by over 50% in Northeast Ohio, which is the region that contains Cuyahoga County and therefore the city of Cleveland.[90]

Broadly speaking, Ohio as a whole has suffered from a decline in unionized manufacturing jobs, which has led to limited opportunities for low education workers in much of the state. Many authors have claimed that the disappearance of high-paying, relatively low-skilled positions led to increased demand for substances such as heroin. For example, in Portsmouth, Ohio, the main employer shut down, and the city now has one of the highest rates of opioid abuse in the country. These changes were

[88] Quinones, *Dreamland*.
[89] Naomi Lamoreaux and Margaret Levenstein, “The Decline of an Innovative Region.”
[90] Matthew Hrubey, “Northeast Ohio Manufacturing Brief.”

most dramatic in the Appalachian region of Ohio, where the economy was previously dominated by coal mining and steel manufacturing along the Ohio river. The job market has never recovered in Ohio's Appalachian counties.[91] Figure 2.8 shows that household income is still noticeably lower in Appalachia.

1.3 Supply vs Demand Side Explanations

Explanations for the opioid epidemic in the United States can be broadly characterized as either supply-side or demand-side. Supply-siders claim that an increase in the supply of opioids triggered the 21st century epidemic, while demand-siders believe that social and economic factors are responsible. Supply-siders attribute the increase in the overall opioid supply–and therefore opioid deaths–to the rise of prescription painkillers like OxyContin, the simultaneous price decrease and supply increase of heroin outside of major metropolitan areas, and the introduction of synthetic opioids such as Fentanyl into the recreational opioid supply chain. If addicts are myopically irrational, then supply-side factors will play a major role in determining overdose deaths. In contrast, demand-siders focus on changes in pain treatment, poor economic outcomes in particular regions of the United States, and the overall phenomena of deaths of despair. If demand-siders are correct, then economic and demographic indicators should accurately predict fatal opioid overdose rates. On the other hand, if supply-siders are correct, then economic and demographic indicators other than income should not provide much explanatory value, and instead statistics such as the prescribing rate should have the most explanatory power. Under the rational theory of addiction, both supply-side and demand-side explanations are plausible.

[91] Quinones, *Dreamland*.

Chapter 2

Data and Methods

2.1 Model

In order to assess the determinants of opioid abuse and fatal overdose, this thesis will examine the correlation between county-level economic and social indicators and a county's fatal overdose rate. The fatal overdose rate was selected because quantifying opioid abuse directly is challenging, and there is little data available. In contrast, reliable statistics on the county-level fatal overdose rate are available as far back as 1999 for some counties. While the overdose rate includes overdose deaths from other narcotics, the vast majority of overdose deaths include at least some usage of opioids. Furthermore, it seems safe to assume that there is a strong correlation between the level of opioid abuse in a county and that county's fatal overdose rate. Throughout the rest of this thesis, the fatal overdose rate is modeled as a function of disability rates, education levels, income, racial demographics, opioid prescribing rates, and population density, with year fixed effects, and in some specifications county fixed effects.[1]

The modeling function was designed off of the literature review. Many commentators have emphasized that manual labor leads to disability, which leads to prescription painkillers, which leads to opioid addiction and sometimes fatal overdose.[2] Therefore, disability levels and prescribing rates are included in the model. I hypothesize that both will be positively correlated to the fatal overdose rate. Commentators have also claimed that the opioid epidemic has been driven by opioid abuse spreading from a few poor, predominantly black, urban areas to rural America, which is predominantly white.[3] Hence, racial demographics and population density are included in the model. I hypothesize that low population density will be associated with higher fatal overdose rates. The impact of racial demographics is more ambiguous, as the literature suggests that areas with a high percentage of people of color likely already had an above-average overdose rate, but that other areas would have greater increases in the overdose rate. Finally, the model includes education levels and income. I hypothesize

[1] Hanck et al., "10.3 Fixed Effects Regression."

[2] Macy, *Dopesick*; Meier, *Pain Killer*; Quinones, *Dreamland*.

[3] Macy, *Dopesick*; Meier, *Pain Killer*; Quinones, *Dreamland*.

that education will have a protective effect, but income will be associated with more overdoses, since more income means greater ability to purchase opioids, and therefore more opportunities to overdose. If I had access to it, I would also include naloxone distribution data, as naloxone reduces overdose deaths.

2.2 Data

The majority of my independent variables were sourced from the census American Community Survey. The American Community Survey, or ACS, "provides a detailed portrait of the social, economic, housing, and demographic characteristics of America's communities."[4] ACS data is available on a geographic hierarchy, going from census tracts to the United States as a whole, with areas with a higher population level appearing in more surveys. This thesis uses ACS data aggregated at the county level.[5] While the one-year survey is preferable for time series modeling, it only includes counties with a population of 65,000 or greater, which eliminates many Ohio counties.[6] In fact, the one-year survey only includes 39 out of Ohio's 88 counties. Since the counties are selected for inclusion based on county population, there is selection bias in the sample. This means that the results may be an inaccurate reflection of reality if there is correlation between a county's population and the county's fatal drug overdose rate. Given that the literature suggests that rural areas have suffered from greater increases in overdose rates, it is likely that there is correlation between county population and the overdose rate, meaning that there is probably significant selection bias in the one-year survey dataset. Therefore, this thesis will run the same models with both the one-year and five-year surveys.

The fatal overdose rate, prescribing rate, and density level all come from CDC data. They are sourced from the "Drug Poisoning Mortality by County" dataset, which is published by the National Center for Health Statistics. The death rate is available as a crude rate, an age-adjusted rate, and an imputed rate. The model will be tested on all three independent variables. The density level is a qualitative categorical variable ranging from "noncore" to "large central metro". The prescribing rate is indexed to 100. The data was paired with the census and overdose data using the FIPS code, which uniquely identifies counties.[7]

[4] "Understanding the ACS."
[5] "Geographic Areas Covered in the ACS."
[6] "Understanding the ACS"; "Geographic Areas Covered in the ACS."
[7] Calgary, "NCHS - Drug Poisoning Mortality by County."

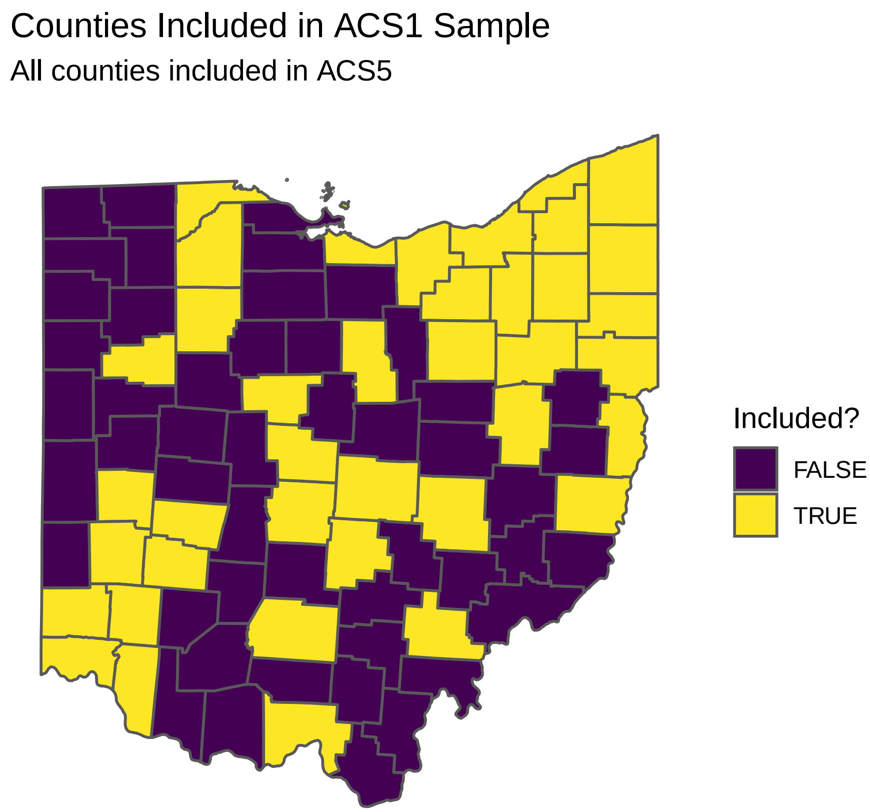

Figure 2.1: Counties included in the data

2.2.1 Variable Summary Statistics

We will now examine tables 2.1 and 2.2. The five year estimates include more observations than the one year estimates. The majority of variables are in percentage form in order to isolate the role of county population on the fatal drug overdose rate. These variables are identified by the "%" in their name. Percentages are calculated dividing the raw count from the Census/CDC by the total population of the county that year. Percentages are stored in the format XX.X%, rather than .XXX%.

Table 2.1: One Year Estimates (218 Observations)

Statistic	Mean	Median	St. Dev.	Min	Max
Fatal Overdose Crude Rate	27.99	24.30	14.66	6.87	101.80
Fatal Overdose Age-Adjusted Rate	34.30	30.50	15.96	12.10	110.20
Fatal Overdose Imputed Rate	27.87	24.16	14.65	6.87	101.80
% Black	8.27	6.39	7.36	0.47	30.11
Density: Noncore	0.00	0	0.00	0	0
Density: Small Metro	0.10	0	0.31	0	1
Density: Micropolitan	0.22	0	0.41	0	1
Density: Large Fringe Metro	0.29	0	0.45	0	1
Density: Medium Metro	0.31	0	0.46	0	1
Density: Large Central Metro	0.08	0	0.27	0	1
Prescribing Rate	95.34	93.65	22.62	47.10	164.20
Median Individual Income	26,202.62	25,445	4,961.23	13,095	46,425
Median Household Income	51,453.64	48,808.5	12,078.56	29,657	106,933
% with Highschool or Less	46.33	45.88	8.92	20.85	64.71
% with Some College	29.07	29.10	2.98	17.52	36.24
% with Bachelors or More	24.59	23.80	9.03	10.10	54.86
% Disabled: Males Under 5	0.90	0.00	1.89	0.00	19.66
% Disabled: Males 5 to 17	7.62	7.58	2.94	1.32	18.09
% Disabled: Males 17 to 34	7.98	7.45	3.36	1.30	29.72
% Disabled: Males 35 to 64	14.73	14.24	4.47	4.38	31.36
% Disabled: Males 65 to 74	26.46	25.91	6.56	8.55	52.12
% Disabled: Males 75 and Up	46.76	46.34	7.85	23.19	71.44
% Disabled: Females Under 5	0.58	0	1.46	0	13
% Disabled: Females 5 to 17	4.91	4.69	2.62	0.00	17.08
% Disabled: Females 17 to 34	6.72	6.33	2.98	0.00	20.56
% Disabled: Females 35 to 64	14.76	14.49	4.43	4.65	30.98
% Disabled: Females 65 to 74	23.88	23.70	5.67	10.17	46.26
% Disabled: Females 75 and Up	49.32	49.08	7.05	30.41	76.38

Table 2.2: Five Year Estimates (257 Observations)

Statistic	Mean	Median	St. Dev.	Min	Max
Fatal Overdose Crude Rate	32.60	29.80	15.50	6.87	104.30
Fatal Overdose Age-Adjusted Rate	39.56	36.50	17.78	12.10	119.50
Fatal Overdose Imputed Rate	31.82	28.62	15.36	6.87	104.30
% Black	4.14	2.08	5.68	0.00	29.74
Density: Noncore	0.27	0	0.45	0	1
Density: Small Metro	0.08	0	0.27	0	1
Density: Micropolitan	0.28	0	0.45	0	1
Density: Large Fringe Metro	0.16	0	0.37	0	1
Density: Medium Metro	0.17	0	0.38	0	1
Density: Large Central Metro	0.03	0	0.18	0	1
Prescribing Rate	85.23	85.00	27.33	0.90	190.50
Median Individual Income	25,385.38	25,011.00	4,205.07	12,641.00	45,772.00
Median Household Income	49,378.11	47,609	9,766.91	33,773	104,322
% with Highschool or Less	53.07	55.20	9.28	22.13	77.84
% with Some College	27.97	28.15	3.14	14.43	35.12
% with Bachelors or More	18.96	16.07	8.11	7.67	54.35
% Disabled: Males Under 5	1.05	0.5	1.40	0	9
% Disabled: Males 5 to 17	7.92	7.65	2.58	2.09	16.44
% Disabled: Males 17 to 34	8.27	7.82	2.85	2.69	23.97
% Disabled: Males 35 to 64	15.83	14.87	4.69	5.67	32.75
% Disabled: Males 65 to 74	28.51	27.68	5.58	15.51	52.99
% Disabled: Males 75 and Up	48.15	47.53	5.49	30.86	69.74
% Disabled: Females Under 5	0.59	0.3	0.94	0	9
% Disabled: Females 5 to 17	4.94	4.79	1.78	1.65	12.03
% Disabled: Females 17 to 34	7.14	6.78	2.36	1.77	15.45
% Disabled: Females 35 to 64	15.38	15.11	4.29	5.65	29.12
% Disabled: Females 65 to 74	25.12	24.70	4.92	12.98	41.80
% Disabled: Females 75 and Up	50.08	50.07	5.23	27.45	66.41

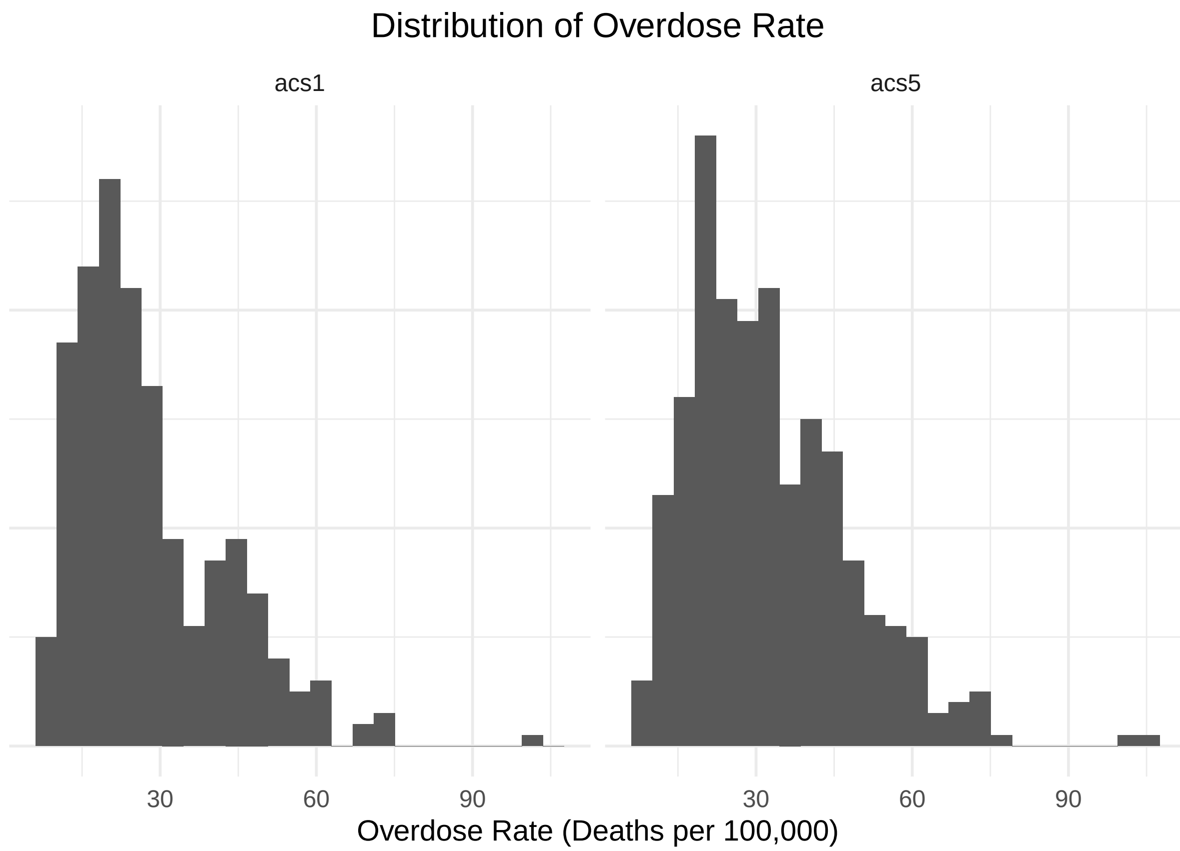

Figure 2.2: Distribution of drug overdose rate

The three fatal overdose rate measures have fairly similar values, but the age-adjusted rate is higher than the other two. This makes sense, as it factors how fatal overdose often occurs at ages where other causes of death are uncommon. A typical county in the one year estimates has around 28 people die of an overdose per 100,000. With five year estimates, that number increases to 32. The worst hit counties have approximately three times that death rate, with just over 100 people dying per year per 100,000. The least hit counties have under 10 deaths per year per 100,000. Overall, the overdose death rate is systemically higher with the five year estimates, which suggests that smaller counties have higher overdose rates.

As shown in figure 2.2, the distribution of the fatal drug overdose rate between counties suggests that censoring may be occurring from the bottom. This is because the right-side tail is significantly longer and fatter than the left-side tail.[8] If it is occurring, however, the censoring is fairly minimal. Overall, the overdose rate is higher with the five year estimates. Figure 3.3 shows that the overdose rate varies geographically. In southern Ohio, overdoses appear to be systematically more common. This meshes with the less academic literature, which generally claimed that former coal and steel counties were the most affected by opioid addiction and overdose.[9]

[8] Hill, Griffiths, and Lim, *Principles of Econometrics*.
[9] Meier, *Pain Killer*; Quinones, *Dreamland*.

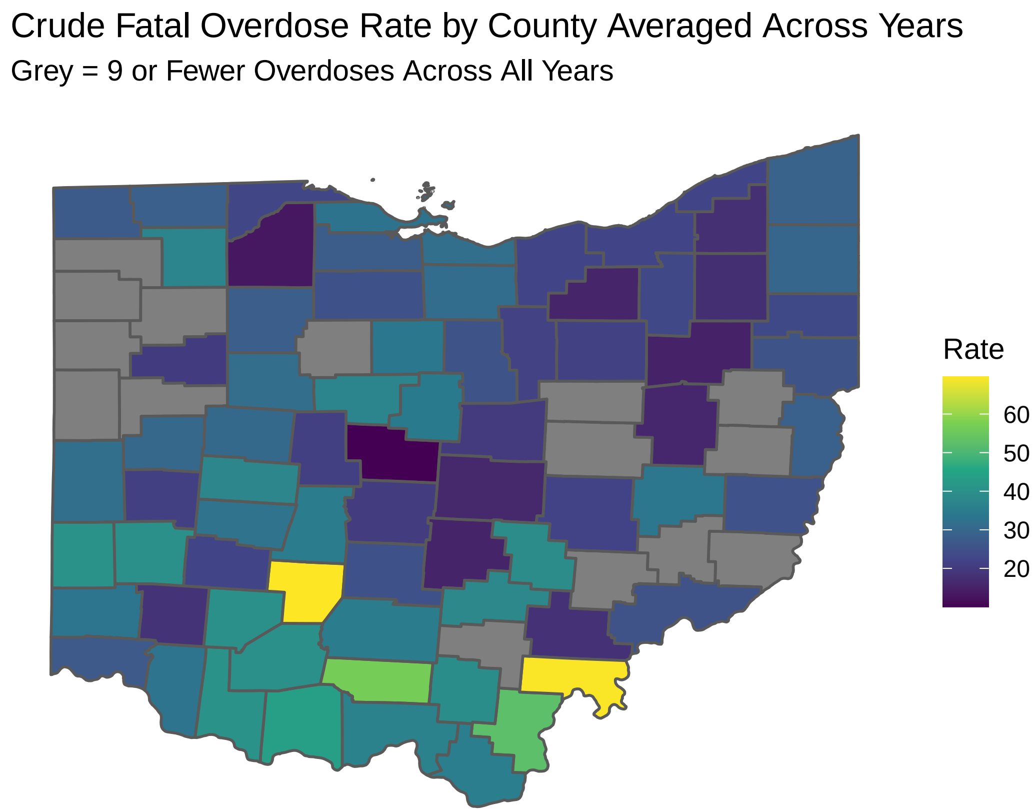

Figure 2.3: Map of Ohio counties by overdose rate

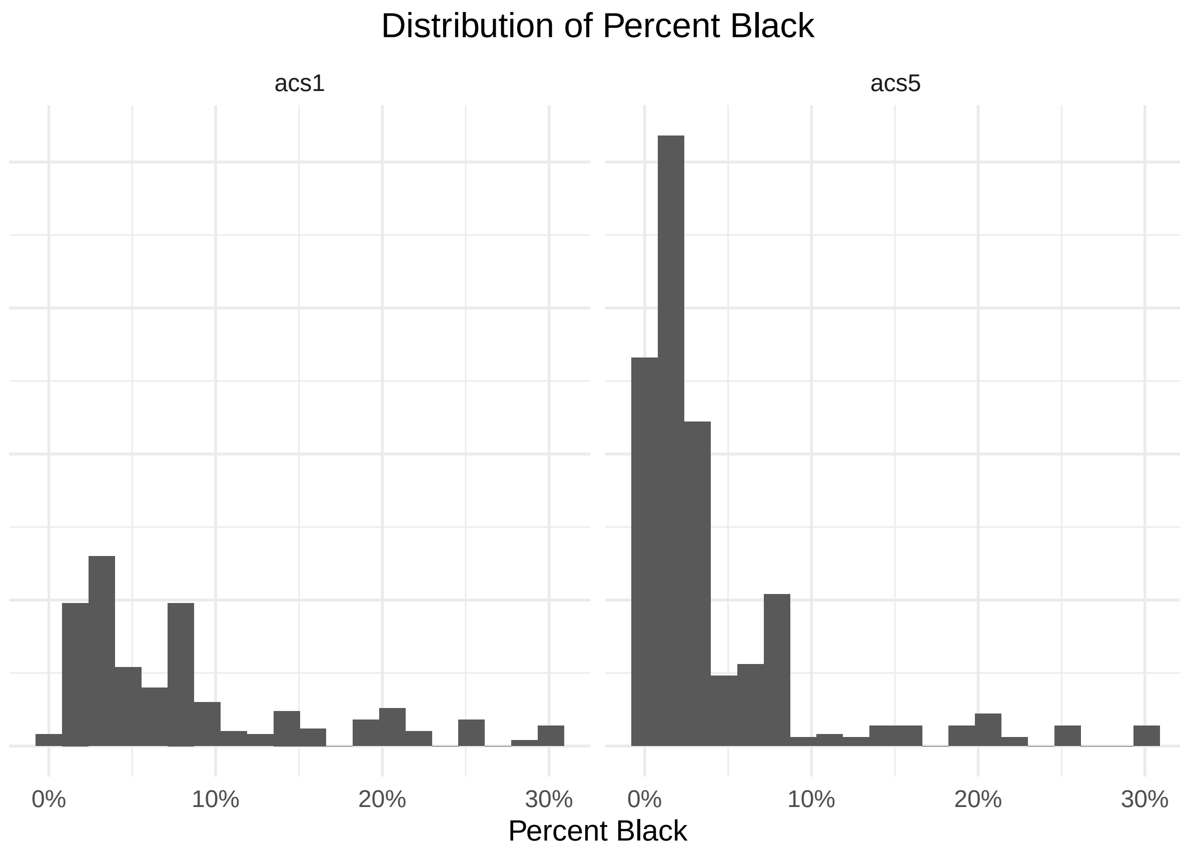

Figure 2.4: Distribution of percent black by county

Race is included as the variable percent black. Racial demographic data is represented this way because census demographic data that distinguishes between Caucasian and Latinx is significantly more challenging to work with, as the categories provided do not neatly add up the total population of the county. Since heroin was considered an urban black drug from the late 1930s until recently, percent black seemed an effective enough variable for assessing the role of race in drug overdose rates.[10] The average county is approximately 4% black in the five year estimates, and 8% in the one year estimates. Some counties report zero black residents. The highest percentage of residents that are black is just over 30%.

Figure 2.4 shows that the distribution of percent black by county with one year estimates is fairly even. While observations do not occur in a perfect Gaussian bell curve, there is no reason to believe that the data is censored. With five year estimates, however, there is a massive cluster of counties between zero and ten percent black.

[10]Macy, *Dopesick*; Quinones, *Dreamland*; White, *Slaying the Dragon*.

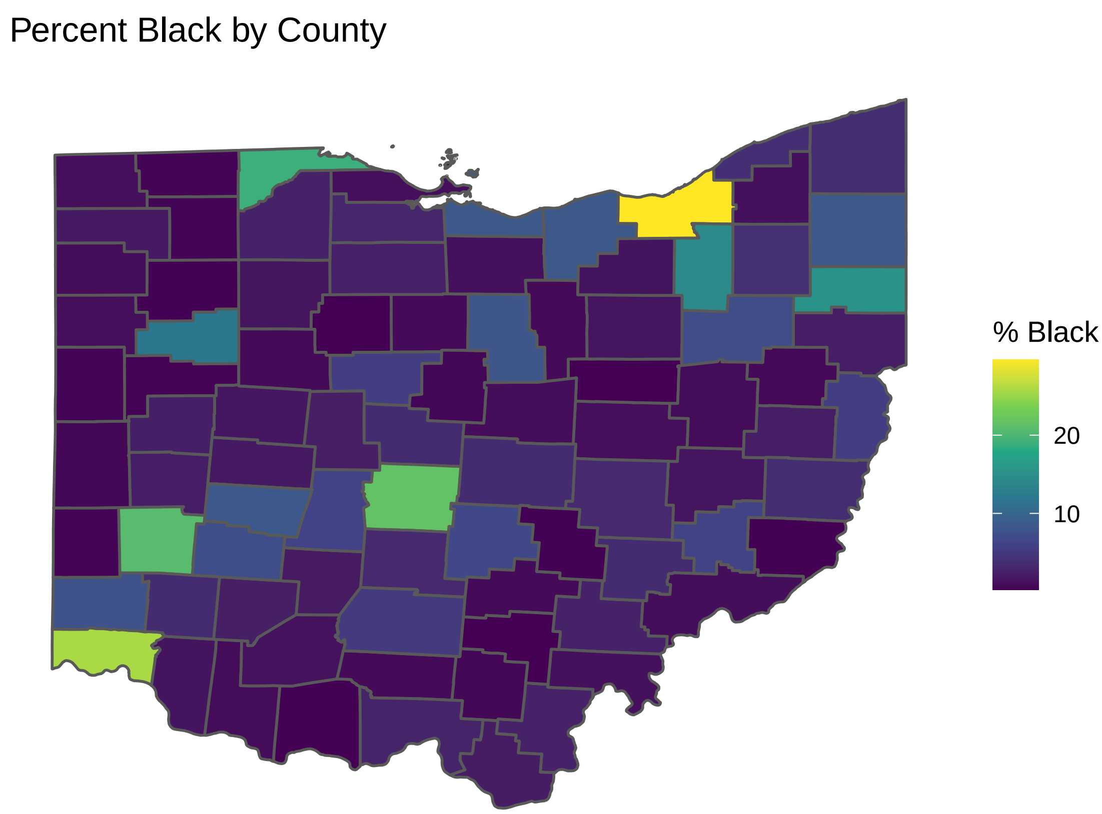

Figure 2.5: Map of Ohio counties by percent of the county's population that is black

Figure 2.5 is a map of Ohio by percent black. The yellow county is Cuyahoga County, which contains the city of Cleveland. Before the 1990s, Cleveland was considered to be the only region in Ohio to contain a significant heroin market.[11] Therefore, we would expect Cleveland to have started off with an above average drug overdose death rate. With the rise of the Xalisco boys and the introduction of OxyContin, heroin markets spread across the state.[12] Hence, we would expect Cleveland, and therefore Cuyahoga County, to have a higher than average overdose rate prior to the mid 90s, and for other counties to have a larger increase in their overdose death rate.

[11] Quinones, *Dreamland*.
[12] Macy, *Dopesick*; Quinones, *Dreamland*.

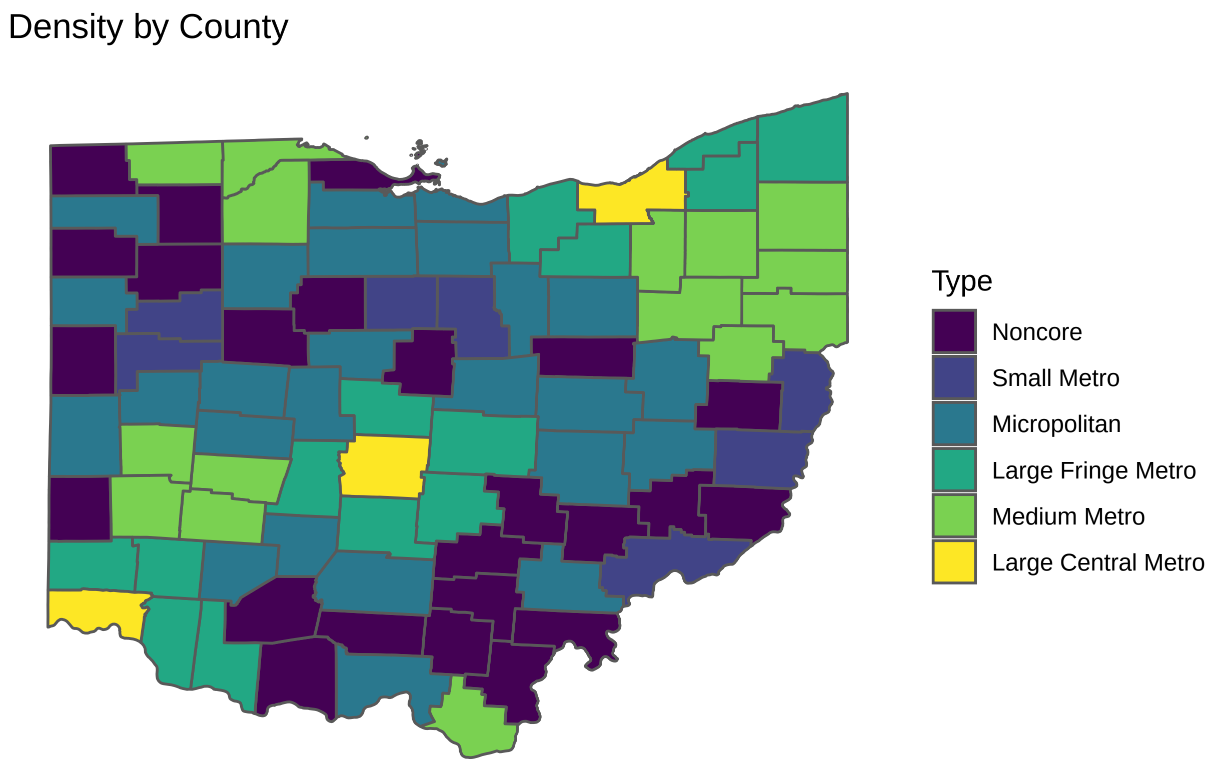

Figure 2.6: Map of Ohio counties by density type

Density levels vary significantly between the one year and five year estimates. “Noncore” refers to a rural county that is not affiliated with any metropolitan area. In the one year estimates, no counties are “noncore”, whereas 27% are in the five year estimates. This makes sense, as “noncore” counties are very low in population, and therefore are not included in the one year estimates. The rest of this paragraph will use the five year estimates, since they are representative of Ohio as a whole. Excluding “noncore” counties, most counties in Ohio range from medium sized towns to medium sized cities, with over 60% being “micropolitan”, “large fringe metro”, or “medium metro”. The few remaining counties are either small towns or the seats of Cleveland, Columbus, or Cincinnati, as shown in figure 2.6. Figure 2.6 also shows that the lowest density counties are concentrated in the Appalachian region of Ohio.

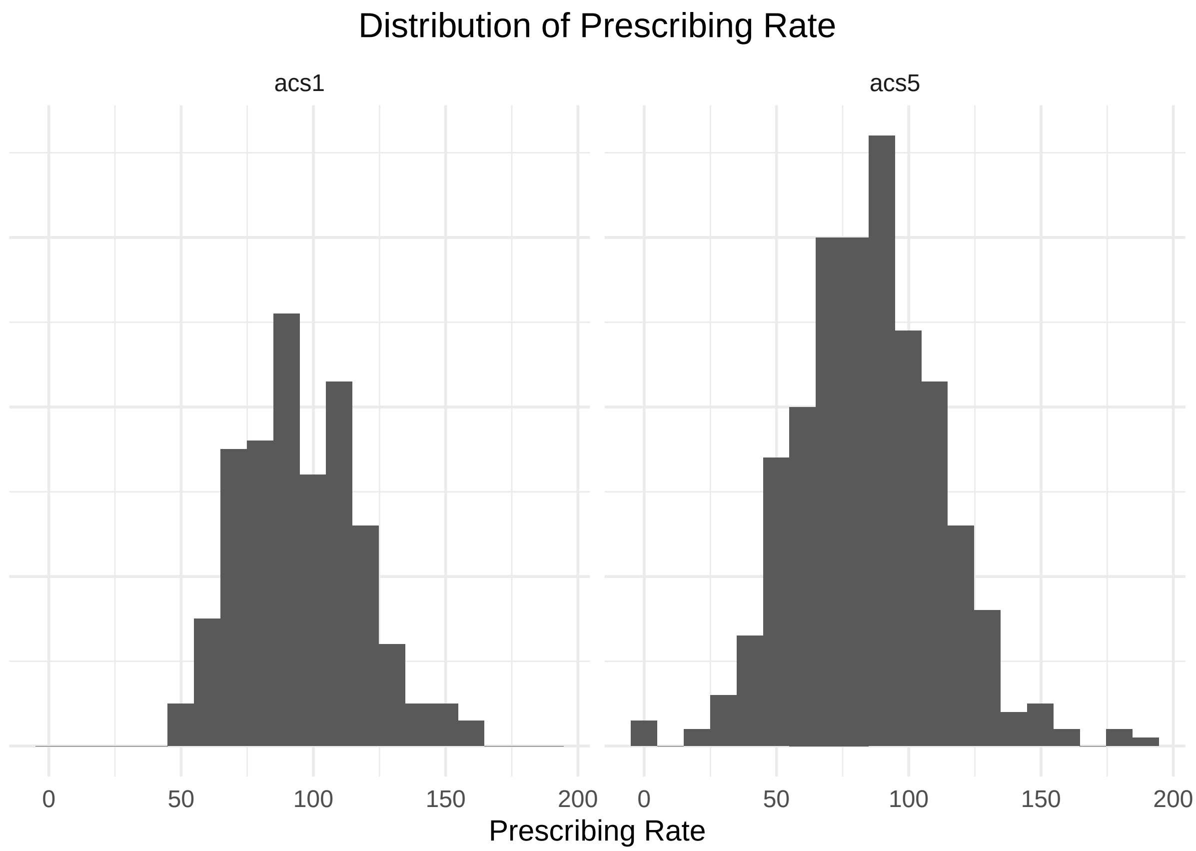

Figure 2.7: Distribution of prescribing rates

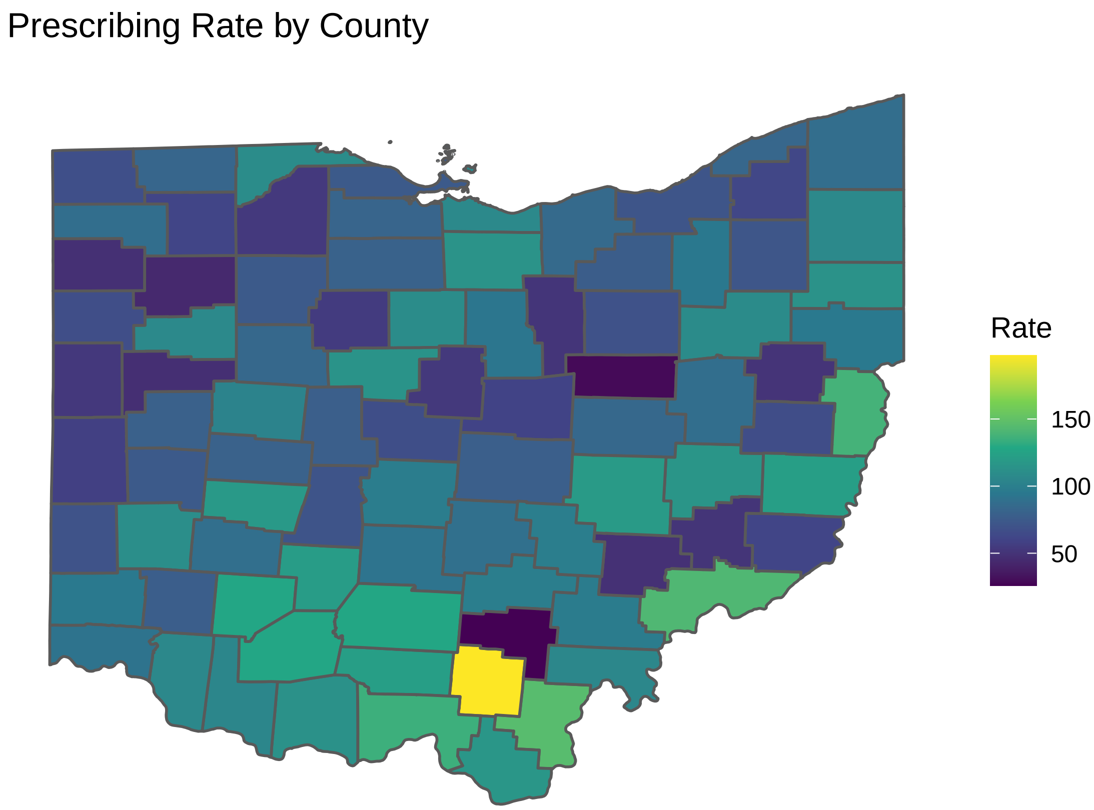

Figure 2.8: Map of Ohio counties by prescribing rate

There is massive variation in the prescribing rate. Prescribing rates are higher and vary less in the one year estimates. In the five year estimates, prescribing rates vary by over 20,000%, which is shocking. With those estimates, a typical county has roughly half the maximum number of prescriptions, and almost hundred times the minimum number of prescriptions. Figure 2.7 shows that prescribing rates are distributed in an almost perfectly Gaussian manner. Figure 2.8 shows that prescribing rates are higher in southern Ohio. This confirms the common narrative that the Appalachian region of Ohio had higher rates of prescription painkiller use, which potentially led into opioid abuse, addiction, and fatal overdose.[13]

[13]Macy, *Dopesick*; Meier, *Pain Killer*; Quinones, *Dreamland*.

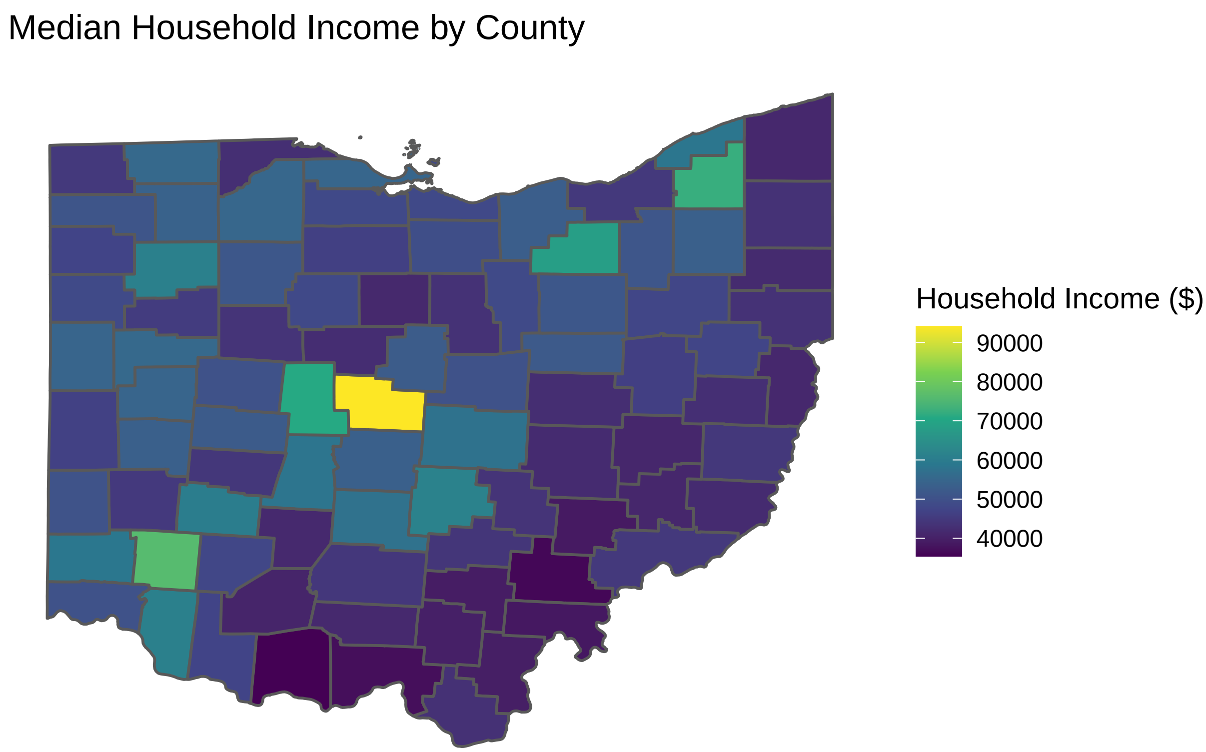

Figure 2.9: Map of Ohio counties by household income

Income levels do not vary between the one year and five year estimates. This suggests that there is little correlation between income levels and low county population, and that the richest counties appear in both samples. Individual income is consistently just over half of household income. The wealthiest counties have over three times the level of income as the poorest counties. Figure 2.9 shows that median household income is distributed geographically unequally. The Appalachian portion of Ohio is systemically poorer.

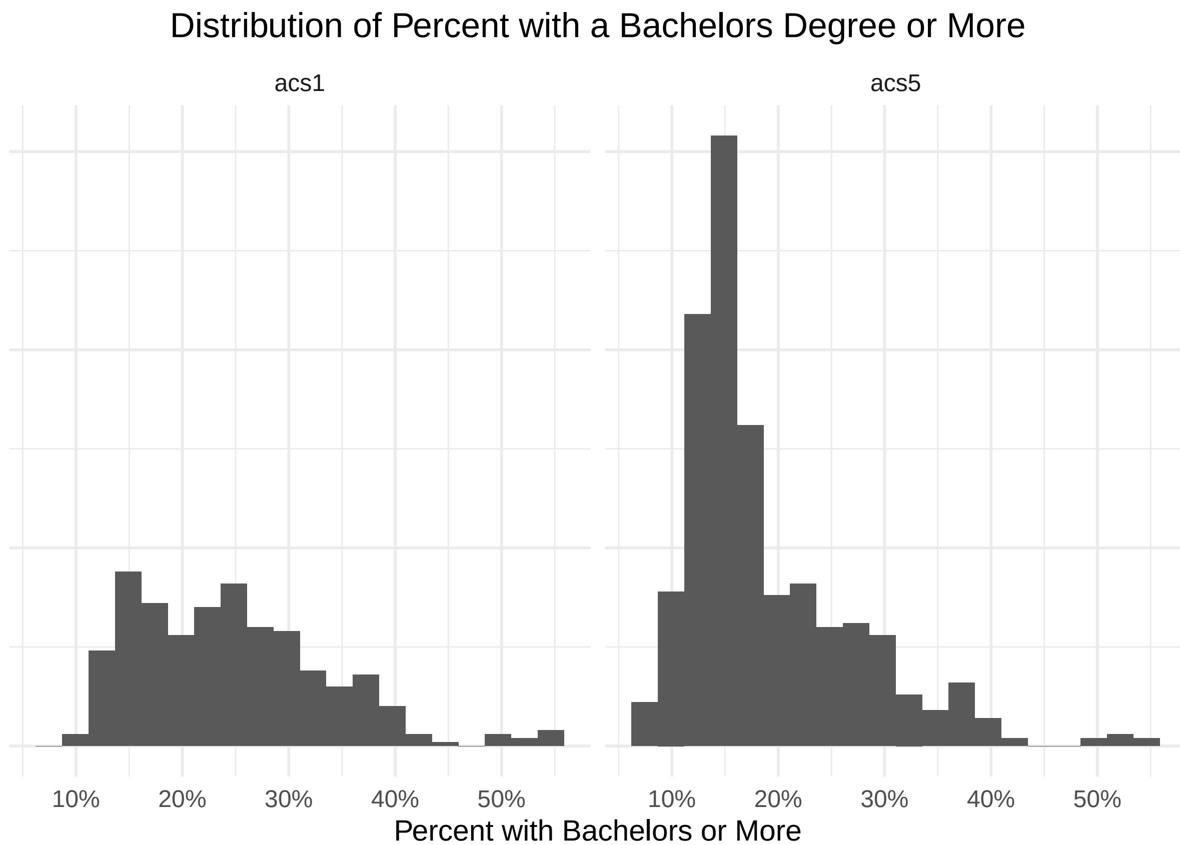

Figure 2.10: Distribution of percent with a bachelors degree or more by county

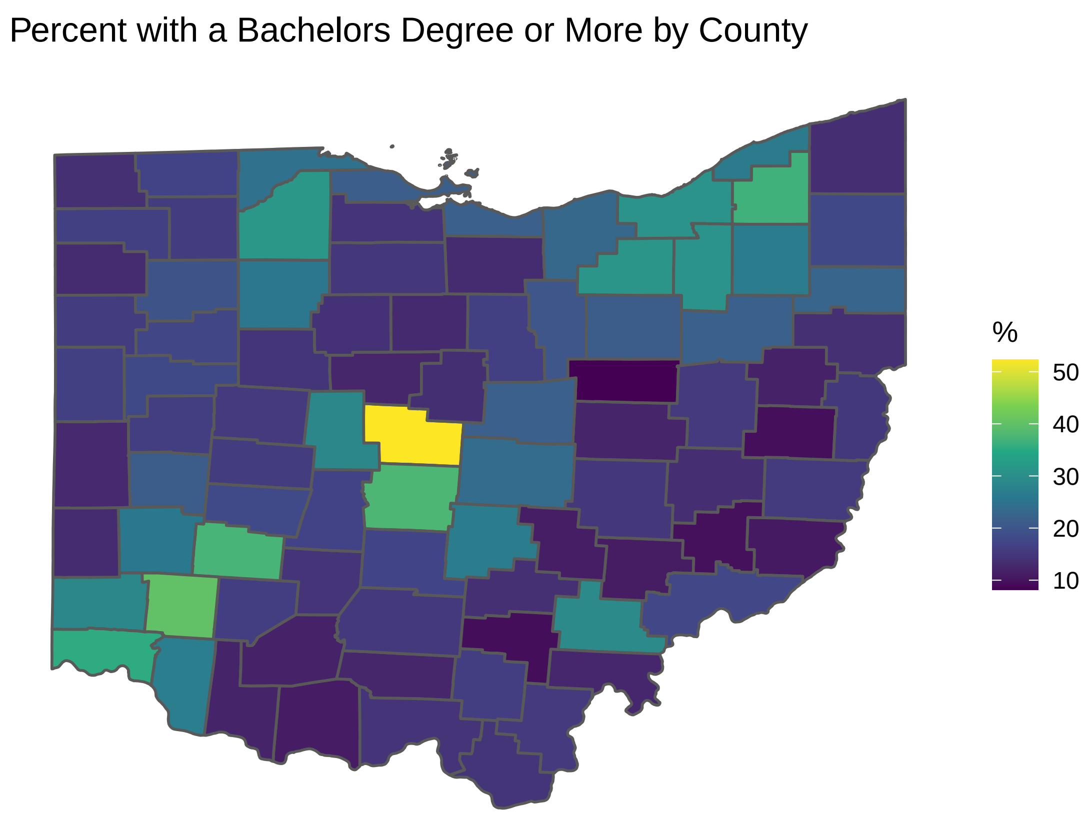

Figure 2.11: Map of Ohio counties by percent with bachelors or more

There is significant variation in education levels between counties. While in some counties less than ten percent of the adult population has a college degree, in others more than half of the population does. Education levels are higher in the one year estimates, suggesting that rural, low population counties are less educated on average. There are no apparent data issues with the variable percent with a bachelors degree or more. As seen with the race variable, the five year estimates have a large cluster towards the lower end of the distribution. This cluster can be seen in figure 2.10. Figure 2.11 shows that like with income and opioid prescriptions, the Appalachian region of Ohio is worse off than the rest of the state.

Disability is broken into age and sex bins. These bins are kept small because in order to aggregate them, I would need each county-year pair's population broken down into age and sex bins. The type of disability was ignored, as the literature suggested that painful, physical disabilities would have the greatest impact, and the census-provided disability bins only separated out deafness and blindness. Unsurprisingly, it appears that disability rates soar after the age of 65. This might be because of individuals gaining access to healthcare through Medicare coverage, and therefore getting a formal diagnosis. Male disability rates are consistently higher than female disability rates until the age of 75. Disability rates are slightly higher in the five year estimates, suggesting that rural, low population counties have higher disability rates than average counties.

2.3 Methods

After determining the broad categories of variables I needed through my literature review, I identified relevant census tables with the help of Mahria Lebow, Reed's data services librarian. We identified tables by searching census table shells for keywords like "disability" and "median income."[14] After identifying the necessary variables, I used the R package Tidycensus to download census data. The package is an API wrapper for data.census.gov, and allows "R users to return Census and ACS data as tidyverse-ready data frames, and optionally returns a list-column with feature geometry for many geographies". The "list-column with feature geometry" allows the R user to easily draw maps using the downloaded census data and ggplot2.[15]

Plots, graphs, and maps that appear within this thesis were produced using ggplot2 unless otherwise noted. ggplot2 is a R package that is part of the Tidyverse universe of R packages. The package allows an R user to quickly produce aesthetically appealing graphs and maps using any tidy dataset. Visualizations made in ggplot2 are designed using a standardized "grammar of graphics", which helps keep the visual appearance of a variety of different types of visualizations consistent.[16] One major advantage of working with Tidyverse-compliant packages such as ggplot2 and Tidycensus is that they are designed to work together easily. This allows a R user to go directly from pulling down census data to making maps without having to reshape data or otherwise perform tedious data cleaning, wrangling, and preparation tasks.[17]

I performed initial regressions using ordinary least squares multiple regression. These econometric models are similar to simple linear regression, but allow for multiple explanatory variables. Excluding the intercept, all parameters show the change in the dependent variable given a unit change in that particular explanatory variable *ceterus paribus*, meaning with all other explanatory variables held constant. For this econometric model to work, several assumptions must be fulfilled, such as having homoskedastic errors and no exact collinearity between explanatory variables.[18] While most of the assumptions are fulfilled, it is possible that there is heteroskedacity in the errors, as the census reports a higher margin of error for smaller counties.

In addition to the simple linear regression models, I attempted to model the dependent variable as censored. This model, referred to as a Tobit model, is used when a sizable portion of the observations of the dependent variable takes a particular value, often zero.[19] For example, a national survey of deaths per household would be censored, as most households would record zero deaths for any particular year. When censoring occurs, least squares regression cannot draw an accurate line through the center of the scattered data, leading to biased and inconsistent parameter estimates. To rectify this, Tobit models calculate the likelihood probability by splitting the probabilities between censored and uncensored observations, and then multiplying

[14] Lebow, "Census Help."

[15] Walker, "Tidycensus," n.d.; Walker, *Tidycensus*, 2020.

[16] Wickham, *Ggplot2*.

[17] Walker, "Tidycensus," 2020; Wickham, *Ggplot2*.

[18] Hill, Griffiths, and Lim, *Principles of Econometrics*.

[19] Hill, Griffiths, and Lim.

these probabilities. This accounts for the data falling into two categories–censored and uncensored–and results in less biased and more consistent parameter estimates than ordinary least squares regression models.[20] Censored regression was done using the censReg package,[21] In all cases, I converted the regression models into tables using the package Stargazer, which summarizes regressions and prints visually appealing LaTeX tables.[22]

[20]Hill, Griffiths, and Lim.
[21]Henningsen, "censReg."
[22]Marek Hlavac, "Stargazer."

Chapter 3

Results

This chapter proceeds with the models described in the previous chapter. I will interpret the regression tables resulting from the models, and then provide policy recommendations based on these results. All models include year fixed effects.

3.1 Statistical Results

3.1.1 Household vs Individual Income

Table 3.1 examines how the model changes when individual income is substituted for household income. As will be seen throughout this chapter, changing between the American Community Survey one year and five year estimates has the greatest impact on results. The coefficients for household and individual income point in opposite directions, but given the lack of statistical significance and the incredibly low magnitudes of the coefficients, it almost certainly meaningless. In general, switching between income types has minimal effects on the coefficients within a survey. Moving from household to individual income makes percent black significant for one year estimates, but percent black is significant with both five year estimate models. The same is true for the percent with a bachelors degree or more variable. The percent of males aged 35 to 64 with a disability is significant with household and not individual income for one year estimates, but is significant with both income measures when using five year estimates. Due to household income intuitively seeming more relevant than individual income and there not being a clear statistical advantage of either variable, future models will use household income.

In all four model specifications, an increase in the opioid prescribing rate is associated with an increase in the fatal opioid overdose rate.

3.1.2 One Year vs Five Year Estimates

Columns 2 and 4 in table 3.1 examine the differences between modeling with American Community Survey one year and five year estimates. ACS1 refers to the one year estimates, whereas ACS5 refers to the five year estimates. There are several significant changes that occur when switching between one and five year estimates. For one, the

Table 3.1: Individual versus Household Income with One and Five Year Estimates

	Dependent variable:			
	‘Fatal Overdose Crude Rate‘			
	ACS1 Household	ACS1 Individual	ACS5 Household	ACS5 Individual
	(1)	(2)	(3)	(4)
Median Household Income	−0.0003 (0.0002)		−0.00000 (0.0002)	
Median Individual Income		0.0003 (0.0004)		0.00004 (0.0004)
Prescribing Rate	0.149*** (0.050)	0.133** (0.052)	0.140*** (0.041)	0.132*** (0.042)
Density: Small Metro			−12.923*** (3.370)	−13.029*** (3.644)
Density: Micropolitan	4.198 (3.073)	4.722 (3.053)	−6.822** (2.743)	−7.758*** (2.915)
Density: Large Fringe Metro	11.548*** (3.028)	10.151*** (3.148)	−0.460 (3.125)	−1.360 (3.155)
Density: Medium Metro	6.776** (2.783)	7.908*** (2.690)	−5.250* (3.085)	−6.030* (3.305)
Density: Large Central Metro	2.440 (4.811)	3.362 (4.768)	−14.706*** (5.324)	−16.757*** (5.389)
% Black	0.316 (0.194)	0.485*** (0.174)	0.887*** (0.187)	0.896*** (0.172)
% with Some College	−0.145 (0.258)	−0.155 (0.260)	−0.381 (0.251)	−0.396 (0.252)
% with Bachelors or More	−0.019 (0.220)	−0.374** (0.184)	−0.451** (0.189)	−0.445*** (0.153)
% Disabled: Males Under 5	−0.387 (0.322)	−0.339 (0.323)	−0.406 (0.531)	−0.555 (0.534)
% Disabled: Males 5 to 17	0.253 (0.266)	0.220 (0.266)	0.326 (0.367)	0.175 (0.370)
% Disabled: Males 18 to 34	0.299 (0.282)	0.285 (0.283)	0.999** (0.403)	0.877** (0.422)
% Disabled: Males 35 to 64	−0.466* (0.281)	−0.286 (0.295)	−0.869** (0.440)	−0.949** (0.471)
% Disabled: Males 65 to 74	0.007 (0.137)	0.013 (0.137)	0.492** (0.194)	0.371* (0.196)
% Disabled: Males 75 and Up	0.053 (0.098)	0.049 (0.099)	−0.051 (0.159)	−0.101 (0.173)
% Disabled: Females Under 5	0.814 (0.513)	0.870* (0.515)	0.432 (0.620)	0.460 (0.622)
% Disabled: Females 5 to 17	−0.307 (0.304)	−0.354 (0.304)	−2.115*** (0.538)	−2.161*** (0.539)
% Disabled: Females 18 to 34	−0.525* (0.294)	−0.569* (0.293)	−0.810** (0.399)	−0.998** (0.415)
% Disabled: Females 35 to 64	0.619* (0.331)	0.638* (0.332)	0.815** (0.410)	1.224*** (0.433)
% Disabled: Females 65 to 74	0.222 (0.141)	0.223 (0.141)	0.265 (0.255)	0.377 (0.264)
% Disabled: Females 75 and Up	0.005 (0.109)	0.049 (0.110)	0.028 (0.195)	0.084 (0.194)
Observations	218	218	257	244
R^2	0.528	0.525	0.561	0.578
Adjusted R^2	0.475	0.471	0.518	0.534
Residual Std. Error	8.806 (df = 195)	8.839 (df = 195)	8.769 (df = 233)	8.523 (df = 220)
F Statistic	9.928*** (df = 22; 195)	9.790*** (df = 22; 195)	12.967*** (df = 23; 233)	13.105*** (df = 23; 220)
Note:				*p<0.1; **p<0.05; ***p<0.01

coefficient for the prescribing rate goes down slightly when using five year estimates, although to a degree that is almost unnoticeable. In both cases the prescribing rate is statistically significant at the 1% level. The significance and impact of the density level dummies changes as well. With one year estimates, medium density areas are associated with a significantly higher overdose rate. In contrast, density has a statistically significant protective effect when using five year estimates. This is likely due to the five year estimates containing more small, rural counties, which the literature suggested have the highest overdose rates in Ohio. The coefficient of "Percent Black" more than doubles when the five year estimates are used, and is only significant with that dataset. While the coefficient for percent with a bachelors degree or more is close to zero and statistically insignificant with one year estimates, it has a statistically significant protective effect when using five year estimates. With five year estimates, as the percent of males aged 18 to 34 with a disability rises, the fatal opioid overdose rate rises. The protective effect of the percent of males aged 36 to 64 with a disability increases in both magnitude and statistical significance when using five year estimates instead of one year estimates. With five year estimates, the percent of males aged 65 to 74 with a disability is associated with increased overdose deaths. Switching from one year to five year estimates increases the magnitude and statistical significance of the protective effect of disabilities among females aged under five and five to 17. Furthermore, using five year estimates increases the coefficient and significance of the percent of females aged 35 to 64 with a disability variable. I will emphasize the five year estimates throughout the rest of my thesis because the models using the five year estimates have greater R-squared values than the models using one year estimates, meaning that the models using five year estimates explain more of the variance in the dataset.

3.1.3 Fatal Overdose Rate Metrics

Table 3.2 shows the differences between using the crude fatal overdose rate, the age-adjusted fatal overdose rate, and the imputed overdose rate when working with American Community Survey five year estimates. While there are minor differences between these model specifications, they all return very similar results. The crude and imputed models include approximately 100 more observations than the age-adjusted model, which makes it difficult to separate out the influence of using an age-adjusted rate from the influence of decreased observations. Adjusting the fatal overdose rate for age decreases the significance of the prescribing rate to the 10% level from the 1% level. With all three models, the prescribing rate has a small, but significant, protective effect. Using the age-adjusted fatal overdose rate increases the protective effect of population density on fatal overdoses, but decreases the significance of that effect. This probably means that there is correlation between the age distribution of a county and its population density. Using the age-adjusted rate makes all male disability rates insignificant, and increases the impact of female disability rates. This may be correlated with the disability rates being broken down into age bins. The imputed rate produces results are almost identical to the crude rate results. This is unsurprising, as the imputed rate is simply the crude rate with a few more obser-

Table 3.2: How does the type of overdose rate metric influence the results (AS5)?

	Crude	Age-Adjusted	Imputed
	(1)	(2)	(3)
Median Household Income	−0.00000 (0.0002)	0.0001 (0.0004)	0.00001 (0.0002)
Prescribing Rate	0.140*** (0.041)	0.151* (0.077)	0.135*** (0.041)
Density: Small Metro	−12.923*** (3.370)	−13.567 (9.824)	−11.136*** (3.330)
Density: Micropolitan	−6.822** (2.743)	−13.202 (8.821)	−4.985* (2.674)
Density: Large Fringe Metro	−0.460 (3.125)	−9.749 (8.603)	1.067 (3.097)
Density: Medium Metro	−5.250* (3.085)	−13.169 (8.684)	−3.485 (3.036)
Density: Large Central Metro	−14.706*** (5.324)	−23.284** (10.181)	−12.960** (5.331)
% Black	0.887*** (0.187)	0.744** (0.313)	0.906*** (0.188)
% with Some College	−0.381 (0.251)	−0.646 (0.414)	−0.384 (0.252)
% with Bachelors or More	−0.451** (0.189)	−0.327 (0.402)	−0.440** (0.188)
% Disabled: Males Under 5	−0.406 (0.531)	−0.890 (0.930)	−0.282 (0.533)
% Disabled: Males 5 to 17	0.326 (0.367)	1.076 (0.674)	0.353 (0.367)
% Disabled: Males 18 to 34	0.999** (0.403)	−0.775 (0.732)	0.978** (0.403)
% Disabled: Males 35 to 64	−0.869** (0.440)	−1.082 (0.889)	−0.766* (0.441)
% Disabled: Males 65 to 74	0.492** (0.194)	0.552 (0.343)	0.492** (0.193)
% Disabled: Males 75 and Up	−0.051 (0.159)	0.284 (0.337)	0.034 (0.157)
% Disabled: Females Under 5	0.432 (0.620)	3.801*** (1.391)	0.599 (0.622)
% Disabled: Females 5 to 17	−2.115*** (0.538)	−2.938*** (0.982)	−2.101*** (0.539)
% Disabled: Females 18 to 34	−0.810** (0.399)	0.374 (0.820)	−0.765* (0.402)
% Disabled: Females 35 to 64	0.815** (0.410)	1.928** (0.805)	0.718* (0.412)
% Disabled: Females 65 to 74	0.265 (0.255)	0.259 (0.437)	0.284 (0.257)
% Disabled: Females 75 and Up	0.028 (0.195)	−0.725* (0.385)	−0.065 (0.193)
Observations	257	142	259
R^2	0.561	0.665	0.552
Adjusted R^2	0.518	0.599	0.508
Residual Std. Error	8.769 (df = 233)	9.016 (df = 118)	8.854 (df = 235)
F Statistic	12.967*** (df = 23; 233)	10.168*** (df = 23; 118)	12.591*** (df = 23; 235)

Note: *p<0.1; **p<0.05; ***p<0.01

vations. Given that using the age-adjusted rate reduces the number of observations significantly, and the imputed rate only provides two more observations while significantly complicating the dependent variable, the rest of this thesis will use the crude rate.

3.1.4 County Fixed Effects

Among other things, table 3.3 examines what changes occur in the model when county fixed effects are included. Including county fixed effects increases the R-squareds by a little over 50%. This is unsurprising, as adding cross-sectional unit fixed effects typically causes a significant increase in the R-squared. As before, the five year estimates explain more of the variance in the sample than the one year estimates. With five year estimates and county fixed effects, the model is able to explain over 80% of the variation in the fatal overdose rate. Including fixed effects changes the coefficients to the point of reversing the signs in some cases. These changes will be examined in the following paragraphs.

I will now extract final results from table 3.3. Regardless of which specification is used, median household income has no effect on the fatal overdose rate. Before adding county fixed effects, an increase in the prescribing rate is associated with an increase in the fatal overdose rate. This is true of both one year and five year estimates. After controlling for fixed effects, an increase in the prescribing rate is correlated with a decrease in the fatal overdose rate. These relationships are statistically significant at the one percent level for all models other than county fixed effects with five year estimates. The change in the sign of the coefficients implies that some unobservable variable is driving both the prescribing rate and the overdose rate, and that there is not a direct causal relationship between prescription opioids and overdoses. While the literature emphasizes that there is a relationship, the dataset used in this thesis starts around the time that the pill-mill crisis in Ohio started to subside, which could potentially explain the disconnect.

Without county fixed effects, an increase in the percentage of the population that is black is associated with an increase in the fatal overdose rate. This is true of both one year and five year estimates, although the effect is stronger and statistically significant solely when using the five year estimates. After including the county fixed effects, the coefficients are reversed. Neither one year or five year estimates are statistically significant, and the five year estimate coefficient is approximately ten times as large as the one year estimate coefficient. This suggests that after controlling for unobservables, counties that have an increase in the percentage of their population that is black have decreased overdose deaths. It is possible that Cuyahoga county, which has both an extremely high rate of opioid overdoses and one of the largest percentage of people of color of any Ohio county, causes this reversal. There is significant evidence that physicians discriminated against people of color during the pill mill boom, and were less likely to write them a painkiller prescription. This ultimately led to a lower rate of opioid abuse, and therefore overdose, among people of color. Said racial discrimination, however, likely caused a higher rate of misuse

Table 3.3: Final Models

	Dependent variable:			
	‘Fatal Overdose Crude Rate‘			
	ACS1 without FE	ACS1 with FE	ACS5 without FE	ACS5 with FE
	(1)	(2)	(3)	(4)
Median Household Income	−0.0003 (0.0002)	−0.0004* (0.0002)	−0.00000 (0.0002)	0.001 (0.001)
Prescribing Rate	0.149*** (0.050)	−0.408*** (0.102)	0.140*** (0.041)	−0.123 (0.134)
Density: Small Metro			−12.923*** (3.370)	−29.700* (17.938)
Density: Micropolitan	4.198 (3.073)	−6.711 (13.355)	−6.822** (2.743)	−50.607** (20.359)
Density: Large Fringe Metro	11.548*** (3.028)	−1.070 (15.212)	−0.460 (3.125)	−70.650 (45.792)
Density: Medium Metro	6.776** (2.783)	−28.356** (13.922)	−5.250* (3.085)	−66.210* (34.950)
Density: Large Central Metro	2.440 (4.811)	11.532 (15.372)	−14.706*** (5.324)	48.020 (75.896)
% Black	0.316 (0.194)	−0.380 (0.987)	0.887*** (0.187)	−3.835 (2.658)
% with Some College	−0.145 (0.258)	0.924** (0.388)	−0.381 (0.251)	0.595 (1.008)
% with Bachelors or More	−0.019 (0.220)	0.377 (0.484)	−0.451** (0.189)	0.136 (1.401)
% Disabled: Males Under 5	−0.387 (0.322)	−0.113 (0.277)	−0.406 (0.531)	−0.128 (0.701)
% Disabled: Males 5 to 17	0.253 (0.266)	0.500** (0.226)	0.326 (0.367)	0.748 (0.566)
% Disabled: Males 18 to 34	0.299 (0.282)	0.397* (0.231)	0.999** (0.403)	0.227 (0.563)
% Disabled: Males 35 to 64	−0.466* (0.281)	−0.165 (0.250)	−0.869** (0.440)	−1.490** (0.728)
% Disabled: Males 65 to 74	0.007 (0.137)	0.036 (0.116)	0.492** (0.194)	−0.880** (0.348)
% Disabled: Males 75 and Up	0.053 (0.098)	0.038 (0.080)	−0.051 (0.159)	0.158 (0.252)
% Disabled: Females Under 5	0.814 (0.513)	0.457 (0.426)	0.432 (0.620)	−1.985** (0.939)
% Disabled: Females 5 to 17	−0.307 (0.304)	0.122 (0.256)	−2.115*** (0.538)	0.370 (0.806)
% Disabled: Females 18 to 34	−0.525* (0.294)	−0.086 (0.255)	−0.810** (0.399)	−0.392 (0.533)
% Disabled: Females 35 to 64	0.619* (0.331)	0.075 (0.311)	0.815** (0.410)	1.624* (0.833)
% Disabled: Females 65 to 74	0.222 (0.141)	0.191 (0.116)	0.265 (0.255)	−0.139 (0.355)
% Disabled: Females 75 and Up	0.005 (0.109)	0.057 (0.092)	0.028 (0.195)	−0.122 (0.265)
Observations	218	218	257	257
R^2	0.528	0.786	0.561	0.809
Adjusted R^2	0.475	0.712	0.518	0.716
Residual Std. Error	8.806 (df = 195)	6.522 (df = 161)	8.769 (df = 233)	6.730 (df = 172)
F Statistic	9.928*** (df = 22; 195)	10.584*** (df = 56; 161)	12.967*** (df = 23; 233)	8.690*** (df = 84; 172)
Note:				*p<0.1; **p<0.05; ***p<0.01

among people of color who did receive prescription painkillers.[1]

Like many other variables, including county fixed effects dramatically changes the coefficients of the education variables. Without fixed effects, both having some level of college education and having a bachelors degree has a protective effect against fatal overdoses, although the only statistically significant effect is that of having a bachelors or more when using five year estimates. After including county fixed effects, an increase in education levels is associated with an increase in fatal overdoses. This is only statistically significant when looking at some college with one year estimates. In all cases, the coefficients are of a rather small magnitude. The change in the sign of the coefficients when county fixed effects are included means that from a cross section perspective, education has a protective effect against fatal overdose, but from a per-county time series perspective, education increases the rate of fatal overdose.

This paragraph will examine the effect of male[2] disability rates. For ages five to seventeen, an increase in the rate is correlated with an increase in the fatal overdose rate. This effect is stronger when county fixed effects are included, which suggests that fluctuations in the rate within counties matters more than differences in the rate between counties. The effect is only statistically significant with fixed effects and one year estimates. The correlation is also true for ages 18 to 34, although the within versus between distinction is more ambiguous, and the results are also statistically significant with five year estimates without county fixed effects. For males aged 35 to 64, the disability rate has a protective effect which is statistically significant in three out of the four specifications. This contradicts the prevailing media narrative, which claims that a concentration of manual labor jobs in some areas led to an increased rate of disability among the older, predominantly male people who worked those jobs in those areas, which ultimately led to those areas having extremely high rates of opioid abuse and overdose. For those between the ages of 65 and 74, there is no meaningful effect with one year estimates. With five year estimates, an increase in the disability rate leads to an increase in fatal overdoes in the cross section dimension, and a decrease in the time series dimension. Both effects are statistically significant at the five percent level.

I will now look at female disability rates. For those under the age of five, an increase in the disability rate is correlated with an increase in the fatal overdose rate for all models except for five year estimates coupled with county fixed effects. That model is the only statistically significant one, however. For those aged 5 to 17, the disability rate has a protective effect between counties but is associated with an increase in fatal overdoses within counties. The protective effect between counties potentially reflects some underlying difference between how disabilities are diagnosed in different counties. For females aged 18 to 34, disabilities appear to have a protective effect against fatal overdose. The effect is statistically significant and larger in magnitude when county fixed effects are not included. In contrast, an increase in the disability

[1] Frakt and Monkovic, "A 'Rare Case Where Racial Biases' Protected African-Americans"; Swift et al., "Racial Discrimination in Medical Care Settings and Opioid Pain Reliever Misuse in a U.S. Cohort."

[2] This section uses the terms "male" and "female" to indicate that the dataset only captures biological sex at birth, and not gender identity.

rate for females aged 35 to 64 appears to increase the rate of fatal overdose. This is statistically significant in three out of the four specifications. Overall, this suggests that a diagnosed disability has a protective effect for younger females but a harmful effect for older females. I suspect that the protective effect among younger females reflects increased medical capacity and competence rather than being directly causal, especially since the effect is much larger between counties than within counties. In contrast, the coefficients for older females do not unambiguously change when county fixed effects are included, which means that the effect matters both between and within counties. This suggests that there is a direct causal relationship between the disability rate and the overdose rate. Curiously, neither the media nor the literature focuses on female disability rates, despite these results being less ambiguous than the male disability rates.

Finally, I will look at density. The models using the one year estimates do not have coefficients for small metro because the one year estimates do not include any counties with a population under 65,000. With the five year estimates, that density level is associated with lower overdose deaths both with and without county fixed effects. Micropolitan also has a protective effect which gets dramatically stronger with five year estimates and county fixed effects. This suggests that changes in density within counties matter much more than between counties. The same is true for large fringe metro, although the one year estimates without county fixed effects show a statistically significant increase in overdose deaths. Excluding column 1, medium metros also have a protective effect which gets dramatically stronger when county fixed effects are included. This is statistically significant for all models. Finally, large central metros appear to have higher than average overdose deaths, especially after including county fixed effects. In general, it seems like there is a barbell effect, where the extremes of density–very rural and very urban–are correlated with higher overdose rates than other density levels.

3.1.5 Censored Regression

In order to address potential data censoring, I also tried running a Tobit model, which is a form of censored regression. I was unable to get Tobit estimates, however, as the `censReg` package returns "Error: there are no censored observations". This is likely due to the large number of independent variables relative to the number of observations, as well as ambiguous censoring. Regressions ran with one year estimates, fewer variables, and neither county nor year fixed effects did converge, however, and showed no significant differences between an OLS and censored regression model. This indicates that there is little to no censoring in the data.

3.2 Policy Implications

While public policy around the opioid epidemic has emphasized reducing the number of opioid prescriptions, my results indicate that prescribing rates are no longer relevant when considering overdose deaths within the state of Ohio. This suggests that relaxing prescribing guidelines to increase access to effective pain treatment might be reasonable, but it would be prudent to wait for more evidence before doing so, especially given the extensive clinical research showing the addictiveness of opioids. It is possible that these results instead show that the Ohio and federal governments have become effective at preventing the diversion and misuse of prescription painkillers. To minimize risk, the state should continue prescription monitoring programs in any case to ensure that policymakers rapidly learn of any changes.

The results show a somewhat ambiguous role for education. Within counties, an increase in education levels is associated with an increase in overdose deaths. Therefore, policies that increase education levels are not an appropriate approach for reducing overdose deaths, although they are likely still worthwhile due to the broad positive effects of education. The cross section results, however, show that counties with higher education levels tend to have lower fatal overdose rates. This suggests that overdose prevention resources should be especially targeted at low-education counties in order to maximize their benefits.

The results suggest that people who live in extremely high or low density areas are more likely to die of a fatal overdose. From this, I can infer that moving people into medium density housing would reduce the number of fatal overdoses in Ohio. This Goldilocks effect would be difficult to achieve outside of the long-run however, as housing stock changes slowly. In the medium-run, further research could potentially identify what about medium density is so beneficial (or what about extremely dense and extremely rural is so harmful), and try to bring those elements to more communities in Ohio. Previous research into social capital and the influence of community on health will be useful for guiding this future research. In the short-run, these results indicate that Ohio should target opioid overdose prevention materials to cities and rural areas rather than suburbs. For example, naloxone distribution programs could be especially well-funded in those regions.

While many of the disability rate variables returned ambiguous coefficients, several were unambiguous enough to create clear policy prescriptions out of. While the media has emphasized the role of male disability from blue-collar employment on increased opioid abuse in the past two decades, the regressions clearly indicate that male disability has either no statistical role in overdose deaths or protects against them. Therefore, policymakers should put less of their effort into male disability and instead focus on female disability. The results show that for females, the disability rate among those aged 18 to 34 has a protective effect, whereas the rate among those aged 35 to 64 increases overdose deaths. Given the harms associated with the older female disability rate, extra resources should be directed towards members of that population in order to curtail deaths. Programs could include targeted opioid abuse education and increased access to holistic pain management among other services. In general, any programs targeted at men that are believed to be effective should be broadened to cover women as well, as the focus on men appears to have led to policymakers overlooking women. Furthermore, researchers should investigate why the disability rate among females aged 18 to 34 has a protective effect. I suspect it is due to underlying county-level factors that make early diagnoses more common. If further research indicates that is the case, then those factors should be spread to other counties. I would hazard a guess that access to quality healthcare with minimal opportunity cost is key.

Conclusion

The current opioid epidemic is the worst substance abuse epidemic in US history. Opioids are both uniquely effective at treating pain and uniquely addictive among substances of abuse. While opioid abuse has a variety of negative health effects, the largest problem with its usage is overdosing, in which an excessive quantity of opioids causes the user's respiratory system to shut down, leading to death. With synthetic opioids such as Fentanyl, death can come in as little as two minutes after consumption. Deaths from opioid overdoses kill more Americans each year than car crashes, gun violence, or HIV/AIDS did at its peak. In this thesis, I examined the economic and demographic determinants of the fatal opioid overdose rate in counties in Ohio.

The results find that the overdose death rate is higher in counties with lower education levels, a higher percentage of people of color, a higher percentage of disabled older women, and either very high or very low population density. Overdose deaths are less common in counties with a high level of middle-aged disabled men and in medium density areas. These results are useful for targeting resources such as naloxone distribution and treatment programs that include MAT towards communities and individuals that will benefit from them most. In particular, they indicate that policymakers have been overlooking women as victims of the opioid epidemic, and should focus on bringing them into prevention and treatment programs. My future work on the HEALing communities study at RTI will help clarify which programs are the most effective, and which communities they can help the most.

Appendix A

Code

```
# This chunk ensures that the thesisdown package is
# installed and loaded. This thesisdown package includes
# the template files for the thesis.
if(!require(devtools))
  install.packages("devtools", repos = "http://cran.rstudio.com")
if(!require(thesisdown))
  devtools::install_github("ismayc/thesisdown")
library(thesisdown)
# Load the libraries and data used in this Rmd file
library(tidyverse)
library(broom) # for manipulating regression output
library(here)
library(knitr) # for kable
library(kableExtra)
library(forcats)
library(citr)
library(rvest)
library(glue)
library(censReg)
library(stargazer) # for regression output
library(tidycensus) # putting this last stops the intermittent st_drivers() erro
options(knitr.table.format.args = list(scientific = FALSE,
        big.mark = ",",
        digits = 5),
        knitr.table.booktabs = T)
opts_chunk$set(include = TRUE,
               echo = FALSE,
               message = FALSE,
               warning = FALSE) # have R code only appear in appendix
get_census_table <- function(year, table, survey = "acs1") { # defaults to "acs1"
  df <- get_acs("county",
```

```
                year = year,
                table = table,
                survey = survey,
                state = "OH",
                output = "wide",
                cache_table = TRUE) %>%
    rename(county = NAME) %>%
    mutate(county = str_remove(county, " County, Ohio")) %>%
    mutate(year = year,
           survey = survey)
}

# wrapper for get_census_table that handles a year range
get_census_table_multiple_years <- function(years, table, survey = "acs1") { # defaults
  map_df(years, get_census_table, table, survey)
}
# Pulls down data from census if it is not already stored as a .Rda object in data/
if(!file.exists(here("data", "census.Rda"))){

  # DISABILITY
  if(!file.exists(here("data", "disability.Rda"))) {

    disability <- bind_rows(get_census_table_multiple_years(2010:2018, "B18101", "acs1"
                            get_census_table_multiple_years(2012:2018, "B18101", "acs5"
      mutate(disability_male_percent_under5 = B18101_004E / B18101_003E,
             disability_male_percent_5to17 = B18101_007E / B18101_006E,
             disability_male_percent_18to34 = B18101_010E / B18101_009E,
             disability_male_percent_35to64 = B18101_013E / B18101_012E,
             disability_male_percent_65to74 = B18101_016E / B18101_015E,
             disability_male_percent_75andup = B18101_019E / B18101_018E,
             disability_female_percent_under5 = B18101_023E / B18101_022E,
             disability_female_percent_5to17 = B18101_026E / B18101_025E,
             disability_female_percent_18to34 = B18101_029E / B18101_028E,
             disability_female_percent_35to64 = B18101_032E / B18101_031E,
             disability_female_percent_65to74 = B18101_035E / B18101_034E,
             disability_female_percent_75andup = B18101_038E / B18101_037E) %>%
      select(GEOID, survey, county, year, starts_with("disability"))

    save(disability, file = here("data", "disability.Rda"))

  } else {

    load(here("data", "disability.Rda"))
```

```
}

# RACE
if(!file.exists(here("data", "race.Rda"))) {

  race <- bind_rows(get_census_table_multiple_years(2010:2018, "B02001", "acs1"
                    get_census_table_multiple_years(2010:2018, "B02001", "acs5")
    mutate(percent_white = B02001_002E / B02001_001E,
           percent_black = B02001_003E / B02001_001E) %>%
    select(GEOID, survey, county, year, percent_white, percent_black)

  save(race, file = here("data", "race.Rda"))

} else {

  load(here("data", "race.Rda"))

}

# MEDIAN INDIVIDUAL INCOME
if(!file.exists(here("data", "income_individual.Rda"))) {

  income_individual <- bind_rows(get_census_table_multiple_years(2010:2018, "B0
                                 get_census_table_multiple_years(2010:20
    mutate(income_individual_median = B06011_001E) %>%
    select(GEOID, survey, county, year, income_individual_median)

  save(income_individual, file = here("data", "income_individual.Rda"))

} else {

  load(here("data", "income_individual.Rda"))

}

# MEDIAN HOUSEHOLD INCOME
if(!file.exists(here("data", "income_household.Rda"))) {

  income_household <- bind_rows(get_census_table_multiple_years(2010:2018, "B19
                                get_census_table_multiple_years(2010:2018, "B19
    mutate(income_household_median = B19013_001E) %>%
    select(GEOID, survey, county, year, income_household_median)

  save(income_household, file = here("data", "income_household.Rda"))
```

```
  } else {

    load(here("data", "income_household.Rda"))

  }

  # EDUCATION
  if(!file.exists(here("data", "education.Rda"))) {

    education <- bind_rows(get_census_table_multiple_years(2010:2018, "B15003", "acs1")
                           get_census_table_multiple_years(2012:2018, "B15003", "acs5")
      mutate(education_percent_less_than_highschool = ((B15003_002E + B15003_003E + B150
             education_percent_some_college = ((B15003_019E + B15003_020E + B15003_021E)
             education_percent_bachelors_or_more = ((B15003_022E + B15003_023E + B15003_
      select(GEOID, survey, county, year, starts_with("education"))

    save(education, file = here("data", "education.Rda"))

  } else {

    load(here("data", "education.Rda"))
  }

  census <- left_join(disability, race) %>%
    left_join(education) %>%
    left_join(income_individual) %>%
    left_join(income_household) %>%
    mutate(year = as.numeric(year),
           survey = as_factor(survey),
           county = as_factor(county))

  # save the census data as an RDA file
  save(census, file  = here("data", "census.Rda"))

} else {

  load(here("data", "census.Rda"))

}
if(!file.exists(here("data", "overdose.Rda"))) {

  # table sourced from https://wonder.cdc.gov/controller/datarequest/D76;jsessionid=C5
  # suppressed = 9 or fewer deaths
  # county, year with suppressed rows on
```

```
# all drug-related causes (includes alcohol and the like)
# fix suppression with https://doi.org/10.2105/AJPH.2014.301900
# rates per 100,000
# citation: Centers for Disease Control and Prevention, National Center for He
overdose_real <- read_tsv(here("data", "cdc_drug_overdose_deaths.txt")) %>%
  select(-Notes, -`Year Code`) %>% # na in all cases for Notes, Year Code is du
  rename(GEOID = `County Code`,
         year = Year,
         county = County,
         overdose_deaths = Deaths,
         cdc_population = Population,
         fatal_overdose_crude_rate = `Crude Rate`,
         fatal_overdose_age_adjusted_rate = `Age Adjusted Rate`) %>%
  # create dummies for unreliable / suppressed
  mutate(overdose_deaths_suppressed = if_else(overdose_deaths == "Suppressed", T
         fatal_overdose_crude_rate_unreliable = if_else(fatal_overdose_crude_rat
         fatal_overdose_crude_rate_suppressed = if_else(fatal_overdose_crude_rat
         fatal_overdose_age_adjusted_rate_unreliable = if_else(fatal_overdose_ag
         fatal_overdose_age_adjusted_rate_suppressed = if_else(fatal_overdose_ag
  # parse columns with suppressed/unreliable into numbers
  mutate(overdose_deaths = parse_number(overdose_deaths),
         fatal_overdose_crude_rate = parse_number(fatal_overdose_crude_rate),
         fatal_overdose_age_adjusted_rate = parse_number(fatal_overdose_age_adju
  mutate(county = str_remove(county, " County, OH")) %>%
  # make GEOID a character to make it easy to make it a factor after merging
  mutate(GEOID = as.character(GEOID))

# https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/
# citation: Rossen LM, Bastian B, Warner M, Khan D, Chong Y. Drug poisoning mo
overdose_modeled <- read_csv(here("data", "OverdoseDeathRate.csv")) %>%
  filter(State == "Ohio") %>%
  select(GEOID = FIPS,
         county = County,
         year = Year,
         fatal_overdose_modeled_rate = `Model-based Death Rate`,
         cdc_population = Population,
         urban_rural = `Urban/Rural Category`) %>%
  mutate(county = str_remove(county, " County, OH"),
         GEOID = as.character(GEOID),
         year = as.numeric(year),
         urban_rural = as_factor(urban_rural))

overdose <- left_join(overdose_real, overdose_modeled)
```

```
  save(overdose, file = here("data", "overdose.Rda"))

} else {

  load(here("data", "overdose.Rda"))

}
# download prescription data for one particular year
prescriptionYear <- function(year) {
  year <- as.character(year)
  df <- glue("https://www.cdc.gov/drugoverdose/maps/rxcounty{year}.html") %>%
    read_html() %>%
    html_node("table") %>%
    html_table() %>%
    mutate(year = year)
  colnames(df) <- c("county", "State", "FIPS", "PrescribingRate", "year")
  df <- df %>%
    filter(State == "OH") %>%
    select(-State, -FIPS) %>%
    mutate(county = str_remove(county, ", OH"))
}

if(!file.exists(here("data", "prescriptions.Rda"))) {

  prescriptions <- map_dfr(2006:2018, prescriptionYear) %>%
    mutate(county = as_factor(county),
           PrescribingRate = as.numeric(PrescribingRate),
           year = as.numeric(year))

  save(prescriptions, file = here("data", "prescriptions.Rda"))

} else {

  load(here("data", "prescriptions.Rda"))

}
if(!file.exists(here("data", "basemap.Rda"))) {

  base_map <- get_acs("county",
                      state = "OH",
                      table = "B02001",
                      geometry = TRUE,
                      output = "wide")
```

```r
  # reduce down to GEOID and geometry
  base_map <- base_map %>%
    select(GEOID, geometry, county = NAME)

  save(base_map, file = here("data", "basemap.Rda"))

} else {

  load(here("data", "basemap.Rda"))
}
if(!file.exists(here("data", "raw_df.Rda"))) {

  raw_df <- full_join(overdose, prescriptions) %>% # full join b/c a lot of rows
    left_join(census) %>%
    mutate_at(vars(contains("percent")), ~ .x * 100) %>% # convert percentages to
    mutate(county = as_factor(county),
           GEOID = as_factor(GEOID)) %>%
    ungroup()
  save(raw_df, file = here("data", "raw_df.Rda"))

} else {

  load(here("data", "raw_df.Rda"))

}
theme_map <- theme_minimal() +
  theme(axis.title.x = element_blank(),
        axis.ticks.x = element_blank(),
        axis.title.y = element_blank(),
        axis.ticks.y = element_blank(),
        axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        panel.grid.major = element_blank())
recodeVars <- function(df) {
  df %>%
    rename(County = county,
           Year = year,
           `Overdose Deaths` = overdose_deaths,
           `Population (CDC)` = cdc_population,
           `Fatal Overdose Crude Rate` = fatal_overdose_crude_rate,
           `Fatal Overdose Age-Adjusted Rate` = fatal_overdose_age_adjusted_rate,
           `Are Overdose Deaths Suppressed?` = overdose_deaths_suppressed,
           `Is the Fatal Overdose Crude Rate Unreliable?` = fatal_overdose_crude_r
           `Is the Fatal Overdose Crude Rate Suppressed?` = fatal_overdose_crude_r
```

```
            `Is the Fatal Overdose Age-Adjusted Rate Unreliable?` = fatal_overdose_age_ad
            `Is the Fatal Overdose Age-Adjusted Suppressed?` = fatal_overdose_age_adjuste
            `Fatal Overdose Modeled Rate` = fatal_overdose_modeled_rate,
            `Prescribing Rate` = PrescribingRate,
            `Percent of Males Aged Under 5 with a Disability` = disability_male_percent_u
            `Percent of Males Aged 5 to 17 with a Disability` = disability_male_percent_5
            `Percent of Males Aged 18 to 34 with a Disability` = disability_male_percent_
            `Percent of Males Aged 35 to 64 with a Disability` = disability_male_percent_
            `Percent of Males Aged 65 to 74 with a Disability` = disability_male_percent_
            `Percent of Males Aged 75 and Up with a Disability` = disability_male_percent
            `Percent of Females Aged Under 5 with a Disability` = disability_female_perce
            `Percent of Females Aged 5 to 17 with a Disability` = disability_female_perce
            `Percent of Females Aged 18 to 34 with a Disability` = disability_female_perc
            `Percent of Females Aged 35 to 64 with a Disability` = disability_female_perc
            `Percent of Females Aged 65 to 74 with a Disability` = disability_female_perc
            `Percent of Females Aged 75 and Up with a Disability` = disability_female_per
            `Percent White` = percent_white,
            `Percent Black` = percent_black,
            `Percent with Highschool or Less` = education_percent_less_than_highschool,
            `Percent with Some College` = education_percent_some_college,
            `Percent with Bachelors or More` = education_percent_bachelors_or_more,
            `Median Individual Income` = income_individual_median,
            `Median Household Income` = income_household_median)
}
df <- raw_df %>%
  # fix urban rural
  filter(!is.na(urban_rural)) %>%
  group_by(county) %>%
  summarize(Density = first(urban_rural)) %>%
  ungroup() %>%
  right_join(raw_df, by = c("county" = "county")) %>%
  recodeVars() %>%
  select(-urban_rural) %>%
  # calculate crude rate when it is not provided
  mutate(`Fatal Overdose Crude Rate` = if_else(!is.na(`Fatal Overdose Crude Rate`),
                                       `Fatal Overdose Crude Rate`,
                                       (`Overdose Deaths` / `Population (CDC)`)
  # create combined fatal overdose rate that includes imputed values
  mutate(`Fatal Overdose Rate (Includes Imputed)` = if_else(is.na(`Fatal Overdose Crude
                                                    `Fatal Overdose Modeled Rate
                                                    `Fatal Overdose Crude Rate`)
df_acs1 <- df %>%
  filter(survey == "acs1")
```

```
df_acs5 <- df %>%
  filter(survey == "acs5")
df %>%
  filter(Year > 2005,
         Year < 2017) %>%
  group_by(County, Year) %>%
  summarize(PopAdjustedRate = mean(`Prescribing Rate`, na.rm = TRUE) * mean(`Popul
            Deaths = mean(`Overdose Deaths`, na.rm = TRUE)) %>%
  ungroup() %>%
  group_by(Year) %>%
  summarize(PopAdjustedRate = sum(PopAdjustedRate, na.rm = TRUE),
            Deaths = mean(Deaths, na.rm = TRUE)) %>%
  ggplot(aes(x = Year, y = PopAdjustedRate)) +
  geom_point() +
  geom_line() +
  theme_classic() +
  labs(title = "Opioid Prescriptions in Ohio by Year",
       subtitle = "Dataset covers 2006-2016",
       y = "Prescriptions",
       x = "Year")
df %>%
  filter(Year > 1999,
         Year < 2019) %>%
  group_by(County, Year) %>%
  summarize(deaths = mean(`Overdose Deaths`, na.rm = TRUE)) %>%
  ungroup() %>%
  group_by(Year) %>%
  summarize(deaths = sum(deaths, na.rm = TRUE)) %>%
  ggplot(aes(x = Year, y = deaths)) +
    geom_point() +
    geom_line() +
    theme_classic() +
    labs(x = "Year",
         y = "Annual Fatal Drug Overdoses",
         title = "Overdose Deaths by Year",
         subtitle = "Excludes Counties Reporting Fewer than Ten Fatal Overdoses in
base_map %>%
  mutate(county = str_remove(county, " County, Ohio")) %>%
  ggplot(aes(label = county)) +
  geom_sf() +
  theme_map +
  geom_sf_text(aes(label = county), size = 2.5) +
  labs(title = "Counties in Ohio")
#################################
```

```
# Disability Variable Ordering #
#################################
base_disability_list <- c("disability_percent_under5", "disability_percent_5to17", "disa

# adds a suffix to a string
# used for generating the male and female disability lists
add_suffix <- function(string, suffix) {
  string <- paste0(string, suffix)
  string
}

# create male, female, and unified disability variable ordering list
# and then turn them back into usable vectors
# instead of lists (to avoid the [[]] nonsense and ambiguity with tidyselect)
male_disability_ordering <- base_disability_list %>%
  map(add_suffix, "_male") %>%
  as.character()
female_disability_ordering <- base_disability_list %>%
  map(add_suffix, "_female") %>%
  as.character()
disability_ordering <- c(male_disability_ordering, female_disability_ordering)

################################
# Education Variable Ordering #
################################
education_ordering <- c("education_b_percent_highschool_or_less", "education_b_percent_c
                        "education_s_percent_less_than_highschool", "education_s_percent
                        "education_s_percent_ged", "education_s_percent_some_college", "
                        "education_s_percent_graduate")

#############################
# Master Variable Ordering #
#############################
misc_variable_ordering <- c("OD_rate", "income_pc_individual", "percent_white", "percent
master_variable_ordering <- c(misc_variable_ordering, education_ordering, disability_ord
counties_included <- df %>%
  mutate(is_acs1 = if_else(survey == "acs1", TRUE, FALSE),
         is_acs5 = if_else(survey == "acs5", TRUE, FALSE)) %>%
  group_by(County, GEOID) %>%
  summarize(acs1 = sum(is_acs1, na.rm = TRUE),
            acs5 = sum(is_acs5, na.rm = TRUE)) %>%
  filter(!is.na(GEOID)) %>%
  ungroup() %>%
  mutate(included = if_else(acs1 > 0, TRUE, FALSE))
```

```
base_map %>%
  left_join(counties_included, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(geometry = geometry, fill = included)) +
  geom_sf() +
  labs(fill = "Included?",
       title = "Counties Included in ACS1 Sample",
       subtitle = "All counties included in ACS5",
       x = "",
       y = "") +
  theme_map +
  scale_fill_viridis_d()
as.data.frame(df_acs1) %>%
  mutate(`Density: Noncore` = if_else(Density == "Noncore", TRUE, FALSE),
         `Density: Small Metro` = if_else(Density == "Small Metro", TRUE, FALSE),
         `Density: Micropolitan` = if_else(Density == "Micropolitan", TRUE, FALSE)
         `Density: Large Fringe Metro` = if_else(Density == "Large Fringe Metro",
         `Density: Medium Metro` = if_else(Density == "Medium Metro", TRUE, FALSE)
         `Density: Large Central Metro` = if_else(Density == "Large Central Metro"
  select(-Year,
         -GEOID,
         -`Population (CDC)`,
         -`Overdose Deaths`,
         -survey,
         -`Are Overdose Deaths Suppressed?`,
         -`Is the Fatal Overdose Crude Rate Unreliable?`,
         -`Is the Fatal Overdose Crude Rate Suppressed?`,
         -`Is the Fatal Overdose Age-Adjusted Rate Unreliable?`,
         -`Is the Fatal Overdose Age-Adjusted Suppressed?`,
         -`Fatal Overdose Modeled Rate`) %>%
  select(`Fatal Overdose Crude Rate`,
         `Fatal Overdose Age-Adjusted Rate`,
         `Fatal Overdose Imputed Rate` = `Fatal Overdose Rate (Includes Imputed)`,
         `% Black` = `Percent Black`,
         `Density: Noncore`,
         `Density: Small Metro`,
         `Density: Micropolitan`,
         `Density: Large Fringe Metro`,
         `Density: Medium Metro`,
         `Density: Large Central Metro`,
         `Prescribing Rate`,
         `Median Individual Income`,
         `Median Household Income`,
         `% with Highschool or Less` = `Percent with Highschool or Less`,
         `% with Some College` = `Percent with Some College`,
```

```
         `% with Bachelors or More` = `Percent with Bachelors or More`,
         `% Disabled: Males Under 5` = `Percent of Males Aged Under 5 with a Disability`
         `% Disabled: Males 5 to 17` = `Percent of Males Aged 5 to 17 with a Disability`
         `% Disabled: Males 17 to 34` = `Percent of Males Aged 18 to 34 with a Disabilit
         `% Disabled: Males 35 to 64` = `Percent of Males Aged 35 to 64 with a Disabilit
         `% Disabled: Males 65 to 74` = `Percent of Males Aged 65 to 74 with a Disabilit
         `% Disabled: Males 75 and Up` = `Percent of Males Aged 75 and Up with a Disabil
         `% Disabled: Females Under 5` = `Percent of Females Aged Under 5 with a Disabil
         `% Disabled: Females 5 to 17` = `Percent of Females Aged 5 to 17 with a Disabil
         `% Disabled: Females 17 to 34` = `Percent of Females Aged 18 to 34 with a Disab
         `% Disabled: Females 35 to 64` = `Percent of Females Aged 35 to 64 with a Disab
         `% Disabled: Females 65 to 74` = `Percent of Females Aged 65 to 74 with a Disab
         `% Disabled: Females 75 and Up` = `Percent of Females Aged 75 and Up with a Dis
  stargazer(header = FALSE,
            summary.stat = c("mean", "median", "sd", "min", "max"),
            title = "One Year Estimates (218 Observations)",
            font.size = "small",
            digits = 2)
as.data.frame(df_acs5) %>%
  mutate(`Density: Noncore` = if_else(Density == "Noncore", TRUE, FALSE),
         `Density: Small Metro` = if_else(Density == "Small Metro", TRUE, FALSE),
         `Density: Micropolitan` = if_else(Density == "Micropolitan", TRUE, FALSE),
         `Density: Large Fringe Metro` = if_else(Density == "Large Fringe Metro", TRUE,
         `Density: Medium Metro` = if_else(Density == "Medium Metro", TRUE, FALSE),
         `Density: Large Central Metro` = if_else(Density == "Large Central Metro", TRUE
  select(-Year,
         -GEOID,
         -`Population (CDC)`,
         -`Overdose Deaths`,
         -survey,
         -`Are Overdose Deaths Suppressed?`,
         -`Is the Fatal Overdose Crude Rate Unreliable?`,
         -`Is the Fatal Overdose Crude Rate Suppressed?`,
         -`Is the Fatal Overdose Age-Adjusted Rate Unreliable?`,
         -`Is the Fatal Overdose Age-Adjusted Suppressed?`,
         -`Fatal Overdose Modeled Rate`) %>%
  select(`Fatal Overdose Crude Rate`,
         `Fatal Overdose Age-Adjusted Rate`,
         `Fatal Overdose Imputed Rate` = `Fatal Overdose Rate (Includes Imputed)`,
         `% Black` = `Percent Black`,
         `Density: Noncore`,
         `Density: Small Metro`,
         `Density: Micropolitan`,
         `Density: Large Fringe Metro`,
```

```
         `Density: Medium Metro`,
         `Density: Large Central Metro`,
         `Prescribing Rate`,
         `Median Individual Income`,
         `Median Household Income`,
         `% with Highschool or Less` = `Percent with Highschool or Less`,
         `% with Some College` = `Percent with Some College`,
         `% with Bachelors or More` = `Percent with Bachelors or More`,
         `% Disabled: Males Under 5` = `Percent of Males Aged Under 5 with a Disab
         `% Disabled: Males 5 to 17` = `Percent of Males Aged 5 to 17 with a Disab
         `% Disabled: Males 17 to 34` = `Percent of Males Aged 18 to 34 with a Dis
         `% Disabled: Males 35 to 64` = `Percent of Males Aged 35 to 64 with a Dis
         `% Disabled: Males 65 to 74` = `Percent of Males Aged 65 to 74 with a Dis
         `% Disabled: Males 75 and Up` = `Percent of Males Aged 75 and Up with a D
         `% Disabled: Females Under 5` = `Percent of Females Aged Under 5 with a D
         `% Disabled: Females 5 to 17` = `Percent of Females Aged 5 to 17 with a D
         `% Disabled: Females 17 to 34` = `Percent of Females Aged 18 to 34 with a
         `% Disabled: Females 35 to 64` = `Percent of Females Aged 35 to 64 with a
         `% Disabled: Females 65 to 74` = `Percent of Females Aged 65 to 74 with a
         `% Disabled: Females 75 and Up` = `Percent of Females Aged 75 and Up with
  stargazer(header = FALSE,
            summary.stat = c("mean", "median", "sd", "min", "max"),
            title = "Five Year Estimates (257 Observations)",
            font.size = "small",
            digits = 2)
df %>%
  filter(!is.na(`Fatal Overdose Crude Rate`),
         !is.na(survey)) %>% # drop the NA rows that occur because of the missing
  ggplot(aes(x = `Fatal Overdose Crude Rate`)) +
  geom_histogram(bins = 25) +
  theme_minimal() +
  facet_wrap(~survey) +
  labs(y = "",
       x = "Overdose Rate (Deaths per 100,000)",
       title = "Distribution of Overdose Rate") +
  theme(axis.text.y = element_blank(),
        plot.title = element_text(hjust = 0.5))
df %>%
  group_by(County, GEOID) %>%
  summarize(`Fatal Overdose Crude Rate` = mean(`Fatal Overdose Crude Rate`, na.rm
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(fill = `Fatal Overdose Crude Rate`, geometry = geometry)) +
  geom_sf() +
  theme_map +
```

```
  scale_fill_viridis_c() +
  labs(title = "Crude Fatal Overdose Rate by County Averaged Across Years",
       subtitle = "Grey = 9 or Fewer Overdoses Across All Years",
       fill = "Rate")
df %>%
  filter(!is.na(survey)) %>%
  ggplot(aes(x = `Percent Black`)) +
  geom_histogram(bins = 20) +
  theme_minimal() +
  labs(title = "Distribution of Percent Black",
       x = "Percent Black",
       y = "") +
  facet_wrap(~survey) +
  scale_x_continuous(labels = function(x) paste0(x, "%")) + # adds percentage signs; sc
  theme(axis.text.y = element_blank(),
        plot.title = element_text(hjust = 0.5))
df %>%
  group_by(County, GEOID) %>%
  summarize(`Percent Black` = mean(`Percent Black`, na.rm = TRUE)) %>%
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(fill = `Percent Black`, geometry = geometry)) +
  geom_sf() +
  theme_map +
  scale_fill_viridis_c() +
  labs(title = "Percent Black by County",
       fill = "% Black")
# Error in if (type == "point") { : argument is of length zero
df %>%
  filter(!is.na(GEOID)) %>%
  group_by(County, GEOID) %>%
  summarize(Density = last(Density)) %>%
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot() +
  geom_sf(aes(fill = Density, geometry = geometry), show.legend = "polygon") +
  theme_map +
  scale_fill_viridis_d() +
  labs(title = "Density by County",
       fill = "Type")
df %>%
  filter(!is.na(survey)) %>%
  ggplot(aes(x = `Prescribing Rate`)) +
  geom_histogram(bins = 20) +
  theme_minimal() +
  labs(title = "Distribution of Prescribing Rate",
```

```
       x = "Prescribing Rate",
       y = "") +
  facet_wrap(~survey) +
  theme(axis.text.y = element_blank(),
        plot.title = element_text(hjust = 0.5))
# Error in if (type == "point") { : argument is of length zero
df %>%
  filter(!is.na(GEOID)) %>%
  group_by(County, GEOID) %>%
  summarize(`Prescribing Rate` = mean(`Prescribing Rate`, na.rm = TRUE)) %>%
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(fill = `Prescribing Rate`, geometry = geometry)) +
  geom_sf() +
  theme_map +
  scale_fill_viridis_c() +
  labs(title = "Prescribing Rate by County",
       fill = "Rate")
# Error in if (type == "point") { : argument is of length zero
df %>%
  filter(!is.na(GEOID)) %>%
  group_by(County, GEOID) %>%
  summarize(Income = mean(`Median Household Income`, na.rm = TRUE)) %>%
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(fill = Income, geometry = geometry)) +
  geom_sf() +
  theme_map +
  scale_fill_viridis_c() +
  labs(title = "Median Household Income by County",
       fill = "Household Income ($)")
df %>%
  filter(!is.na(survey)) %>%
  ggplot(aes(x = `Percent with Bachelors or More`)) +
  geom_histogram(bins = 20) +
  theme_minimal() +
  labs(title = "Distribution of Percent with a Bachelors Degree or More",
       x = "Percent with Bachelors or More",
       y = "") +
  facet_wrap(~survey) +
  scale_x_continuous(labels = function(x) paste0(x, "%")) + # adds percentage sig
  theme(axis.text.y = element_blank(),
        plot.title = element_text(hjust = 0.5))
df %>%
  group_by(County, GEOID) %>%
  summarize(`Percent with Bachelors or More` = mean(`Percent with Bachelors or Mor
```

```
  full_join(base_map, by = c("GEOID" = "GEOID")) %>%
  ggplot(aes(fill = `Percent with Bachelors or More`, geometry = geometry)) +
  geom_sf() +
  theme_map +
  scale_fill_viridis_c() +
  labs(title = "Percent with a Bachelors Degree or More by County",
       fill = "%")
regression_formula <- function(rate_variable, income_variable, fixed_effects=NULL) {

  # check that rate_variable is valid
  if(!rate_variable %in% c("`Fatal Overdose Crude Rate`",
                           "`Fatal Overdose Age-Adjusted Rate`",
                           "`Fatal Overdose Modeled Rate`",
                           "`Fatal Overdose Rate (Includes Imputed)`")) {
    stop(rate_variable, " is not a valid fatal overdose rate variable. Did you forget to
  }

  # check that income_variable is valid
  if(!income_variable %in% c("`Median Individual Income`",
                             "`Median Household Income`")) {
    stop(income_variable, " is not a valid income variable. Did you forget to wrap it in
  }

  # excludes 1 from each category (currently 5 and under for both sexes, highschool or
  formula_base <- paste(
    "`Prescribing Rate`",
    "`Density`",
    "`Percent Black`",
    "`Percent with Some College`",
    "`Percent with Bachelors or More`",
    "`Percent of Males Aged Under 5 with a Disability`",
    "`Percent of Males Aged 5 to 17 with a Disability`",
    "`Percent of Males Aged 18 to 34 with a Disability`",
    "`Percent of Males Aged 35 to 64 with a Disability`",
    "`Percent of Males Aged 65 to 74 with a Disability`",
    "`Percent of Males Aged 75 and Up with a Disability`",
    "`Percent of Females Aged Under 5 with a Disability`",
    "`Percent of Females Aged 5 to 17 with a Disability`",
    "`Percent of Females Aged 18 to 34 with a Disability`",
    "`Percent of Females Aged 35 to 64 with a Disability`",
    "`Percent of Females Aged 65 to 74 with a Disability`",
    "`Percent of Females Aged 75 and Up with a Disability`",
    sep = " + "
  )
```

```
  # add fixed effects if they're provided
  if(is.null(fixed_effects)) {

    regression_formula <- as.formula(paste0(rate_variable, " ~ ", income_variable,

  } else {

    regression_formula <- as.formula(paste0(rate_variable, " ~ ", income_variable,

  }


  # return formula
  regression_formula

}
# crude rate
crude_rate_formula <- regression_formula("`Fatal Overdose Crude Rate`", "`Median H
crude_rate_acs1 <- lm(crude_rate_formula, df_acs1)
crude_rate_acs5 <- lm(crude_rate_formula, df_acs5)

# age adjusted rate
age_adjusted_rate_formula <- regression_formula("`Fatal Overdose Age-Adjusted Rate
age_adjusted_rate_acs1 <- lm(age_adjusted_rate_formula, df_acs1)
age_adjusted_rate_acs5 <- lm(age_adjusted_rate_formula, df_acs5)

# with imputed values
imputed_formula <- regression_formula("`Fatal Overdose Rate (Includes Imputed)`",
imputed_acs1 <- lm(imputed_formula, df_acs1)
imputed_acs5 <- lm(imputed_formula, df_acs5)

# individual income
crude_rate_formula_individual_income <- regression_formula("`Fatal Overdose Crude
crude_rate_individual_acs1 <- lm(crude_rate_formula_individual_income, df_acs1)
crude_rate_individual_acs5 <- lm(crude_rate_formula_individual_income, df_acs5)

# with county Fixed Effects
county_FE_formula <- regression_formula("`Fatal Overdose Crude Rate`", "`Median Ho
county_FE_acs1 <- lm(county_FE_formula, df_acs1)
county_FE_acs5 <- lm(county_FE_formula, df_acs5)
# show that household and individual are not significantly different
stargazer(
  crude_rate_acs1,
  crude_rate_individual_acs1,
```

```
  crude_rate_acs5,
  crude_rate_individual_acs5,
  covariate.labels = c(
    "Median Household Income",
    "Median Individual Income",
    "Prescribing Rate",
    "Density: Small Metro",
    "Density: Micropolitan",
    "Density: Large Fringe Metro",
    "Density: Medium Metro",
    "Density: Large Central Metro",
    "\\% Black",
    "\\% with Some College",
    "\\% with Bachelors or More",
    "\\% Disabled: Males Under 5",
    "\\% Disabled: Males 5 to 17",
    "\\% Disabled: Males 18 to 34",
    "\\% Disabled: Males 35 to 64",
    "\\% Disabled: Males 65 to 74",
    "\\% Disabled: Males 75 and Up",
    "\\% Disabled: Females Under 5",
    "\\% Disabled: Females 5 to 17",
    "\\% Disabled: Females 18 to 34",
    "\\% Disabled: Females 35 to 64",
    "\\% Disabled: Females 65 to 74",
    "\\% Disabled: Females 75 and Up"
  ),
  title = "Does Individual vs Household Income Significantly Change the Model?",
  omit = c("Year", "Constant"),
  column.labels = c("ACS1 Household", "ACS1 Individual", "ACS5 Household", "ACS5 Individ
  single.row = TRUE,
  float.env = "sidewaystable",
  sep.width = 0,
  font.size = "small",
  header = FALSE
)
stargazer(
  crude_rate_acs5,
  age_adjusted_rate_acs5,
  imputed_acs5,
  covariate.labels = c(
    "Median Household Income",
    "Prescribing Rate",
    "Density: Small Metro",
```

```
    "Density: Micropolitan",
    "Density: Large Fringe Metro",
    "Density: Medium Metro",
    "Density: Large Central Metro",
    "\\% Black",
    "\\% with Some College",
    "\\% with Bachelors or More",
    "\\% Disabled: Males Under 5",
    "\\% Disabled: Males 5 to 17",
    "\\% Disabled: Males 18 to 34",
    "\\% Disabled: Males 35 to 64",
    "\\% Disabled: Males 65 to 74",
    "\\% Disabled: Males 75 and Up",
    "\\% Disabled: Females Under 5",
    "\\% Disabled: Females 5 to 17",
    "\\% Disabled: Females 18 to 34",
    "\\% Disabled: Females 35 to 64",
    "\\% Disabled: Females 65 to 74",
    "\\% Disabled: Females 75 and Up"
  ),
  title = "How does the type of overdose rate metric influence the results (AS5)?"
  omit = c("Year", "Constant"),
  column.labels = c("Crude", "Age-Adjusted", "Imputed"),
  dep.var.caption = "",
  single.row = TRUE,
  float.env = "sidewaystable",
  sep.width = 0.5,
  font.size = "small",
  header = FALSE
)
stargazer(
  crude_rate_acs1,
  county_FE_acs1,
  crude_rate_acs5,
  county_FE_acs5,
  covariate.labels = c(
    "Median Household Income",
    "Prescribing Rate",
    "Density: Small Metro",
    "Density: Micropolitan",
    "Density: Large   e Metro",
    "Density: Medium Metro",
    "Density: Large Central Metro",
    "\\% Black",
```

```
    "\\% with Some College",
    "\\% with Bachelors or More",
    "\\% Disabled: Males Under 5",
    "\\% Disabled: Males 5 to 17",
    "\\% Disabled: Males 18 to 34",
    "\\% Disabled: Males 35 to 64",
    "\\% Disabled: Males 65 to 74",
    "\\% Disabled: Males 75 and Up",
    "\\% Disabled: Females Under 5",
    "\\% Disabled: Females 5 to 17",
    "\\% Disabled: Females 18 to 34",
    "\\% Disabled: Females 35 to 64",
    "\\% Disabled: Females 65 to 74",
    "\\% Disabled: Females 75 and Up"
  ),
  title = "Final Models",
  omit = c("Year", "County", "Constant"),
  column.labels = c("ACS1 without FE", "ACS1 with FE", "ACS5 without FE", "ACS5 with FE"
  single.row = TRUE,
  float.env = "sidewaystable",
  sep.width = 0,
  font.size = "small",
  header = FALSE
)
# disabled because no censored regressions
crude_rate_household <- regression_formula("`Fatal Overdose Age-Adjusted Rate`", "`Media
crude_rate_household_FE <- regression_formula("`Fatal Overdose Age-Adjusted Rate`", "`Me
# picked left basically at random to get rid of "there are no censored observations" e
stargazer(censReg(crude_rate_household, data = df_acs1, logLikOnly = FALSE),
          censReg(crude_rate_household, data = df_acs5, logLikOnly = FALSE),
          censReg(crude_rate_household_FE, data = df_acs1, logLikOnly = FALSE),
          censReg(crude_rate_household_FE, data = df_acs5, logLikOnly = FALSE),
          covariate.labels = c(
    "Median Household Income",
    "Prescribing Rate",
    "Density: Small Metro",
    "Density: Micropolitan",
    "Density: Large Fringe Metro",
    "Density: Medium Metro",
    "Density: Large Central Metro",
    "\\% Black",
    "\\% with Some College",
    "\\% with Bachelors or More",
    "\\% Disabled: Males Under 5",
```

```
    "\\% Disabled: Males 5 to 17",
    "\\% Disabled: Males 18 to 34",
    "\\% Disabled: Males 35 to 64",
    "\\% Disabled: Males 65 to 74",
    "\\% Disabled: Males 75 and Up",
    "\\% Disabled: Females Under 5",
    "\\% Disabled: Females 5 to 17",
    "\\% Disabled: Females 18 to 34",
    "\\% Disabled: Females 35 to 64",
    "\\% Disabled: Females 65 to 74",
    "\\% Disabled: Females 75 and Up"
  ),
          title = "Tobit: Age-Adjusted Rate on Household Income with and without Y
          dep.var.caption = "Fatal Overdose Rate (Age-Adjusted)",
          omit = "Year",
          column.labels = c("ACS1", "ACS5", "ACS1 with FE", "ACS5 with FE"),
          add.lines = list(c("Fixed Effects?", "No", "No", "Yes", "Yes")),
          single.row = TRUE,
          sep.width = 0,
          font.size = "small",
          float.env = "sidewaystable",
          header = FALSE)
# copied from https://yihui.org/en/2018/09/code-appendix/
```

In Chapter ??:

Appendix B

Timeline

1980s: Last physicians from first opioid epidemic retire

1995: Pain becomes fifth vital sign in physician guidelines

1996: Oxycontin is brought to market by Purdue Pharmaceuticals

1999: VA adopts pain as fifth vital sign[1]

2001: First major book on prescription painkiller abuse is written (Meier's *Painkiller*)

2000s: Heroin from Nayarit available in most cities

2007: Purdue (the Oxycontin manufacturers) pleads guilty to misbranding the drug[2]

2010: Oxycontin is reformulated

2010s: Fentanyl and other synthetic opioids enter the black market supply chain

2016: FDA begins to require CME for physicians prescribing opioids[3]

2017: US government labels the epidemic as a public health emergency[4]

2019: HEALing Communities Study announced by the National Institute of Health

[1] Jones et al., "A Brief History of the Opioid Epidemic and Strategies for Pain Medicine."
[2] Jones et al.; Quinones, *Dreamland*.
[3] Jones et al., "A Brief History of the Opioid Epidemic and Strategies for Pain Medicine."
[4] Jones et al.

References

Aliprantis, Dionissi, and Mark E. Schweitzer. “Opioids and the Labor Market.” Working Paper (Federal Reserve Bank of Cleveland). Federal Reserve Bank of Cleveland, May 2018. https://doi.org/10.26509/frbc-wp-201807.

Alpert, Abby, David Powell, and Rosalie Liccardo Pacula. “Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids.” NBER Working Paper. National Bureau of Economic Research, 2017.

Arablouei, Ramtin, and Rund Abdelfatah. “A History of Opioids in America.” *National Public Radio*, April 2019.

Arcidiacono, Davide. “Consumer Rationality in a Multidisciplinary Perspective.” *The Journal of Socio-Economics* 40, no. 5 (October 2011): 516–22. https://doi.org/10.1016/j.socec.2011.01.003.

Badger, Gary J., Warren K. Bickel, Louis A. Giordano, Eric A. Jacobs, George Loewenstein, and Lisa Marsch. “Altered States: The Impact of Immediate Craving on the Valuation of Current and Future Opioids.” *Journal of Health Economics* 26, no. 5 (September 2007): 865–76. https://doi.org/10.1016/j.jhealeco.2007.01.002.

Becker, Gary S., and Kevin M. Murphy. “A Theory of Rational Addiction.” *Journal of Political Economy* 96, no. 4 (1988): 675–700.

Black, John BlackJohn, Nigar HashimzadeNigar Hashimzade, and Gareth Myles-Gareth Myles. “Consumer Rationality.” In *A Dictionary of Economics*. Oxford University Press, 2013.

Bourgois, Philippe I., and Jeff Schonberg. *Righteous Dopefiend*. California Series in Public Anthropology 21. Berkeley: University of California Press, 2009.

Brummett, Chad M., and Steven P. Cohen. *Managing Pain: Essentials of Diagnosis and Treatment*. Cary, UNITED STATES: Oxford University Press, Incorporated, 2013.

Calgary, Open. “NCHS - Drug Poisoning Mortality by County: United States | Data | Centers for Disease Control and Prevention.” https://data.cdc.gov/NCHS/NCHS-Drug-Poisoning-Mortality-by-County-United-Sta/p56q-jrxg, n.d.

Carroll, Jennifer J., Brandon D. L. Marshall, Josiah D. Rich, and Traci C. Green. "Exposure to Fentanyl-Contaminated Heroin and Overdose Risk Among Illicit Opioid Users in Rhode Island: A Mixed Methods Study." *International Journal of Drug Policy* 46 (August 2017): 136–45. https://doi.org/10.1016/j.drugpo.2017.05.023.

Case, Anne, and Angus Deaton. "Mortality and Morbidity in the 21st Century." Brookings, 2017.

CDC. "Fentanyl." *Center for Disease Control.* https://www.cdc.gov/drugoverdose/opioids/fentanyl.html, June 2019.

Ciccarone, Daniel. "Fentanyl in the US Heroin Supply: A Rapidly Changing Risk Environment." *International Journal of Drug Policy* 46 (August 2017): 107–11. https://doi.org/10.1016/j.drugpo.2017.06.010.

Cicero, Theodore J., Matthew S. Ellis, and Hilary L. Surratt. "Effect of Abuse-Deterrent Formulation of OxyContin." Letter, July 2012. https://doi.org/10.1056/NEJMc1204141.

Collett, B J. "Opioid Tolerance: The Clinical Perspective." *British Journal of Anaesthesia* 81, no. 1 (July 1998): 58–68. https://doi.org/10.1093/bja/81.1.58.

Coplan, P. M., H. D. Chilcoat, S. F. Butler, E. M. Sellers, A. Kadakia, V. Harikrishnan, J. D. Haddox, and R. C. Dart. "The Effect of an Abuse-Deterrent Opioid Formulation (OxyContin) on Opioid Abuse-Related Outcomes in the Postmarketing Setting." *Clinical Pharmacology and Therapeutics* 100, no. 3 (September 2016): 275–86. https://doi.org/10.1002/cpt.390.

Culyer, A. J. *The Dictionary of Health Economics.* Chelthenham, UK ; Northampton, MA: Edward Elgar, 2005.

Esch, Caitlin. "How One Sentence Helped Set Off the Opioid Crisis." *Marketplace*, December 2017.

Fairbairn, Nadia, Phillip O. Coffin, and Alexander Walley. "Naloxone for Heroin, Prescription Opioid, and Illicitly Made Fentanyl Overdoses: Challenges and Innovations Responding to A Dynamic Epidemic." *The International Journal on Drug Policy* 46 (August 2017): 172–79. https://doi.org/10.1016/j.drugpo.2017.06.005.

Frakt, Austin, and Toni Monkovic. "A 'Rare Case Where Racial Biases' Protected African-Americans." *The New York Times*, November 2019.

Frank, Richard G., and Harold A. Pollack. "Addressing the Fentanyl Threat to Public Health." *New England Journal of Medicine* 376, no. 7 (February 2017): 605–7. https://doi.org/10.1056/NEJMp1615145.

Frieden, Thomas R., and Debra Houry. "Reducing the Risks of Relief the CDC Opioid-Prescribing Guideline." *New England Journal of Medicine* 374, no. 16

(April 2016): 1501–4. `https://doi.org/10.1056/NEJMp1515917`.

"Geographic Areas Covered in the ACS." U.S. Census Bureau, 2020.

Gruber, J., and B. Koszegi. "Is Addiction "Rational"? Theory and Evidence." *The Quarterly Journal of Economics* 116, no. 4 (November 2001): 1261–1303. `https://doi.org/10.1162/003355301753265570`.

Gruber, Jonathan. "Smoking's 'Internalities'." *MIT Health & Medicine*, 2002, 6.

Gwartney, James D., ed. *Microeconomics: Private & Public Choice*. 11th ed. Mason, OH: Thomson/South-Western, 2006.

Hanck, Christoph, Martin Arnold, Martin Schmelzer, and Alexander Gerber. "10.3 Fixed Effects Regression." In *Introduction to Econometrics with R*. Essen, Germany: University of Duisburg-Essen, 2019.

Haney, Taylor, and Andrea Hsu. "Doctor Who Wrote 1980 Letter on Painkillers Regrets That It Fed the Opioid Crisis." *NPR.org*. https://www.npr.org/sections/health-shots/2017/06/16/533060031/doctor-who-wrote-1980-letter-on-painkillers-regrets-that-it-fed-the-opioid-crisi, n.d.

Hempstead, Katherine, and Emel O. Yildirim. "Supply-Side Response to Declining Heroin Purity: Fentanyl Overdose Episode in New Jersey." *Health Economics* 23, no. 6 (2014): 688–705. `https://doi.org/10.1002/hec.2937`.

Henningsen, Anne. "censReg," December 2019.

Hill, R. Carter, William E. Griffiths, and G. C. Lim. *Principles of Econometrics*. 4th ed. Hoboken, NJ: Wiley, 2011.

Jones, Mark R., Omar Viswanath, Jacquelin Peck, Alan D. Kaye, Jatinder S. Gill, and Thomas T. Simopoulos. "A Brief History of the Opioid Epidemic and Strategies for Pain Medicine." *Pain and Therapy* 7, no. 1 (June 2018): 13–21. `https://doi.org/10.1007/s40122-018-0097-6`.

Kahneman, Daniel. *Thinking, Fast and Slow*. 1st ed. New York: Farrar, Straus and Giroux, 2011.

Kastin, Abba. *Handbook of Biologically Active Peptides*. San Diego, UNITED STATES: Elsevier Science & Technology, 2013.

Krueger, Alan B. "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate." Brooks Papers on Economic Activity. Brookings, August 2017.

Lebow, Mahria. "Census Help," n.d.

Macy, Beth. *Dopesick: Dealers, Doctors, and the Drug Company That Addicted America*. First edition. New York: Little, Brown and Company, 2018.

Maguire, Karen. "The Opioid Crisis in Appalachia: The Effect of Blue-Collar Employment." *Applied Economics Letters* 26, no. 18 (February 2019): 1480–4.

Marek Hlavac. "Stargazer." Central European Labour Studies Institute, May 2018.

Marshall, Brandon D. L., Maxwell S. Krieger, Jesse L. Yedinak, Patricia Ogera, Priya Banerjee, Nicole E. Alexander-Scott, Josiah D. Rich, and Traci C. Green. "Epidemiology of Fentanyl-Involved Drug Overdose Deaths: A Geospatial Retrospective Study in Rhode Island, USA." *International Journal on Drug Policy* 46 (2017): 130–35. https://doi.org/10.1016/j.drugpo.2017.05.029.

Matthew Hrubey. "Northeast Ohio Manufacturing Brief." Urban Publications. Center for Economic Development, January 2011.

Meier, Barry. *Pain Killer: An Empire of Deceit and the Origin of America's Opioid Epidemic*. Second edition. New York: Random House, 2018.

Morgan, Michael M, and MacDonald J Christie. "Analysis of Opioid Efficacy, Tolerance, Addiction and Dependence from Cell Culture to Human: Opioid Efficacy, Tolerance and Addiction." *British Journal of Pharmacology* 164, no. 4 (October 2011): 1322–34. https://doi.org/10.1111/j.1476-5381.2011.01335.x.

Musto, D. F. "Iatrogenic Addiction: The Problem, Its Definition and History." *Bulletin of the New York Academy of Medicine* 61, no. 8 (October 1985): 694–705.

Naomi Lamoreaux, and Margaret Levenstein. "The Decline of an Innovative Region: Cleveland, Ohio, in the Twentieth Century." UCLA, Unniversity of Michigan, and NBER, September 2008.

Nutt, David, Leslie A. King, William Saulsbury, and Colin Blakemore. "Development of a Rational Scale to Assess the Harm of Drugs of Potential Misuse." *The Lancet* 369, no. 9566 (March 2007): 1047–53. https://doi.org/10.1016/S0140-6736(07)60464-4.

O'Donnell, Julie K., R. Matthew Gladden, and Puja Seth. "Trends in Deaths Involving Heroin and Synthetic Opioids Excluding Methadone, and Law Enforcement Drug Product Reports, by Census Region United States, 20062015." *MMWR. Morbidity and Mortality Weekly Report* 66, no. 34 (September 2017): 897–903. https://doi.org/10.15585/mmwr.mm6634a2.

Popovici, Ioana, Johanna Catherine Maclean, Bushra Hijazi, and Sharmini Radakrishnan. "The Effect of State Laws Designed to Prevent Nonmedical Prescription Opioid Use on Overdose Deaths and Treatment." *Health Economics* 27, no. 2 (February 2018): 294–305. https://doi.org/10.1002/hec.3548.

Porter, J, and H Jick. "Addiction Rare in Patients Treated with Narcotics." *New England Journal of Medicine* 302, no. 2 (January 1980): 123–23. https://doi.org/10.1056/NEJM198001103020221.

Quinones, Sam. *Dreamland: The True Tale of America's Opiate Epidemic*. Paperback edition. New York: Bloomsbury Press, 2016.

Rastegar, Darius, and Michael Fingerhood. *The American Society of Addiction Medicine Handbook of Addiction Medicine*. New York, UNITED STATES: Oxford University Press, Incorporated, 2015.

Socias, M Eugenia, and Evan Wood. “Epidemic of Deaths from Fentanyl Overdose.” *BMJ*, September 2017, j4355. `https://doi.org/10.1136/bmj.j4355`.

Swift, Samuel L., M. Maria Glymour, Tali Elfassy, Cora Lewis, Catarina I. Kiefe, Stephen Sidney, Sebastian Calonico, Daniel Feaster, Zinzi Bailey, and Adina Zeki Al Hazzouri. “Racial Discrimination in Medical Care Settings and Opioid Pain Reliever Misuse in a U.S. Cohort: 1992 to 2015.” *PLoS ONE* 14, no. 12 (December 2019). `https://doi.org/10.1371/journal.pone.0226490`.

Trickey, Erick. “Inside the Story of America’s 19th-Century Opiate Addiction.” *Smithsonian*. https://www.smithsonianmag.com/history/inside-story-americas-19th-century-opiate-addiction-180967673/, n.d.

“Understanding the ACS: The Basics,” 2020.

Van Zee, Art. “The Promotion and Marketing of OxyContin: Commercial Triumph, Public Health Tragedy.” *American Journal of Public Health* 99, no. 2 (February 2009): 221–27. `https://doi.org/10.2105/AJPH.2007.131714`.

Walker, Kyle. “Tidycensus,” 2020.

———. “Tidycensus,” n.d.

———. *Tidycensus: Load Us Census Boundary and Attribute Data as 'Tidyverse' and 'Sf'-Ready Data Frames*, 2020. `https://CRAN.R-project.org/package=tidycensus`.

White, William L. *Slaying the Dragon: The History of Addiction Treatment and Recovery in America*. Bloomington, Ill: Chestnut Health Systems/Lighthouse Institute, 1998.

Wickham, Hadley. *Ggplot2: Elegant Graphics for Data Analysis*. Second edition. Use R! Cham: Springer, 2016.

Zhang, Sarah. “The One-Paragraph Letter from 1980 That Fueled the Opioid Crisis.” *The Atlantic*. https://www.theatlantic.com/health/archive/2017/06/nejm-letter-opioids/528840/, June 2017.