THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND CONSUMPTION OF OXYCODONE AND HYDROCODONE AT THE COUNTY LEVEL

A Thesis
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Master of Public Policy

By

Nathan Legg, B.A.

Washington, DC

April 9, 2020

THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND CONSUMPTION OF HYDROCODONE AND OXYCODONE AT THE COUNTY LEVEL

Nathan Legg, B.A.

Thesis Advisor: Adam Thomas, Ph.D.

Abstract

Since the start of commercial production of oxycodone and hydrocodone in the 1990s, consumption of prescription painkillers has consistently increased, as has the number of deaths attributable to the use of prescription opioids and related substances (such as, heroin and synthetic opioids). Previous studies have found that poor economic conditions are linked to worsening health outcomes and increases in risky behaviors such as substance abuse. A burgeoning literature examines this connection, focusing on the interrelationships between economic conditions, health outcomes, and overdose rates. This study attempts to examine the relationship between local economic conditions and prescription opioid use. Using novel and newly available data from the Drug Enforcement Agency on county-level opioid consumption, and data from the Bureau of Labor Statistics on county-level unemployment rates, I find that increases in unemployment rates are, in fact, *negatively* related to prescription opioid use, although subgroup analysis suggests that this relationship differs somewhat in counties with different demographic and socioeconomic characteristics.

Table of Contents

List of Figures

List of Tables

Introduction

In October of 2017, acting Secretary of Health and Human Services (HHS) Eric Hargan declared the abuse of opioids a public health emergency (Hargan 2017). That same year, the US health care system dispensed nearly 200 million opioid prescriptions, with roughly 17% of the population having at least one prescription filled (Centers for Disease Control and Prevention 2018). Over this same period, there were more than 70,000 fatal drug-related overdoses. Some 67% of these events involved some type of opioid (Scholl et al. 2018). HHS estimates that 130 Americans perish every day from opioid abuse (Department of Health and Human Services 2019).

The Centers for Disease Control and Prevention (CDC) provides prescription guidelines based on the long-term health impacts of opioids, with the goal of mitigating potential harm to patients (Dowell and Chou 2016). However, prescribing doctors have tended to rely on personal judgement when making prescription decisions (Kilaru 2014). In addition, Paulozzi et al. (2014) have identified differences in prescription practices based on geographic location. Rural areas in Southern, Appalachian, and Western states have higher rates of opioid prescriptions per capita than the rest of the country (Rolheiser, Cordes and Subramanian 2018). This variation in prescription standards is not correlated with differences in health status and shows no indication of improving health outcomes (Paulozzi et al. 2014). According to Elinore McCance-Katz of the Substance Abuse and Mental Health Services Administration (2017), roughly half of prescription opioid abusers received their drugs from family or friends.

Drug-related deaths in the United States totaled more than 60,000 in 2016, a 21.4% increase from 2015. Two-thirds of these deaths involved some type of opioid (Scholl et al. 2018). Cicero et al. (2014) have found that the majority of new heroin users began their opioid abuse through the misuse of prescription opioids. The authors also identified a shift in the demographics of opioid users. In previous decades, opioid use had been concentrated in urban areas among minority populations and primarily consisted of illegal drugs such as heroin. In the late 2000s, however, opioid use became increasingly common in rural areas and among white populations (Cicero et al. 2014). Indeed, one reason for the overall rise in prescription opioid abuse may be regional differences in the sharing of prescription drugs among family and friends, which is more acceptable in rural areas (McCance-Katz 2017).

Much of the literature on the causes of the opioid epidemic focuses on the increased availability and affordability of prescription opioids, especially as the implementation of Medicare Part D moved costs from patients to insurers (Zhou et al. 2018). However, some researchers have focused on the relationship of general macroeconomic conditions and drug use. For example, Hollingsworth (2017) found that unemployment rates are positively related to drug-related mortality rates and to opioid-overdose-related hospital visits. In addition, in an examination of falling labor force participation rates, Krueger (2017) found that over half of males who had dropped out of the labor force took some sort of pain relief medication. However, relatively few studies directly assess the relationship between economic conditions and the use of prescription opioids.

In this paper, I estimate the impacts of local unemployment rates on the per-person use of oxycodone and hydrocodone. I use Drug Enforcement Administration data recently published by the *Washington Post* to measure prescription opioid use in a given area. These data provide information on the exact number of pills sent to each county in the United States in each month. I combine these data with Bureau of Labor Statistics unemployment data to estimate the relationship between unemployment rates and prescription opioid use at the county level.

Background

My period of analysis (2009 to 2012) coincides with the period of economic recovery after the Great Recession. The Recession caused large spikes in unemployment across the United States (Hacker et al. 2012). Moreover, compared to recessions in the 1980s and 1990s, the recovery was comparatively slow (Hoffman 2014). By 2013, the United States had yet to replace 15% of the jobs lost in 2008 and 2009 (Zmitrowicz and Khan 2014; Farber 2015). Additionally, the recovery was geographically inconsistent. Certain areas lagged others in job growth substantially; this was particularly true in the Ohio Valley and Appalachian regions (Economic Innovation Group 2017). These areas tended to have disproportionately large populations who lacked high school degrees, and job creation in these areas was generally insufficient to return even to 2000 employment levels (Economic Innovation Group 2017).

The slow nationwide recovery was accompanied by declining labor force participation rates. In 2015, participation fell to a forty-year low of 62.4% (Zmitrowicz and Khan 2014; Krueger 2017). The decline was even more pronounced among the prime working age population (50.6% in 2013). The slow recovery rate and decline in labor force participation were partly related to the aging of the population and pre-Recession trends, primarily an increased demand for higher education among those in the prime working age (Krueger 2017). Another aspect of the slow recovery was the limited recovery of the construction sector. Prior to the Recession, the United States was enjoying a construction boom, but weak housing markets after 2009 meant that this sector never fully recovered (Hoffman 2014). Krueger (2017) also identified dissatisfaction with employment as a strong correlate of falling labor force participation.

Literature Review

Given the relatively recent onset of the opioid crisis, there is limited direct research on the nexus of economic trends and prescription opioid abuse. The extent of opioid abuse, and the transition to misuse of prescription opioids, are difficult to measure (Currie et al. 2018). Researchers have been limited in their ability to measure drug abuse, other than through the use of survey data or mandatory reporting mechanisms, such as the cause of death listed on death certificates (Hollingsworth 2017). However, a large body of literature addresses the relationship between economic conditions and mental and physical health. Additionally, researchers have increasingly focused on the role played by economic trends in rates of opioid abuse and other risky behaviors.

Economic Factors and Health Outcomes

A considerable body of literature indicates that economic downturns are associated with negative health outcomes. Economic conditions have been found to be related to both physical and mental well-being at the individual and societal levels. Individuals who experience financially stressful situations tend to have poorer health outcomes (Brackbill et al. 1995; Laitenen 2002). More specifically, studies of the relationship between health and employment have found that, in general, the unemployed were more likely to face negative health outcomes than those with consistent employment (Jin 1997; Dooley 1996; McGree 2015). In addition, Laitenen (2002) found that those with an unhealthy Body Mass Index (BMI) tend to stress-eat, consume more alcohol, and engage in other unhealthy behaviors. Unemployment and uncertain working conditions were among the key stressors that the author identified as correlates of a high BMI.

Brackbill et al. (1995) studied hypertension among the general population. After controlling for demographic and health factors, they found that people who experienced unemployment reported experiencing more hypertension than the employed. Rates of hypertension were particularly high among those who had been unemployed for more than a year. These negative health outcomes manifested in a variety of ways, the most common being cardiac disease, substance abuse, and suicide (Dooley 1997; Pharr 2012).

In addition, unemployment is associated with a higher risk of depression. The unemployed also have more negative self-assessments of mental health than the employed (Goldsmith 1997; Holland 2012). Moreover, in an examination of an area's internet search trends and the number of applications for unemployment insurance in that area, Tefft (2011) found that searches for "depression" and "anxiety" were more common in places with higher numbers of unemployment insurance claims. Additionally, Mossakowski (2009) found that unemployment during youth was associated with feelings of depression much later in life.

Economic Factors and Risk-Taking Behaviors

Several studies have examined the linkages between economic factors and risk-taking behaviors. Some of these assess the extent to which variation in levels of opioid abuse can explain variation in labor market outcomes. For example, in 2017 Krueger performed a study of the decline in labor force participation among prime working age males. The author found that increased opioid use can explain a substantial portion of the decline in this group's labor force participation during the first fifteen of the 21st century. Other studies assess the extent to which limited economic opportunity is predictive of risky economic behavior. For example, Kearney and Levine (2012) described the feelings of hopelessness that often accompany a perceived lack of economic opportunity. The authors found that early childbearing is more common in places with higher levels of income inequality. Both strains of the literature suggest that there is an important link between economic factors and risky behavior.

Economics of Hopelessness and Deaths of Despair

The "economics of hopelessness" theory dominates the literature on the relationship between economic factors and opioid use. Case and Deaton (2015) found that, contrary to the experience of other developed countries and other demographic groups within the United States, mortality rates for non-Hispanic white men rose by 34 deaths per 100,000 between 2000 and 2015. During the same period, Hispanics experienced a reduction of 60 deaths per 100,000, and the mortality rate of black non-Hispanics fell by 200 per 100,000. The authors identified self-destructive behaviors as especially prevalent among non-Hispanic white males. They noted that this population had experienced increases in rates of suicide, alcohol-related liver disease, and poisonings from drug abuse. However, while death rates rose for all non-Hispanic white men, these increases were concentrated among those with lower levels of educational attainment. Hollingsworth et al. (2017) also found evidence of large increases in drug use and overdoses among non-Hispanic white men.

In 2017, Case and Deaton expanded on their 2015 work, studying deteriorating economic outcomes among the groups that experienced rising mortality rates (Case and Deaton 2017). They theorized that these groups believed that they were suffering from cumulative economic and social disadvantages (e.g. limited career opportunities and marriage prospects) as their standards of living declined. They argued that, as manual labor positions became less common and less likely to ensure financial security, these individuals began to feel increasingly hopeless and turned to risky or self-destructive behaviors, which are associated with increased rates of mortality. This phenomenon, they argued, is most pronounced among those without a college degree, as these individuals tend to experience "deaths of despair" at a much higher rate.

There is some disagreement in the literature about Case and Deaton's research. Ruhm (2018) challenged Case and Deaton's findings, specifically with regard to the rise of drug use. He concluded that the rise in drug-related deaths is related not to "despair," but to changes in drug availability and potency. He argued that if desperation over economic conditions was driving drug abuse, we would have seen a decline in such abuse around 2010, as the economy improved. Instead there was an acceleration in the number of "deaths of despair" during this period. A more compelling reason for the increase in drug-related deaths, he argued, was changes to health care policy in the 2000s that made access to prescription pain medication easier. He also pointed out that, beginning in 2010, the introduction of newer, more potent and dangerous synthetic opioids such as fentanyl was associated with an increase in the number of deaths. In support of this perspective, Currie et al. (2018) found there were stronger differences in opioid prescription patterns by region than by local economic conditions.

My Study's Contributions to the Literature

This study attempts to resolve the disagreement between proponents of the "deaths of despair" hypothesis and alternative explanations of the opioid crisis by using new data to study the relationship between local economic factors and prescription opioid use. The clandestine nature of illicit and improper drug use has made the estimation of general opioid use difficult. As a result, the majority of studies on this topic have relied on self-reported measures of drug use, insurance claim data, or CDC mortality data. Self-reports of illicit drug use are unlikely to produce accurate estimates, as individuals may misreport such use to avoid potential legal consequences or due to personal shame. Mortality data are useful for assessing the number of deaths from opioid abuse, but they provide no information on the size of the population that habitually uses opioids but does not die and claims data fail to account for a key segment of the population; those without insurance.

In contrast, data from the Drug Enforcement Administration's ARCOS system, which tracks the manufacturing and transportation of every monitored prescription drug in the country, allows researchers, for the first time, to perform empirical analyses that exploit information on the number of pills entering a county over time. Analyses of these data thus allow me to better understand the relationship between employment rates and actual prescription opioid use at the county level.

Conceptual Framework

Based on my literature review, I expect to find that poor economic conditions are positively associated with the use of prescription opioids. As noted, several studies have linked poor economic conditions with deaths related to opioids. However, these studies have focused on mortality rates, while my study focuses on opioid consumption. I predict that people in counties with high unemployment rates will consume opioids at a higher rate than people in counties with lower rates of unemployment. I also expect to find a stronger relationship between prescription opioid use and unemployment than studies that focus on the relationship between unemployment and opioid-related deaths. Studies focused on mortality are plagued by the problem of properly assigning causes of death, and by the fact that only a relatively small number of people overdose. My study avoids this problem. In order to reduce bias in my estimates, my model accounts for a variety of potentially confounding factors, including a county's economic and demographic characteristics, as well as the extent of health care access within the county. These relationships are presented graphically in Figure 1 and are described further in the following paragraphs.

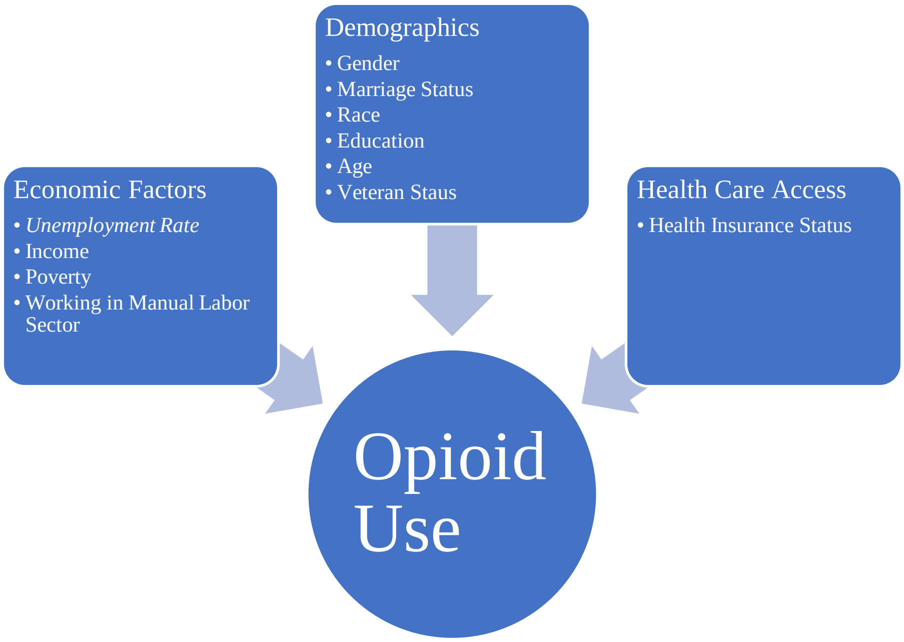

Figure 1. Influences on Opioid Consumption

Economic Factors

Economic factors aside from employment may also be related to opioid use. For example, some studies have found that, as income levels rise, deaths from opioids tend to fall (Hollingsworth 2017; Ruhm 2017; Visconti 2015). However, one study found that among those with higher incomes deaths from prescription opioids are more common than deaths from other drugs such as heroin or cocaine (Visconti 2015). Another found that opioid use was associated with poverty status (Case and Deaton 2017).

An area's employment profile may also affect opioid use. For instance, the use of opioids may be more common in areas where a large portion of the population works in industries whose workers are more likely to experience physical hardship or chronic pain. Thus, for example, regions in which a large share of the workforce is employed in the mining or forestry industries may have larger numbers of people suffering from chronic pain related to their employment. These individuals would presumably be more likely to pursue prescription pain relief.

Health Care Access

Many studies of opioid abuse rely on health insurer claims information (Cochran 2014; Sullivan 2008), reflecting the fact that health insurance allows many individuals to access legal, prescription opioids. However, research suggests that, in actuality, those most likely to self-report prescription opioid abuse are uninsured (Wu et al. 2016; Becker 2008). These studies conclude that a lack of health insurance prevents individuals from accessing treatment for addiction, exacerbating opioid abuse because there is no health care provider to intervene preemptively.

Demographics

Certain demographic characteristics have been shown to be correlated with opioid consumption. Much of the literature on opioids focuses on rising drug-related death rates among prime working-age whites (Case and Deaton 2015; Ruhm 2017). Case and Deaton (2015) specifically identify rising mortality rates from accidental poisonings (drug overdoses) among white populations. Race has been addressed in most studies of the opioid epidemic when available (Case and Deaton 2015; Hollingsworth 2017; Currie 2018). Per the "deaths of despair" arguments proposed by Case and Deaton, opioid use also tends to decline as educational level increases (Currie et al. 2018; Kelly et al. 2008). In addition, previous studies have examined the relationship between marital status and opioid use (Hollingsworth 2017; Ruhm 2017; Toblin 2014).

Finally, veterans have been identified as a population especially vulnerable to opioid abuse (Wu 2010). Advances in battlefield healthcare mean that growing numbers of veterans are surviving traumatic injury and returning to the United States with chronic pain (Seal 2012).

Veteran status is therefore likely to be associated with prescription opioid use and abuse, especially among prime working-age males (Wu 2010; Seal 2012).

Data and Methodology

Data

My data cover 3,142 counties or county equivalents from 2009 to 2012.[1] I use monthly data for my drug use and unemployment variables, and annual data for my control variables. These data come from a variety of sources as detailed in Table 1, and described in the following paragraphs.

My data on drug use are drawn from the Drug Enforcement Administration's ARCOS system. This information was published by the *Washington Post* and is freely available online at the *Washington Post* website. DEA ARCOS tracks the creation and transportation of controlled substances in the United States to their point of distribution. The ARCOS data allowed me to determine the number of hydrocodone and oxycodone pills that were brought into each county over the course of each month during my period of analysis. I divided that number by the county's population size to estimate the number of pills-per-capita for each county-month. My unemployment rate data are taken from the Local Area Unemployment Survey conducted by the Bureau of Labor Statistics. This survey is the most comprehensive measure of the percentage of the labor force that is currently seeking employment.

[1] Data on opioid prescriptions are available from the *Washington Post* for the years 2006 through 2012. The Bureau of Labor Statistics provides unemployment data for that same period of analysis, and I use American Community Survey data from the Census Bureau to create my demographic control variables. ACS data are consistently available at the county level beginning in 2009. Thus, I limit my period of analysis to the period 2009-2012.

As noted above, I control for several demographic and economic variables, and the data for these variables come from a variety of databases. The bulk of these data are taken from the US Census Bureau's American Community Survey, five-year series. This survey collects data on population size and distributions of sex, race, age, education, marriage status, sector of work, and veteran status at the county level. I used the Census Bureau's Small Area Health Insurance Estimate for my health insurance information, and the Bureau's Small Area Income and Poverty Estimate for median household income and poverty rates.[2]

Methodology

I estimate an ordinary least squares (OLS) regression model with county and time fixed effects to analyze the relationship between unemployment and prescription drug use. The inclusion of county fixed effects in my regression allows me to control for factors that are unique to a county and do not change over time. For example, cultural norms related to pain medication or other drug use are likely to change slowly (if at all) over time, but are very likely to differ by county. Month fixed effects allow me to control for broad factors that do not vary across counties but that change over time, for example, national-level opioid awareness campaigns or changes in national marketing campaigns for opioids. Because I have county-month panel data, I am also able to include state-year fixed effects dummies in my regressions. These allow me control for unobserved state level changes over time that impact drug use and unemployment rates. Examples of such changes include evolving state-level attitudes about opioid use, state polices that decriminalize marijuana use, or the implementation of state level opioid abuse programs. I thus estimated the model as follows:

[2] These data are collected at the county-year level. I assigned each annual value to the appropriate county-month observation.

$$drug\ use_{it} = \beta_0 + \beta_1 unemployment_{it} + \beta_2 poverty_{it} + \beta_3 income_{it} + \beta_4 manual\ labor_{it} + \beta_5 health\ insurance_{it} + \beta_6 veterans_{it} + \beta_7 male_{it} + \beta_8 married_{it} + \beta_9 white_{it} + \beta_{10} high\ school_{it} + \beta_{11} bachelors_{it} + \beta_{12} age_{it} + \alpha_i + \gamma_t + \delta_i{*}\gamma_t + \mu_{it}$$

where i is a county index, t is a month index, α_i represents county fixed effects, γ_t represents month fixed effects, δ_i represents a vector of state dummies, and μ_{it} represents the error term. Table 1 provides definitions for all variables included in the regression.

Table 1. Definitions of Variables

Variable	Definition	Source
Dependent Variable		
Drug Use	A continuous variable measuring the per-capita number of oxycodone or hydrocodone pills shipped to a county in a specific month, divided by the population of that county	Automation of Reports and Consolidated Ordering System, Drug Enforcement Administration. Data provided by the Washington Post.
Independent Variable		
Unemployment	A continuous variable measuring the proportion of those seeking jobs who are not employed, among the civilian non-institutionalized population aged 16 and over	Local Area Unemployment Survey from the Bureau of Labor Statistics
Economic Factors		
Poverty	A continuous variable measuring the portion of the population that lives below the poverty line	Small Area Income and Poverty Estimate from the United States Census Bureau
Income	A continuous variable measuring the median household income in a county	Small Area Income and Poverty Estimate from the United States Census Bureau
Manual Labor	A continuous variable measuring the portion of the population over the age of 16 that works in the natural resources, construction, maintenance, production, transportation, or material moving sectors	American Community Survey from the United States Census Bureau

Table 1. Definitions of Variables (cont.)

Variable	Definition	Source
Health Care Access		
Health Insurance	A continuous variable measuring the portion of the population under the age of 65 that has health insurance	Small Area Health Insurance Estimate from the United States Census Bureau
Demographic Factors		
Male	A continuous variable measuring the portion of the population that is male	American Community Survey from the United States Census Bureau
Married	A continuous variable measuring the portion of the population that is married	American Community Survey from the United States Census Bureau
White	A continuous variable measuring the portion of the population that is white	American Community Survey from the United States Census Bureau
High School Degree	A continuous variable measuring the portion of the population that has only a high school degree	American Community Survey from the United States Census Bureau
Bachelor's Degree or better	A continuous variable measuring the portion of the population that has a bachelor's degree or higher	American Community Survey from the United States Census Bureau
Prime Working Age	A continuous variable measuring the portion of the population that is between the ages of 25 and 54	American Community Survey from the United States Census Bureau
Veteran	A continuous variable measuring the portion of the population that is a veteran	American Community Survey from the United States Census Bureau

Descriptive Statistics

Table 2 presents descriptive statistics for my dependent and key independent variables, as well as for the demographic and employment characteristics included as control variables in my regressions.[3] All estimates are weighted by average county population size over my period of analysis. There is wide variation across county-month observations in terms of the number of prescription pills per person per county. The average number of pills per person per month at the county level is 3.3. The smallest number of pills per person was found in North Slope, Alaska (less than 1/100th of a pill per person); the largest number of pills per person was in Charleston, South Carolina (almost 45 pills per person in April 2009).[4] The mean county unemployment rate is 9.1%, but there is also substantial variation in this variable. Some counties in North Dakota — for example Williams and Divide — have very low unemployment rates (around 1%). The highest unemployment rate is 31.9%, in Imperial County, California in July 2011.

---

[3] My dataset contains 143,172 county-month observations, covering 2,983 counties or county equivalents from 2009 to 2012. The counties not included in this dataset are excluded due to a lack of data from the Drug Enforcement Administration on opioids. These counties may not have received any opioids during the relevant time period. Alternatively, residents of these counties may have filled prescriptions in other counties, but such a consideration is beyond the scope of this analysis. The Petersburg Census Area in Alaska was created in 2008, and did not receive any opioids until 2010. I have included this census area starting in 2010, when opioid data were first collected.

[4] Charleston serves as a regional opioid distributor for local military service members, with individuals coming from other counties to obtain opioids (*Washington Post* 2019).

Table 2. Descriptive statistics for Dependent, Key Independent, and Control Variables

Variable	Sample Size	Mean	Minimum	Maximum	Standard Deviation
Oxycodone or hydrocodone pills per person	143,172	3.3	0.003	44.8	1.8
Percentage of county population that is unemployed	143,172	9.1	1	31.9	2.6
Economic Factors					
Percentage of county population below the poverty line	143,172	15.4	2.9	53	5.5
Median household income in dollars	143,172	52,394	20,990	121,250	13,731
Percentage of county population that works in manual labor	143,172	22.3	4.1	73.1	6.6
Health Care Access					
Percentage of county population under 65 that does not have health insurance	143,172	17.3	2.9	39.9	5.9
Demographic Characteristics					
Percentage of county population that is male	143,172	49.2	42.3	76.4	1.3
Percentage of county population that is married	143,172	49.9	23.4	76.3	6.5
Percentage of county population that is white	143,172	74.2	11.2	100	16.4
Percentage of county population that has only a high school degree	143,172	57.1	21.6	80.9	8.5
Percentage of county population that has a bachelor's degree or better	143,172	28	3.7	72.8	10.3
Percentage of county population that is prime working age (25-54)	143,172	41.6	16.8	65.2	3.9
Percentage of county population that is a veteran	143,172	9.7	2.5	32.4	3.2

Figure 2 reports time trends for the number of prescription pills used per capita in my sample. The graph shows an upward trend in this variable during the first three years of my panel, and a downward trend in the final year. Figure 3 reports time trends for the average county unemployment rate in my sample. The average unemployment rate increased initially but fell in the second through fourth years. At the aggregate level, these trends are somewhat dissimilar. My multiple regressions measure the relationships between these variables in a more nuanced and sophisticated way.

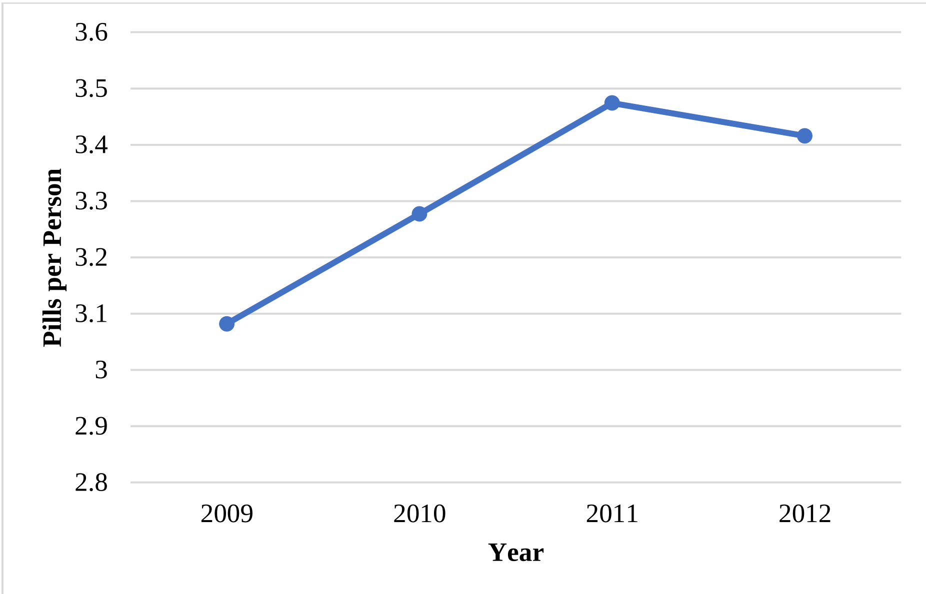

Figure 2. Average number of pills per person by year- 2009-2012

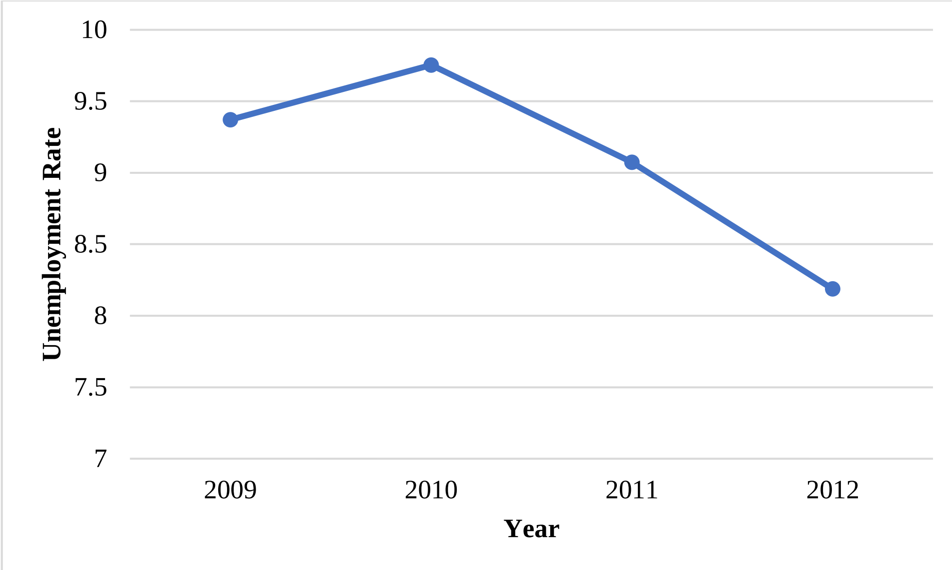

Figure 3. Average unemployment rate by year- 2009-2012

Regression Results

My regression results are summarized in Tables 3 and 4. In Table 3, Model 1 is a simple ordinary least squares (OLS) regression that includes only my dependent and key independent variables, while Model 2 introduces time-varying county-level controls to account for health access, economic, and demographic characteristics. Model 3 adds county fixed effects, which control for unobserved but fixed county-level characteristics over my period of analysis. Model 4 introduces month fixed effects, which control for unobserved factors that change over time, but that do not vary across counties. Finally, Model 5 adds state-year dummies, which control for unobserved state-level attributes that do not vary across counties, but that do change over my period of analysis. Robust standard errors are reported for all coefficients. All regressions are weighted by average county population size.[5]

[5] A table reporting unweighted regression results can be found in the Appendix. The results of my primary unweighted specifications are similar to those of my weighted specifications. However, my unweighted subgroup

I hypothesized that there is a positive relationship between county-level unemployment rates and prescription pill consumption. However, I arrive at conflicting findings regarding this relationship. In Models 1 and 2, which do not include fixed effects, there is a positive and statistically significant relationship between unemployment rates and prescription opioid rates. Model 1 suggests that a one-percentage-point increase in the county unemployment rate is associated with a per-capita increase of 0.09 pills per month, or an additional 1.08 pills per year. The unemployment coefficient in Model 2 is also positive and significant, but smaller in magnitude.

The introduction of fixed effects leads to a reversal in the sign of the predicted relationship of interest. In all three models that include fixed effects (Models 3 through 5), increases in the county unemployment rate are associated with statistically significant decreases in the number of prescription pain pills prescribed. In Model 3, which only includes county fixed effects, an increase in unemployment of one percentage point is correlated with a reduction in per-capita pills prescribed of 0.02, or 0.24 pills per year. The results of Models 4 and 5, in which I introduce time and state-year fixed effects are largely similar to those of Model 3.

---

analyses differ somewhat from my weighted specifications. For instance, the relationship between unemployment and opioid use is more strongly negative in counties with an above-median concentration of males. Additionally, whereas my relationship of interest among counties with above-median levels of manual labor is negative in my weighted specifications, it is positive in the unweighted specifications. My weighted and unweighted findings differ in the same way when I disaggregate my sample according to poverty rates. Finally, while my relationship of interest varies according to educational attainment in my weighted regressions, this is not the case in my unweighted regressions.

Table 3. Primary Specification Regression Results

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS with control variables	County Fixed Effects	County and Month Fixed Effects	County, Month, and State-Year Fixed Effects
Key Independent Variable					
% Unemployed	0.09***	0.06***	-0.02**	-0.03***	-0.02***
	(0.005)	(0.003)	(0.008)	(0.009)	(0.006)
Economic Controls					
Poverty Rate		0.11***	0.03***	0.0003	0.001
		(0.004)	(0.007)	(0.007)	(0.005)
Median Income ($10,000)		0.01	-0.01	-0.01	-0.05
		(0.001)	(0.003)	(0.003)	(0.004)
% in Manual Labor		-0.01***	-0.01*	0.004	-0.01**
		(0.003)	(0.008)	(0.009)	(0.007)
Health Care Access Control					
% Uninsured		0.02***	0.04***	0.03**	-0.02
		(0.003)	(0.013)	(0.013)	(0.011)
Demographic Controls					
% Male		-0.22***	0.10***	0.10***	0.05***
		(0.005)	(0.024)	(0.024)	(0.016)
% Married		-0.01**	0.02*	0.02***	0.01
		(0.003)	(0.009)	(0.008)	(0.005)
% White		0.04***	-0.01	0.0003	0.01
		(0.001)	(0.009)	(0.010)	(0.009)
% with only a High School Degree		0.05***	0.13***	0.08***	0.03***
		(0.003)	(0.011)	(0.011)	(0.011)
% with a Bachelor's Degree or More		0.01***	0.14***	0.06***	-0.004
		(0.003)	(0.015)	(0.016)	(0.012)
% Prime Working Age		0.09***	-0.07***	-0.05***	-0.02**
		(0.002)	(0.014)	(0.014)	(0.010)
% Veterans		0.13***	-0.06**	0.04	-0.02
		(0.005)	(0.025)	(0.026)	(0.016)
Constant	2.51***	1.36***	-9.70***	-8.50***	-0.64
	(0.038)	(0.338)	(1.949)	(1.943)	(1.364)
Observations	143,172	143,172	143,172	143,172	143,172
R-squared (within)	0.016	0.249	0.094	0.240	0.379

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 4, I introduce several interaction terms into my analysis in order to determine whether there is variation between different types of counties in terms of my relationship of interest. Specifically, I interact my unemployment measure with dichotomous measures related to the percentage of a county's population that is male, the percentage of the county's population that is married, the percentage of county's population that is employed in manual labor, the percentage of the county's population that lives in poverty, and the percentage of the county's population that has a bachelor's degree or better.[6] For all five interactions, I generated binary variables indicating whether a county was above or below the weighted median.

Male Interaction

Model 1 in Table 4 shows that, in counties with comparatively small male populations, a one-percentage-point increase in the unemployment rate is associated with a statistically significant reduction of .03 pills per person. In counties with comparatively large male populations, a one percentage point increase in the unemployment rate is correlated with a reduction of (-0.03+0.02) 0.01 pills per person. This relationship is statistically significant as reflected in the results of the f-test shown at the bottom of the table.

Married Interaction

Model 2 indicates that, among counties with comparatively small married populations, unemployment and the number of pills per county are not significantly related. However, for counties with comparatively large married populations, this relationship is statistically significant, as seen in the results of the f-test shown at the bottom of the table. Specifically, among counties with comparatively large married populations, a one-percentage-point increase

[6] I also estimated regressions interacting unemployment with controls for median income, health insurance status, percentage white, and percentage veteran. None of these interacted coefficients was statistically significant.

in the unemployment rate is associated with a statistically significant decrease (-0.004-0.02) of 0.024 pills per capita.

Manual Labor Interaction

Model 3 indicates that unemployment and the number of pills per county are not significantly related for counties with comparatively small populations that work in manual labor. However, for counties with populations that work in manual labor at comparatively high levels, this relationship is statistically significant. Specifically, among counties with comparatively larger numbers of manual laborers, a one-percentage-point increase in the unemployment rate is associated with a statistically significant decrease of (-0.001-0.02) 0.021 pills per capita.

Poverty Interaction

Model 4 shows that, in counties with comparatively low poverty rates, a one-percentage-point increase in unemployment is associated with a statistically significant reduction of .01 pills per person. In counties with comparatively high poverty rates, a one percentage point increase in the unemployment rate is correlated with a statistically significant reduction of (-0.01-0.01) 0.02 pills per person.

Bachelor's Degree Interaction

Model 5 shows that, in counties with comparatively low levels of secondary education, a one-percentage-point increase in unemployment is associated with a statistically significant reduction of .03 pills per person. In counties with comparatively high levels of secondary education, a one percentage point increase in the unemployment rate is correlated with an increase of (-0.03+0.06) 0.03 pills per person. Thus, counties with above-median levels of higher education, as defined by the possession of a bachelor's degree or more, are the only subgroup that conforms with my prediction of a positive relationship between unemployment rates and prescription opioid use.

Table 4. Interaction Regression Results

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	Male Interaction	Married Interaction	Manual Labor Interaction	Poverty Interaction	Bachelor's Interaction
Key Independent Variables					
% Unemployed	-0.03***	-0.004	-0.001	-0.01*	-0.03***
	(0.006)	(0.008)	(0.012)	(0.006)	(0.006)
Unemployment*Male	0.02**				
	(0.006)				
High Male	-0.08				
	(0.058)				
Unemployment* Married		-0.02***			
		(0.009)			
High Married		0.15*			
		(0.084)			
Unemployment* Manual Labor			-0.02**		
			(0.011)		
High Manual Labor			0.21**		
			(0.097)		
Unemployment* Poverty				-0.01*	
				(0.008)	
High Poverty				0.14*	
				(0.080)	
Unemployment* Bachelor's					0.06***
					(0.016)
High Bachelor's					-0.61***
					(0.189)
Economic Controls					
Poverty Rate	0.001	0.001	0.001	0.001	0.002
	(0.0055)	(0.005)	(0.005)	(0.005)	(0.005)
Median Income ($10,000)	-0.05	-0.05	-0.05	-0.05	-0.04
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
% in Manual Labor	-0.01**	-0.01*	-0.01**	-0.01**	-0.01*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)

Table 4. Interaction Regression Results (cont.)

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	Male Interaction	Married Interaction	Manual Labor Interaction	Poverty Interaction	Bachelor's Interaction
Health Care Access Control					
% Uninsured	-0.02*	-0.02*	-0.02	-0.02	-0.02**
	(0.010)	(0.010)	(0.010)	(0.011)	(0.009)
Demographic Controls					
% Male	0.03**	0.05***	0.04***	0.05***	0.04**
	(0.017)	(0.016)	(0.015)	(0.016)	(0.016)
% Married	0.01	0.01**	0.01*	0.01	0.01*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
% White	0.01	0.01	0.01	0.01	0.01
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
% with only a High School Degree	0.03***	0.03***	0.03**	0.03***	0.02**
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
% with a Bachelor's Degree or More	-0.004	-0.003	-0.004	-0.004	-0.0007
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
% Prime Working Age	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
% Veterans	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.016)	(0.016)	(0.016)	(0.016)	(0.02)
***F*-Statistics and *p*-Values on Joint Hypotheses**					
H_0: Unemployment + Interaction = 0	4.45**	17.85***	17.46***	12.25***	4.40**
	0.0350	0.0000	0.0000	0.0005	0.0360
Constant	0.08	-0.91	-0.51	-0.58	0.52
	(1.403)	(1.368)	(1.366)	(1.356)	(1.206)
Observations	143,172	143,172	143,172	143,172	143,172
R-squared (within)	0.380	0.381	0.380	0.380	0.384

Robust standard errors in parentheses. All regressions include County, Time, and State-Year Fixed Effects.

*** p<0.01, ** p<0.05, * p<0.1

Conclusion

My findings suggest that increases in the unemployment rate in a given county are associated with decreases in per capita prescription opioid use. My simplest models suggest a positive association, but the introduction of entity and time fixed effects reverse the sign of this relationship. The estimated relationship is relatively small (roughly 2/100ths of a pill per capita for a one percentage point increase in the unemployment rate). This finding runs counter to my hypothesis, and to the deaths of despair hypothesis promoted by Case and Deaton (2015; 2017).

The results of my sub-group analysis also run counter to my expectations. Not only was I expecting the overall relationship between unemployment and opioids to be positive, I expected this relationship to be more strongly positive in places with higher poverty and greater employment in manual labor jobs. However, I find that there is a more strongly *negative* relationship between pill use and unemployment in areas with high rates of poverty and high rates of employment in the manual labor sector. The relationship between unemployment and pill use per capita is also more strongly negative in areas with lower marriage rates, which similarly runs counter to the deaths of despair hypothesis. The only sub-group analysis that followed my predicted hypothesis of a positive relationship was for counties with an above-median rate of college education. However, this group of counties might be expected not to suffer from the deaths of despair problem, and would thus be the most likely to make opioid- use decisions independent of economic circumstances.

My results thus align in opposition to the deaths of despair hypothesis. I find not only that there is not a positive association between unemployment and prescription opioid use, but that there is in fact a negative correlation between the two. These findings generally support Ruhm's

(2018) focus on environmental factors and changes in drug availability and lethality as driving factors in high levels of death related to opioids.

My analysis has several important limitations. First, the fact that pills can cross county lines makes my estimates less precise. While it is likely that most members of the population receive their prescriptions from a pharmacy located in their county of residence, there are likely some individuals who do not. Those who live or work near county borders are likely to make purchasing decisions based on ease of travel, and could therefore cross county lines to obtain prescription opioids. With the data currently available, it is difficult to address this issue. Second, the diversion of pills from their intended recipients to illegal markets damages our ability to estimate precise relationships. Oxycodone and hydrocodone (the medications addressed in my study) are especially likely to be diverted (Inciardi 2007) and are among the most likely to be shared by friends or family (McCance-Katz 2017).

Finally, several omitted variables are likely associated with both unemployment and prescription opioid use. Both the general health of the county and the quality of doctors in a county would ideally be controlled for. I believe that both of these omitted variables are upwardly biasing my estimated unemployment coefficients. It seems likely that high rates of poor health are correlated positively with both unemployment and opioid use, while the quality of doctors is likely negatively correlated with both (Kilaru 2014; Paulozzi 2014).

However, I believe that there is a more important omitted variable to consider: non-prescription opioids such as heroin or fentanyl. Use of non-prescription opioids and its relation to unemployment should generally follow the same patterns as prescription opioid usage. I suspect that non-prescription heroin use would thus be positively correlated with unemployment, but would be negatively correlated with prescription opioid use. Relevant to the latter point is the fact that individuals often transition from prescription opioids to heroin (Cicero 2014). If my assumptions are correct, the omission of this control would exert a downward bias towards my unemployment coefficients. Due to its illicit nature, heroin and fentanyl use is difficult to track, especially at the county level. However, I believe that - due to the ability to substitute heroin or fentanyl for prescription opioids – non-prescription opioid usage is a key factor to address in future research.

In sum, omitted variable bias problems likely exert both downward and upward bias on my estimates. However, I believe that the omission of a control for non-prescription opioid usage is likely to be the most influential source of bias. While standards of health and doctor quality are important, heroin or fentanyl use is likely to be strongly related to opioid use because either can function as a substitute for prescription opioid pills, making it a key factor. I suspect that, in totality, the omission of the variables described here likely biases my estimates downward, which is to say that the true (unbiased) relationship might still be consistent with the deaths of despair hypothesis.

The policy implications of my study are mixed. While improvements in the economic circumstances of vulnerable populations will almost certainly improve the health outcomes of groups suffering from the opioid epidemic, my research suggests that this may not be the most efficient avenue for reducing opioid dependency. The phenomena of substance abuse and addiction are complex enough that there is no one-size-fits-all solution. Policy makers should draw on a diverse set of tools in order to combat this important public health problem.

Future studies should attempt to control for heroin use via proxies used elsewhere such as the number of opioid-related overdoses and emergency room visits per capita (Hollingsworth 2017; Ruhm 2016). Because I used national level data, I faced constraints in terms of the variables that I was able to incorporate into my analysis. Census Bureau data are valuable, but are unable to support controls for some variables that are key to addressing the question that I focus on. Researchers should consider conducting localized analyses focusing on states whose public health departments would be able to provide data on some of the variables for which I was not able to control — for example, proxies for heroin or fentanyl use. Future research would ideally also focus on states with substantial county-level variation in opioid use (e.g., Oklahoma or Oregon). Additionally, qualitative studies would likely be useful here because they might be better able to assess the extent of both prescription and non-prescription opioid use.

Identification of the key linkages between prescription opioid use (or abuse) and heroin use is key to understanding the roots of the opioid epidemic. My sub-group analyses potentially support these veins of research. I find that high-manual-labor and high-poverty areas experience greater decreases in opioid use as unemployment rises. It is possible that these reductions in opioid use correspond to increases in the use of other drugs. For example, those who become unemployed might lose access to prescription opioids (via loss of income or health insurance) and instead begin consuming other drugs such as heroin. Because prescription opioids and heroin have similar chemical properties (Centers for Disease Control and Prevention 2018), I believe the two are likely to be substitutes for one another. This would be consistent with the findings of Case and Deaton (2015; 2017). The factors that drive drug use are enormously complex, and further research could aid in identifying attainable policy solutions to the opioid epidemic.

Appendix

Table A.1 Unweighted Primary Specification Regression Results

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS with control variables	County Fixed Effects	County and Month Fixed Effects	County, Month, and State-Year Fixed Effects
Key Independent Variable					
% Unemployed	0.17***	0.08***	-0.05***	-0.02***	-0.01***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
Economic Controls					
Poverty Rate		0.10***	0.03***	-0.01	-0.004
		(0.002)	(0.004)	(0.004)	(0.003)
Median Income ($10,000)		-0.01***	0.02***	-0.01**	-0.004*
		(0.001)	(0.003)	(0.002)	(0.002)
% in Manual Labor		-0.05***	-0.02***	0.002	0.002
		(0.001)	(0.005)	(0.005)	(0.004)
Health Care Access Control					
% Uninsured		0.01***	-0.03***	-0.02***	-0.02***
		(0.001)	(0.006)	(0.006)	(0.007)
Demographic Controls					
% Male		-0.28***	0.04***	-0.0007	-0.002
		(0.004)	(0.012)	(0.010)	(0.009)
% Married		-0.04***	-0.02***	0.002	0.002
		(0.002)	(0.004)	(0.004)	(0.004)
% White		0.06***	-0.008*	-0.004	-0.002
		(0.0006)	(0.005)	(0.004)	(0.005)
% with only a High School Degree		-0.03***	0.08***	0.02***	0.01*
		(0.002)	(0.006)	(0.006)	(0.006)
% with a Bachelor's Degree or More		-0.06***	0.08***	0.01	0.003
		(0.002)	(0.008)	(0.008)	(0.008)
% Prime Working Age		0.15***	-0.05***	-0.008	-0.005
		(0.003)	(0.008)	(0.007)	(0.006)
% Veterans		0.08***	-0.06***	0.002	-0.01
		(0.002)	(0.011)	(0.010)	(0.010)
Constant	2.13***	10.74***	-0.70	2.58***	3.57***
	(0.017)	(0.285)	(0.995)	(0.931)	(0.918)
Observations	143,172	143,172	143,172	143,172	143,172
R-squared (within)	0.060	0.237	0.116	0.249	0.294

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2 Unweighted Interaction Regression Results

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	Male Interaction	Married Interaction	Manual Labor Interaction	Poverty Interaction	Bachelor's Interaction
Key Independent Variables					
% Unemployed	-0.02***	-0.008	0.003	-0.006*	-0.01***
	(0.005)	(0.005)	(0.007)	(0.004)	(0.004)
Unemployment*Male	-0.04				
	(0.043)				
High Male	0.01**				
	(0.005)				
Unemployment* Married		0.006			
		(0.05)			
High Married		-0.007			
		(0.005)			
Unemployment* Manual Labor			0.13*		
			(0.071)		
High Manual Labor			-0.02**		
			(0.007)		
Unemployment* Poverty				0.14***	
				(0.035)	
High Poverty				-0.01***	
				(0.004)	
Unemployment* Bachelor's					-0.24***
					(0.066)
High Bachelor's					0.02***
					(0.007)
Economic Controls					
Poverty Rate	-0.004	-0.004	-0.005	-0.006*	-0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Median Income ($10,000)	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% in Manual Labor	0.002	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Health Care Access Control					
% Uninsured	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)

Table A.2 Unweighted Interaction Regression Results (cont.)

Dependent Variable	Prescription Opioid Pills per Capita				
	(1)	(2)	(3)	(4)	(5)
	Male Interaction	Married Interaction	Manual Labor Interaction	Poverty Interaction	Bachelor's Interaction
Demographic Controls					
% Male	-0.01	-0.003	-0.003	-0.003	-0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
% Married	0.002	0.005	0.003	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
% White	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
% with only a High School Degree	0.01*	0.01*	0.01*	0.01*	0.01*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
% with a Bachelor's Degree or More	0.003	0.003	0.003	0.003	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
% Prime Working Age	-0.004	-0.005	-0.005	-0.005	-0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
% Veterans	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
***F*-Statistics and *p*-Values on Joint Hypotheses**					
H_0: Unemployment + Interaction = 0	8.56***	18.10***	17.43***	19.24***	1.15
	0.0035	0.0000	0.0000	0.0000	0.2838
Constant	3.96***	3.47***	3.49***	3.55***	3.61***
	(0.912)	(0.924)	(0.922)	(0.917)	(0.917)
Observations	143,172	143,172	143,172	143,172	143,172
R-squared (within)	0.295	0.294	0.294	0.295	0.294

*** p<0.01, ** p<0.05, * p<0.1

References

Becker, William C, David A. Fiellin, Joseph O. Merrill, Beryl Schulman, Ruth Finkelstein, Yngvild Olsen and Susan H. Busch. 2008. "Opioid use disorder in the United States: Insurance status and treatment access." *Drug and Alcohol Dependence* 94 (1–3), 207-213.

Brackbill, P. M. Siegel, P. Z. and Ackermann, S. P. 1995. "Self-Reported Hypertension Among Unemployed People in the United States." *British Medical Journal*, 310: 568.

Case, A. and Deaton A. 2015. "Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century." *Proceedings of the National Academy of Sciences* 112(49):15078–83.

Case, A. and Deaton, A. 2017. "Mortality and morbidity in the 21st century." *Brookings Papers on Economic Activity, 2017,* 397-476.

Centers for Disease Control and Prevention. 2018. "2018 Annual Surveillance Report of Drug-Related Risks and Outcomes — United States." Centers for Disease Control and Prevention, U.S. Department of Health and Human Services. https://www.cdc.gov/drugoverdose/pdf/pubs/2018- cdc-drug-surveillance-report.pdf.

Cicero, TJ, MS Ellis, HL Surratt and SP Kurtz. 2014. "The Changing Face of Heroin Use in the United States: A Retrospective Analysis of the Past 50 Years." *JAMA Psychiatry*. 71(7):821–826.

Cochran, Bryan N, Annesa Flentje, Nicholas C. Heck, Jill Van Den Bos, Dan Perlman, Jorge Torres, Robert Valuck and Jean Carter. 2014. "Factors predicting development of opioid use disorders among individuals who receive an initial opioid prescription: Mathematical modeling using a database of commercially-insured individuals." *Drug and Alcohol Dependence* 138 202-208.

Currie, Janet, Jonas Jin and Molly Schnell. 2018. "U.S. Employment and Opioids: Is There a Connection?" *National Bureau of Economic Research.* https://www.nber.org/papers/w24440.

Department of Health and Human Services. 2019. "The Opioid Epidemic by the Numbers." https://www.hhs.gov/opioids/sites/default/files/2019-09/opioids-infographic.pdf.

Dooley, David, Jonathan Fielding and Lennart Levi. 1996. "Health and Unemployment." *Annual Review of Public Health* 17:449-65.

Dowell D, TM Haegerich and R Chou. 2016. "CDC Guideline for Prescribing Opioids for Chronic Pain - United States." *MMWR* 65(No. RR-1):1–49.

Economic Innovation Group. 2017. "The 2017 Distressed Communities Index." https://eig.org/dci.

Elsby, M. W., B. Hobijn, and A. Sahin. 2010. "The labor market in the great recession." *Brookings Papers on Economic Activity*, 1-48.

Farber, Henry S. 2015. "Job Loss in the Great Recession and its Aftermath: U.S. Evidence from the Displaced Workers Survey." *National Bureau of Economic Research*. https://www.nber.org/papers/w21216.

Goldsmith, Arthur H, Jonathan R. Veum and William Darity. 1997. "Unemployment, joblessness, psychological well-being and self-esteem: Theory and evidence." *The Journal of Socio-Economics* 26 (2), 133-158.

Hacker, Jacob S., Gregory A. Huber, Austin Nichols, Philipp Rehm, and Stuart Craig. 2012. "Economic Insecurity Across the American States new state estimates from the economic security index." *Rockefeller Foundation*. http://www.economicsecurityindex.org/assets/state_reports/ESI_cross_state.pdf.

Hargan, Eric D. October 26, 2017. "Determination that a Public Health Emergency Exists." Washington, DC: Department of Health and Human Services- Office of the Secretary. https://www.hhs.gov/sites/default/files/opioid%20PHE%20Declaration-no-sig.pdf.

Hoffman, Florian and Thomas Lemieux. 2014. "Unemployment in the Great Recession: A Comparison of Germany, Canada and the United States." *National Bureau of Economic Research.* https://www.nber.org/papers/w20694.

Holland, Kelly. 2012. "Effects of Unemployment on Health and Mental Health Based on Gender." Retrieved from Sophia, the St. Catherine University repository website: https://sophia.stkate.edu/msw_papers/38.

Hollingsworth, Alex, Christopher J. Ruhm and Kosali Simon. 2017. "Macroeconomic Conditions and Opioid Abuse." *National Bureau of Economic Research.* https://www.nber.org/papers/w23192.

Inciardi, James, Hilary Surratt, Yamilka Luko and Theodore Cicero. 2007. "The Diversion of Prescription Opioid Analgesics" *Law Enforc Exc Forum* 7(7), 127-141.

Jin, R., C. Shah and T. Svoboda. 1990. "The Impact of Unemployment on Health: A Review of the Evidence." *Journal of Public Health Policy, 18*(3), 275-301.

Kearney, Melissa S. and Phillip B. Levine. 2012. "Why is the Teen Birth Rate in the United States So High and Why Does It Matter?" *Journal of Economic Perspectives* 26(2) 141-166.

Kelly, Judith Parsells, Suzanne F. Cook, David W. Kaufman, Theresa Anderson, Lynn Rosenberg and Allen A. Mitchell. 2008. "Prevalence and characteristics of opioid use in the US adult population." *PAIN* 138 (3), 507-513.

Kilaru, Austin S, Sarah M. Gadsden, Jeanmarie Perrone, Breah Paciotti, Frances K. Barg and Zachary F. Meisel. 2014. "How Do Physicians Adopt and Apply Opioid Prescription Guidelines in the Emergency Department? A Qualitative Study." *Annals of Emergency Medicine* 64 (5), 482-489.

Krueger, A.B. 2017. "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate." *Brookings Papers on Economic Activity* 2017(2), 1-87.

Laitinen, J., E. Ek and U. Sovio. 2002. "Stress-Related Eating and Drinking Behavior and Body Mass Index and Predictors of this Behavior." *Preventive Medicine* 34(1):29-39.

McCance-Katz, Elinore. 2017. "The National Survey on Drug Use and Health: 2017." *Substance Abuse and Mental Health Services Administration.* https://www.samhsa.gov/data/sites/default/files/nsduh-ppt-09-2018.pdf.

McGee, Robin M, and Nancy J. Thompson. 2015. "Unemployment and Depression Among Emerging Adults in 12 States, Behavioral Risk Factor Surveillance System, 2010." *Preventing Chronic Disease* 12.

Mossakowski, K. N. 2009. "The influence of past unemployment duration on symptoms of depression among young women and men in the united states." *American Journal of Public Health 99*(10), 1826-32.

Paulozzi Leonard J., Karin A. Mack and Jason M. Hockenberry. 2014. "Vital Signs: Variation Among States in Prescribing of Opioid Pain Relievers and Benzodiazepines — United States, 2012." Centers for Disease Control and Prevention. https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6326a2.htm?s_cid=mm6326a2_w.

Pharr, Jennifer R, Sheniz Moonie and Timothy J. Bungum. 2012. "The Impact of Unemployment on Mental and Physical Health, Access to Health Care and Health Risk Behaviors." *ISRN Public Health.*

Rolheiser, L. A., J. Cordes and S.V. Subramanian. 2018. "Opioid prescribing rates by congressional districts, united states, 2016." *American Journal of Public Health* 108(9), 1214-1219.

Ruhm, Christopher J. 2016. "Taking the Measure of a Fatal Drug Epidemic" *National Bureau of Economic Research.* https://www.nber.org/papers/w22504.

Ruhm, Christopher J. 2018. "Deaths of Despair or Drug Problems?" *National Bureau of Economic Research.* https://www.nber.org/papers/w24188.

Scholl, L, P. Seth, M. Kariisa, N. Wilson and G. Baldwin. 2019. “Drug and Opioid-Involved Overdose Deaths — United States, 2013–2017.” MMWR Morb Mortal Wkly Rep 67:1419–1427.

Seal, KH, Y. Shi, G. Cohen et al. 2012. “Association of Mental Health Disorders With Prescription Opioids and High-Risk Opioid Use in US Veterans of Iraq and Afghanistan.” *JAMA* 307 (9), 940–947.

Sullivan, Mark D, Mark J. Edlund, Ming-Yu Fan, Andrea DeVries, Jennifer Brennan Braden and Bradley C. Martin. 2008. “Trends in use of opioids for non-cancer pain conditions 2000–2005 in Commercial and Medicaid insurance plans: The TROUP study.” PAIN 138(2), 440-449.

Tefft, N. 2011. “Insights on Unemployment, Unemployment Insurance, and Mental Health.” *Journal of Health Economics, 30*(2), 258–264.

Toblin, R.L., P.J. Quartana, L.A. Riviere, K.C. Walper and C.W. Hoge. 2014. “Chronic Pain and Opioid Use in US Soldiers After Combat Deployment.” *JAMA Intern Med* 174(8):1400–1401.

Visconti, A.J., GM. Santos, N.P. Lemos et al. 2015. “Opioid Overdose Deaths in the City and County of San Francisco: Prevalence, Distribution, and Disparities.” *Journal of Urban Health* 92 (4), 758-772.

Washington Post. 2019. “How to download and use the DEA pain pills database.” https://www.washingtonpost.com/national/2019/07/18/how-download-use-dea-pain-pills-database/?arc404=true.

Wu, Phipson C, Courtney Lang, Noelle K. Hasson, Steven H. Linder and David J. Clark. 2010. “Opioid use in young veterans.” *Journal of Opioid Management* 6 (2).

Wu, Li-Tzy, He Zhu and Marvin S. Swartz. 2016. “Treatment utilization among persons with opioid use disorder in the United States.” *Drug and Alcohol Dependence* 169, 117-127.

Zhou, C., C.S. Florence and D. Dowell. 2016. “Payments for opioids shifted substantially to public and private insurers while consumer spending declined, 1999-2012.” *Health Affairs* 35(5), 824-831A.

Zmitrowicz, Konrad and Mikael Khan. 2014. “Beyond the Unemployment Rate: Assessing Canadian and U.S. Labour Markets Since the Great Recession.” *Bank of Canada Review*.