The Effect of Prescription Opioid Use on Labor Market Conditions

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Abstract

This paper investigates the effects of prescription opioids, for both Schedule II-IV and Schedule II-III controlled opioids, on collective county labor market outcomes. I identify the causal effect of opioid prescriptions per capita on county labor market conditions by employing the use of an instrumental variable, two-stage least-squares, regression model that first predicts opioid prescriptions per capita through the empirical specification of two variables that estimate high-volume opioid prescribers per county. These instrumental variables, acquired from individual-level prescriber datasets from the Medicare Part D Files, measure the number of providers in the top-5 percent of opioid prescriptions per capita and top-1 percent of opioid doses per capita. I find that the current levels of opioid prescriptions per capita have severely negative effects on the unemployment rate, the labor force participation rate, and the employment-to-population ratio. While pain medication, specifically prescription opioids, possess therapeutic characteristics intended to relive chronic-pain, the high risk of abuse and dependence has overpowered the positives of the medication, rendering the drug dangerous to both individuals and economies, especially when prescribed at its current rates. My findings suggest that malpractice among physicians' opioid prescribing behaviors in the U.S. exists and, as such, these individual prescribers are significantly exacerbating the welfare of county-level health and economic opportunities. The opioid crisis, therefore, has pervasive ramifications on the labor market and the larger national economy.

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1 Motivation

The opioid epidemic, involving both prescription and illicit opioids, has claimed the lives of nearly 450,000 individuals in the United States, from 1999-2018 (Mattson et al., 2017).[1] Death counts involving any opioid have only increased since 2017, reaching peak annual growth rates of 25.5 percent from 2001 to 2002 and 27.7 percent from 2015 to 2016 (refer to Appendix Table A1). Upon examination of the past 20 years, the opioid crisis is represented in three distinct waves, initially characterized by prescription opioids, then by heroin, and, finally, by fentanyl (Mattson et al., 2017).

Beginning in the mid-1990s, the first wave of drug overdose deaths emerged (Alpert et al., 2019). In the time period between 1999 and 2018, opioid-involved overdose deaths — involving both illicit and prescribed opioids — have grown by over 481 percent, growing at an average annual rate of 9.5 percent for males, and 11.2 percent for females.[2] While the growth rates for men and women differ by only 1.7 percentage points, men accounted for 295,668 (66.3 percent) of the 446,014 overall opioid overdose deaths, whereas women accounted for only 150,346 of the overall opioid overdose deaths. Between 1999 and 2018, the drug overdose death rate increased by a factor of three with a noticeable inflection point in 2010, as shown in Figure 1.

The second wave of drug overdose deaths began in 2010, marked by the staggering growth of heroin overdose death rates by 44.8 percent, from 2010 to 2011. On the other hand, the prescription opioid-involved overdose deaths, during this period, were not even 4 percent. While heroin is not officially classified as an opioid, its usage is directly linked to that of opioids. Opioids are considered a gateway drug to heroin, as approximately 80 percent of heroin users reported misusing prescription opioids prior to the first use of the aforementioned analgesic narcotic (Jones, 2013; Muhuri et al., 2013). From 2016 to 2018, both prescription opioid-involved and heroin overdose deaths tapered rapidly, each averaging over the three-year span -0.6 percent and 16 percent annual growth rates, respectively.[3] This slowdown in prescription opioid-involved and heroin overdose deaths gave rise to the third wave of drug overdose deaths, beginning in 2013 — fentanyl.

Synthetic narcotic fentanyl, classified as an illicit opioid, has been the fastest growing illegal counterpart to prescription opioids in the last two decades (Mattson et al., 2017). From 2010 to 2017, opioid-involved overdose deaths grew by 10 percent annually on average, while prescription opioid-involved overdose deaths grew by only 1.4 percent annually on average. The overall opioid-involved overdose deaths can be attributed to deaths involving both prescription opioids and fentanyl. Average annual fentanyl overdose death rates outpaced those of prescription opioids by 34 percent, thus, acting as the main driver in the overall increase in all opioid-related deaths. From 2013 to 2018, fentanyl claimed the lives of over 97,000 individuals in the U.S., increasing at an annual growth rate of 54.8 percent.[4]

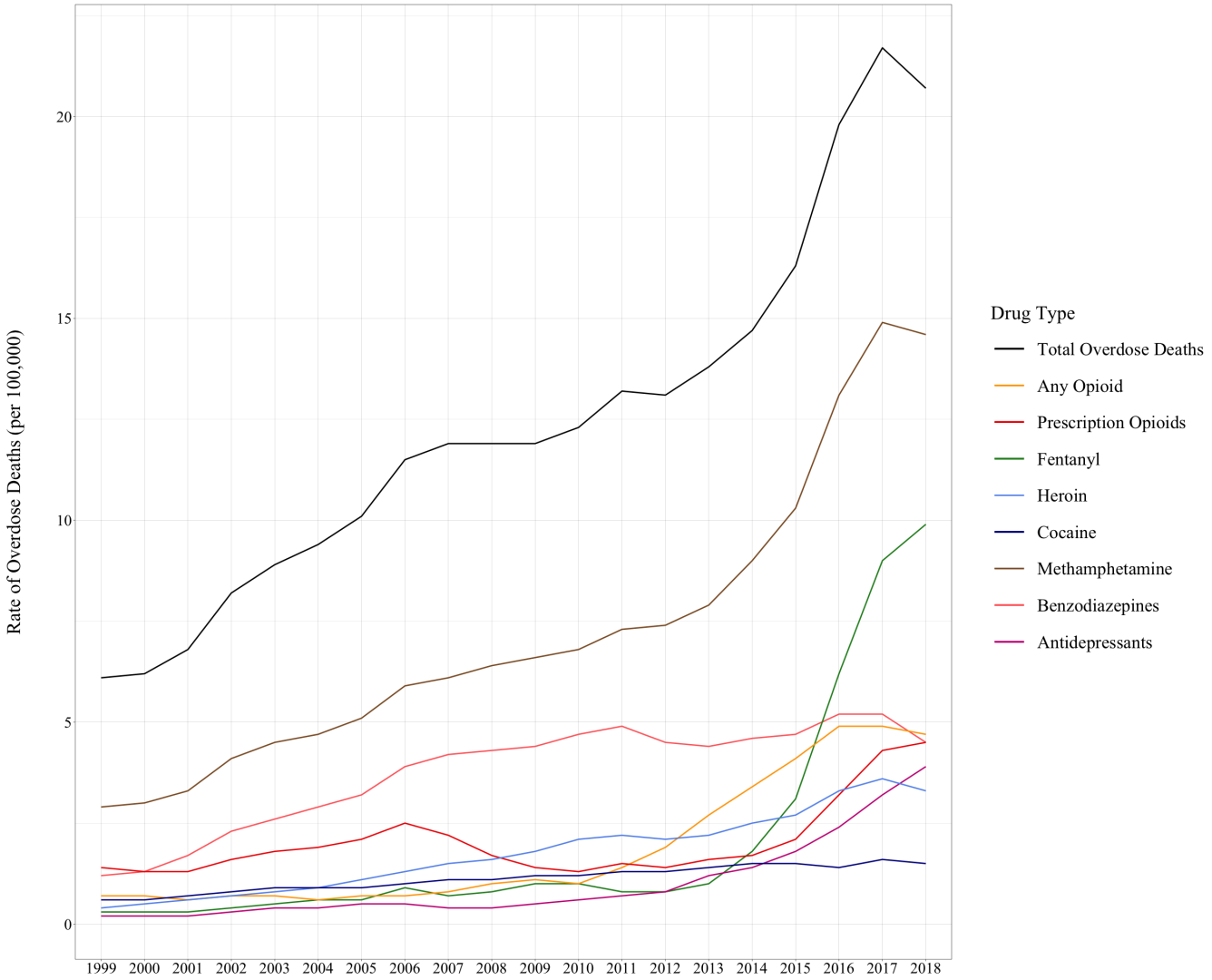
[1] To learn more about overdose deaths in the U.S., visit the National Institute on Drug Abuse's public database, including summarized annual data: https://www.drugabuse.gov/related-topics/trends-statistics/overdose-death-rates.

[2] Statistics for the annual growth in numbers and rates of overdose deaths, by gender, from 1999-2018, are available in Appendix Figures A1 and A2.

[3] From 2017 to 2018, these rates fall to -12.4 percent and -3.1 percent, respectively.

[4] In 2016, this annual growth rate peaked at over 102 percent.

Figure 1: National Drug Overdose Deaths Rate Among All Ages, 1999-2018



Note: The sum of the different rates of drug deaths do not equal the total rate of overdose deaths due to overlap in counting. Each death rate by drug is not mutually exclusive. Rate for Gender variables denoted by secondary axis. Data for 1999-2018 uses ICD-10 codes.
Source: CDC WONDER, Julien Lewin analysis.

The only year to have seen a decrease in opioid-related deaths was 2018 — down 1.7 percent, but still accounting for 46,802 deaths (Mattson et al., 2017). Prescription opioid overdose deaths have been on the decline, as seen by the decrease in prescription opioid-involved overdose deaths by 13.5 percent, from 2017 to 2018 (Wilson, 2020). However, in 2018, still, 69.5 percent of the total 67,367 U.S. drug overdose deaths involved an opioid (Wilson, 2020). Despite the decline in the rate of prescription opioid-involved overdose deaths from 2006 to 2014, as observed in Figure 1, both the distribution and subsequent prescription of opioids increased during that period (Sites et al., 2014).[5]

This decline in the overall rate of prescription opioid deaths, despite growing numbers of prescriptions, can, in part, be attributed to the relative prices of these various drugs. These illicit

[5]Refer to Tables 2 and 3 to see trends in opioid pill distributions per capita by state and year.

alternatives prove cheaper than their prescription opioid counterparts, thus, making them more accessible (National Academies of Sciences, Engineering, and Medicine, 2017). In fact, one entire bag of heroin costs $10, while one opioid pill can cost around $20 (National Academies of Sciences, Engineering, and Medicine, 2017). This price gap is marginally more attractive for individuals who are of a lower socio-economic status, such as those who are out of work. These financial implications are directly connected to the labor market.

A common narrative seen among opioid addicts is that they became hooked on the analgesics prescribed by their providers. Many often lose their job, as a byproduct of addiction, as their job performance is compromised. This is evidenced by the fact that the general population retained their same employer throughout the previous year at a rate of 17 percent points higher than those who suffer from opioid-use disorders (National Safety Council, 2020). The absenteeism, job turnover, and presenteeism resulting from opioid misuse has cost the U.S. up to $53.4 billion in lost productivity (National Safety Council, 2020). Once these addicted employees lose their jobs, they lose their source of income, as well as their health insurance in many cases. This pushes these unemployed people to seek out cheaper alternatives, such as fentanyl and heroin. The switch to cheaper substitutes, as largely motivated by individual struggles in the labor market, can explain the exponential overdose death rates of these two illicit drugs (National Academies of Sciences, Engineering, and Medicine, 2017).

The unemployment rate, therefore, is both a reflection and contributor to this larger opioid addiction issue. Unemployment can be a result of addiction, as well as a motivator given the strenuous fiscal circumstances it fosters. Beyond unemployment, the opioid crisis has bred many negative consequences. According to SAMHSA (2013) and Patrick et al. (2012), the increase in opioid prescriptions have yielded higher rates of death, overdose, misuse, addiction, emergency room visits, and neonatal abstinence syndrome. The host of adverse effects comes at a high cost, as the estimated financial impact of the opioid crisis in 2018 alone was a staggering $696 billion, or roughly 3.4 percent of the country's GDP (Ropero-Miller & Speaker, 2019). The crisis has taken hold of millions of Americans, as an estimated 2.4 million Americans were misusing opioids (Substance Abuse and Mental Health Services Administration, 2017). Therefore, it is clear that the impact of opioid misuse on the labor market and the larger nation is significant.

Despite the magnitude of this issue, across social, political, and economic spheres, only weak policy measures have been enacted in response. Most of the policies implemented, on both federal and local levels, have been focused on discouraging and regulating the number of opioid prescriptions for pain (Kertesz & Gordon, 2019). In 2016, the number of annual opioid prescriptions were equivalent to the number of adults in the population (Califf et al., 2016). Studies have shown that a significant portion of prescriptions were unnecessary, thus, there is a dire need for more stringent prescription control (Kertesz & Gordon, 2019). Prescription dosage and duration has been limited by 23 states, as of 2017 (Kertesz & Gordon, 2019). At the end of 2017, a powerful bill was presented in Congress, restricting first-time opioid prescriptions to 3 dose-days (Kertesz & Gordon, 2019). However, this bill has yet to pass on a federal level. In addition to prescription monitoring,

both federal and state governments have attempted to expand medication-assisted treatment for opioid addiction and make naloxone — a drug that mitigates the effects of opioids in the body used to combat overdoses — more accessible (Levine & Fraser, 2018). These initiatives set in place to fight this crisis are too narrow, focusing solely on pill control and drug accessibility, rather than larger systemic issues contributing to this overdose and drug abuse epidemic. There has been little effort to support the widespread treatment for opioid addiction and to combat the social conditions fostering these addictive ecosystems (Kertesz & Gordon, 2019). There is also a large stigma surrounding addiction, mental health care, and substance abuse treatment, which all fuel this national crisis (Kertesz & Gordon, 2019). Therefore, there needs to be more widespread policy initiatives on both federal and local levels, addressing all dimensions of this crisis. The prescription restrictions are not enough, as these have only given rise to the second and third waves of the crisis: the skyrocketing rates of heroin and fentanyl misuse and fatalities (Mattson et al., 2017). There are many potential policy opportunities regarding labeling and drug re-formulation, however, these efforts will be futile if illicit drugs are not actively included in the crisis response rhetoric moving forward (Califf et al., 2016).

The aforementioned negative consequences and current landscape have prompted a great deal of research with respect to the opioid crisis. Notable papers, including (Aliprantis & Chen, 2017; Aliprantis et al., 2019; Alpert et al., 2019; Chang et al., 2016; Currie et al., 2018; Harris et al., 2019), have uncovered the strong relationship between opioid prescriptions and labor market implications. In this paper, I replicate the work and empirical methodology in Harris et al. (2019), both confirming the findings and extending the analysis to subsequent years. Both Harris et al. (2019) and I conclude that opioid prescriptions per capita lead to strongly adverse effects on county-level labor market conditions, as measured by increasing unemployment rates and declining labor force participation rates and employment-to-population ratios. The implications of my findings suggest that current levels of prescription rates are irresponsible and unnecessarily inflated. Across both my county-level and state-level analyses, the ubiquitous overprescription of opioids has had measurable effects on employment opportunities, affecting millions of Americans and the larger national economy.

2 Data

Data cleaning, transformation, aggregation, merging, analysis, and visualization are performed through Microsoft Excel (MS Excel), RStudio (R), Stata, IBM SPSS Statistics (SPSS), and LyX. The various statistical software programs and platforms are required in order to process different dataset file types, to cross-reference performance measures, and to compare the accuracy of regression outputs.

2.1 Opioid Distributions, ARCOS

The opioid distribution data points are collected annually from 2006 through 2014, from the Drug Enforcement Administration's (DEA) Automation of Reports and Consolidated Orders System (ARCOS) database, which is made accessible by The Washington Post.[6] This dataset tracks the route of every single pain pill sold in the United States — by manufacturers and distributors to pharmacies in every city and county. Pain pill medication is highly sensitive and private information; thus, it is important to note that The Washington Post gained access to the DEA's ARCOS as a result of a court order and appealed to make the data public. The Washington Post has kindly made this "data available at the county and state levels in order to help the public understand the impact of years of prescription pill shipments on their communities" (The Washington Post, 2019). In order to process the raw datafile (100+ GB) containing in-depth pharmacy-level data, such as shipments of drugs to chain pharmacies, retail pharmacies, and practitioners, computationally expensive and challenging tasks are required in order to aggregate proper data.[7] Thus, analyses are performed via the extraction of summary data using of the R package "arcos" available for download from either CRAN Packages or GitHub.[8] These annual summary data include: year, buyer county, buyer state, county-state FIPS-code, total pharmacies, and total shipments of oxycodone and hydrocodone pills.[9] This paper does not utilize the total pharmacies data; however, future research might evaluate the link between pharmacy opioid shipments and neighborhood, city, or county-related economy statistics. The difference between these DEA ARCOS data and the Medicare Part D opioid data (Section 2.2) is that these data represent strictly which pharmacies the pills were shipped to versus individual practitioner prescribing behaviors, respectively.

These summary data has been cleaned by The Washington Post — all data are aggregated to unique county-state FIPS-codes and years. These data are included in order to understand the flow of prescription opioids in the U.S. Additionally, these data assist in the cross-examination of the

[6] The Washington Post article: https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/. This dataset is comprised of a small portion of unbalanced data for years and counties — most of which are in Alaska.

[7] Raw dataset variables: https://www.deadiversion.usdoj.gov/arcos/handbook/full.pdf

[8] GitHub "arcos" package functions: https://github.com/wpinvestigative/arcos

[9] The Washington Post decided not to include the other 10 commonly prescribed opioids in this dataset because they accounted for a small portion of total opioid distributions — Oxycodone and Hydrocodone accounted for nearly 75 percent of the total opioid pill shipments to pharmacies. In some counties, there are central distribution pharmacies that distribute pills throughout the region, which is not captured in the data. Thus, the total opioid distribution pill count is higher in those respective counties.

Table 1: State Profiles, 2006-2014

State	Population[a]	Unemployment Rate[b]	Labor Force Participation Rate[b]	Opioid Distributions Per Capita (ARCOS)[c]	Opioid Prescriptions Per Capita (CDC)[d]
AK	502,527	0.066	0.656	32.21	0.84
AL	4,491,761	0.086	0.529	50.94	1.21
AR	2,606,686	0.077	0.556	48.88	1.10
AZ	6,395,474	0.100	0.534	38.91	0.81
CA	37,290,540	0.103	0.586	46.55	0.83
CO	4,925,173	0.063	0.667	32.34	0.76
CT	3,567,040	0.069	0.656	28.26	0.69
DE	898,328	0.063	0.592	44.90	0.98
FL	15,896,141	0.076	0.539	42.45	0.93
GA	8,528,594	0.086	0.575	44.77	1.04
HI	1,362,769	0.059	0.599	33.98	0.65
IA	2,994,753	0.050	0.667	24.26	0.57
ID	1,532,513	0.066	0.619	38.14	0.85
IL	11,406,755	0.078	0.618	32.59	0.79
IN	6,424,131	0.077	0.612	48.85	1.04
KS	2,668,550	0.048	0.668	39.72	0.85
KY	3,689,041	0.084	0.564	68.02	1.34
LA	3,736,319	0.071	0.536	39.35	0.97
MA	6,572,062	0.066	0.659	29.41	0.70
MD	5,682,976	0.065	0.640	34.69	0.84
ME	1,328,132	0.072	0.608	42.26	0.86
MI	9,689,563	0.102	0.573	44.96	0.95
MN	5,080,445	0.060	0.676	20.85	0.59
MO	3,990,856	0.074	0.596	44.74	0.86
MS	2,461,926	0.095	0.523	43.32	1.13
MT	946,388	0.055	0.607	31.26	0.69
NC	9,420,176	0.086	0.566	44.75	0.97
ND	646,556	0.038	0.660	18.97	0.59
NE	1,734,088	0.036	0.682	24.48	0.67
NH	1,319,236	0.047	0.654	32.65	0.83
NJ	8,778,254	0.077	0.639	27.63	0.64
NM	1,906,075	0.066	0.555	36.73	0.71
NV	2,674,715	0.088	0.586	56.03	1.07
NY	14,276,564	0.069	0.597	31.88	0.57
OH	11,534,461	0.082	0.612	40.35	0.92
OK	3,619,011	0.054	0.581	52.81	0.97
OR	3,823,943	0.089	0.591	53.38	1.09
PA	12,677,569	0.070	0.598	35.14	0.79
RI	1,055,808	0.082	0.654	32.87	0.77
SC	4,606,465	0.100	0.544	41.12	0.91
SD	724,086	0.039	0.667	20.67	0.57
TN	6,042,642	0.087	0.565	70.46	1.45
TX	24,769,912	0.062	0.588	35.16	0.76
UT	2,742,678	0.055	0.653	41.59	0.91
VA	7,667,778	0.063	0.597	45.05	1.03
VT	618,666	0.052	0.678	25.96	0.51
WA	6,718,186	0.084	0.583	42.75	0.86
WI	5,585,362	0.070	0.658	28.67	0.62
WV	1,762,939	0.073	0.507	61.95	1.27
WY	555,792	0.046	0.663	33.05	0.75
U.S.	5,798,608	0.071	0.607	39.21	0.86

Note: Opioid metrics per capita calculates the mean of the total distributions across nine years for all counties per state.

[a] Source: U.S. Census Bureau and National Bureau of Economic Research

[b] Source: Bureau of Labor Statistics

[c] Source: DEA's Automation of Reports and Consolidated Orders System. Julien Lewin analysis.

[d] Source: Centers for Disease Control and Prevention, National Center for Injury Prevention and Control

Medicare Part D to better understand if, indeed, strong correlation exists between counties that were shipped pain pills and physician-level prescribing behavior in those respective counties.

Table 1 reports state-level data as evidence of the representativeness, economic status, and the mean of the total distributions of opioids per capita from 2006 to 2014 for all counties per state. Notably, North Dakota reported an average annual distribution of 18.97 pills per person (the lowest state), whereas Tennessee reported 70.46 opioid pills (the highest state). Similarly, in Tennessee, we observe one of the highest reported unemployment rates during the time period, averaging 8.7 percent annually. Tables 2 and 3 show how opioid distributions per capita change across states and time.[10] Consistently across the nine years, the opioid distributions per capita increase mostly among all states. In 2006, the U.S. average was 12.72 opioids per capita, while in 2014 the national average was 18.19, a growth of 43 percent across the nine-year period. While these values are closely similar to those in Table 1, the values in the last column of this table are calculations of the mean of the annual averages for all counties per state.

2.2 Opioid Prescriptions, CMS

Individual practitioner-level opioid prescriptions data are collected annually from 2013 to 2017, from the U.S. Centers for Medicare & Medicaid Services (CMS) Part D Prescriber Public Use File (PUF) Datasets.[11] The PUF datasets provide information on prescription drugs prescribed by physicians and other health care providers, including type of drug, total cost of the drug, number of original prescriptions and refills, utilization metrics for prescriptions, and many more descriptive statistics. Data are downloaded for both prescriber-level summary and drug-level summary datasets in the file format of tab delimited. The difference between these two datasets is the specificity of reporting dimensions — one reports aggregated opioid and non-opioid prescriptions at the physician-level and the other reports both drug and generic drug-level aggregated opioid and non-opioid prescriptions at the physician-level, respectively. For simplicity, here on out the prescriber-level and drug-level summary datasets will be referred to as the CMS Provider and Drugs datasets, respectively. Following multiple detailed conversations with Dr. Corrie Anderson of Seattle Children's Hospital, I aggregate Schedule II and III drugs from the CMS Drugs dataset in order to optimize my identification strategy by including select "drugs that are seriously dangerous and have been shown to do more harm than good, in many scenarios". This paper analyzes both datasets in order to:

1. Understand the economic effects of all opioid prescriptions,

2. Understand the economic effects of DEA classified Schedule II and III drugs.

Schedule I drugs are defined as drugs with no currently accepted medical use and a high potential for abuse (e.g., heroin, lysergic acid diethylamide (LSD), marijuana, and ecstasy). Schedule II-V drugs are defined as drugs with a range of high to low potential for abuse, with use potentially

[10] The two tables are broken up into two parts — Part 1 and Part 2 — in order to exhibit data readable.

[11] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Part-D-Prescriber

Table 2: Part 1 - Opioid Pills Per Capita by State and Year

State	2006	2007	2008	2009	2010	2011	2012	2013	2014	All Years
AK	23.61	26.23	28.09	29.26	29.72	31.75	31.69	30.83	31.16	29.15
	(14.63)	(14.98)	(15.5)	(16.76)	(16.94)	(16.99)	(17.99)	(18.57)	(18.67)	(16.78)
AL	37.81	42.62	47.15	50.35	54.11	61.19	64.86	64.68	62.4	53.91
	(17.67)	(18.9)	(21)	(22.55)	(24.45)	(27.1)	(28.04)	(27.99)	(27.77)	(23.94)
AR	31.55	36.09	40.66	44.74	49.27	53.2	55.62	54.68	56.06	46.87
	(11.64)	(13.12)	(15.03)	(15.55)	(17.18)	(15.23)	(15.92)	(16.98)	(16.84)	(15.27)
AZ	29.39	32.3	34.68	37.41	38.53	42.59	43.02	41.23	41.11	37.81
	(13.43)	(15.1)	(17.11)	(18.75)	(19.42)	(21.58)	(22.25)	(20.57)	(20.18)	(18.71)
CA	23.86	25.45	26.94	28.67	29.46	31.91	32.26	31.34	30.07	28.88
	(17.85)	(18.88)	(21.67)	(22.72)	(24.14)	(25.83)	(26.46)	(25.21)	(23.66)	(22.93)
CO	22.94	25.72	28.04	29.51	30.91	33.32	33.99	30.93	29.86	29.47
	(12.28)	(13.01)	(14.6)	(16.59)	(17.71)	(19.82)	(21.67)	(18.72)	(17.38)	(16.86)
CT	22.49	25.25	26.54	27.27	28.13	29.63	30.16	29.32	28.16	27.44
	(4.84)	(5.04)	(5.08)	(5.37)	(5.37)	(5.91)	(6.06)	(5.95)	(6.19)	(5.53)
DE	33.51	37.47	43.6	46.6	50.42	53.3	44.68	38.04	36.12	42.64
	(7.23)	(9.67)	(11.66)	(13.45)	(15.75)	(17.69)	(10.07)	(6.35)	(6.24)	(10.9)
FL	38.65	41.14	45.08	50.58	56.63	49.78	39.5	36.59	35.9	43.76
	(12.43)	(13.06)	(14.41)	(17.09)	(19.06)	(18.55)	(15.43)	(14.59)	(14.82)	(15.49)
GA	26.54	29.97	32.36	34.93	38.63	41.98	41.29	39.6	38.4	35.97
	(16.1)	(18.22)	(19.13)	(20.3)	(23.71)	(24.77)	(24.32)	(23.26)	(22.87)	(21.41)
HI	18.2	20.05	21.93	23.35	24.78	25.74	25.91	25.11	23.83	23.21
	(12.36)	(12.15)	(12.34)	(13.75)	(13.94)	(13.03)	(11.92)	(11.28)	(10.11)	(12.32)
IA	19.77	22.15	24.87	26.84	29.03	31.36	31.78	30.63	30.3	27.41
	(7.2)	(7.76)	(8.87)	(9.72)	(10.66)	(11.36)	(11.56)	(11.42)	(11.49)	(10.00)
ID	28.5	29.28	31.46	34.06	38.96	42.83	44.76	44.56	44.02	37.6
	(15.3)	(16.81)	(17.82)	(18.7)	(18.96)	(21.45)	(22.38)	(20.93)	(20.04)	(19.16)
IL	16.72	17.77	19.11	20.77	23.56	26.47	27.38	28.14	27.55	23.05
	(11.52)	(13.3)	(14.55)	(15.37)	(16.38)	(18.59)	(18.57)	(19.05)	(20.41)	(16.41)
IN	32.67	39.33	43.68	47.83	50.75	56.27	58.71	55.98	48.9	48.24
	(14.44)	(16.47)	(18.46)	(20.24)	(20.88)	(22.4)	(22.33)	(21.21)	(17.05)	(19.28)
KS	27.75	31.67	34.47	36.65	38.95	42.44	43.9	42.63	43.06	37.95
	(11.39)	(13.14)	(14.12)	(14.88)	(16.31)	(19.81)	(20.24)	(18.65)	(18.19)	(16.3)
KY	48.35	53.91	58.66	63.54	69.11	75.14	71.42	62.98	61.89	62.78
	(29.82)	(31.02)	(32.8)	(35.91)	(39.87)	(42.52)	(41.08)	(36.21)	(35.54)	(36.08)
LA	39.4	39.96	42.12	42.16	42.22	46.44	47.56	46.58	45.38	43.54
	(14.28)	(13.6)	(14.31)	(14.19)	(13.7)	(16.49)	(17.18)	(17.08)	(17.01)	(15.32)
MA	23.2	26.27	27.18	28.3	28.37	28.98	28.59	27.34	25.82	27.12
	(5.43)	(5.97)	(6.51)	(6.94)	(7.19)	(7.17)	(7.00)	(6.94)	(6.62)	(6.64)
MD	23.23	24.63	26.67	29.46	31.75	33.14	31.43	29.46	28.6	28.71
	(8.99)	(9.73)	(11.19)	(12.33)	(14.36)	(15)	(12.74)	(11.52)	(11.92)	(11.97)
ME	36.05	39.38	41.13	42.35	45.71	47.67	46.17	42.32	40.51	42.37
	(7.64)	(6.19)	(6.36)	(6.53)	(7.32)	(8.26)	(7.42)	(6.23)	(5.82)	(6.86)
MI	28.5	33.47	37.12	40.92	44.97	49.98	51.57	50.19	49.70	42.94
	(13.43)	(14.32)	(15.36)	(17.49)	(18.01)	(19.58)	(20.39)	(22.32)	(23.71)	(18.29)
MN	16.79	18.92	20.44	21.83	23.65	25.28	25.81	24.93	25.02	22.52
	(5.97)	(6.75)	(7.72)	(8.38)	(9.04)	(9.63)	(10.14)	(10.08)	(10.28)	(8.67)
MO	30.62	34.91	38.49	41.43	44.85	49.41	51.46	50.32	50.39	43.54
	(13.66)	(15.46)	(17.23)	(18.93)	(20.08)	(21.07)	(22.65)	(21.99)	(21.87)	(19.21)
U.S.	12.72	13.94	15.19	16.19	16.21	16.95	17.12	17.46	18.11	18.19

Note: "All Years" values calculates the mean of the annual averages for all counties per state.
Data represents doses distributed. Standard deviations in parenthesis.
Source: ARCOS, The Washington Post. Julien Lewin analysis.

Table 3: Part 2 - Opioid Pills Per Capita by State and Year

State	2006	2007	2008	2009	2010	2011	2012	2013	2014	All Years
MS	29.92	34.14	37.54	41.13	45.07	50.32	52.40	51.15	48.91	43.40
	(15.42)	(17.13)	(18.51)	(20.84)	(21.13)	(23.6)	(23.98)	(22.71)	(21.82)	(20.57)
MT	30.00	29.94	32.45	34.76	38.93	41.85	43.06	41.41	39.27	36.85
	(10.9)	(11.42)	(13.22)	(14.65)	(15.76)	(15.62)	(16.78)	(15.38)	(14.42)	(14.24)
NC	31.07	34.45	36.1	39.28	40.42	43.91	44.9	44.58	43.71	39.82
	(14.36)	(15.66)	(16.68)	(17.97)	(18.39)	(19.21)	(19.72)	(20.44)	(20.15)	(18.06)
ND	14.23	16.56	18.14	19.07	19.86	23.57	24.81	24.29	23.83	20.48
	(6.78)	(8.17)	(7.97)	(8.91)	(9.38)	(10.41)	(10.79)	(10.94)	(11.08)	(9.38)
NE	20.05	21.51	23.31	24.9	26.39	28.77	29.49	28.99	28.9	25.81
	(9.68)	(9.21)	(9.46)	(9.85)	(10.72)	(12.27)	(13.63)	(13.6)	(12.88)	(11.25)
NH	23.94	27.46	29.27	31.68	32.85	34.06	33.65	32.26	31.88	30.78
	(3.5)	(4.38)	(4.91)	(5.21)	(5.57)	(5.65)	(6.25)	(5.84)	(6.16)	(5.27)
NJ	19.13	22.3	25.02	24.88	26.35	28.47	27.14	26.09	25.61	25.00
	(7.9)	(8.69)	(9.46)	(9.24)	(9.97)	(10.48)	(10.82)	(11.12)	(11.64)	(9.92)
NM	27.2	30.6	33.88	37.46	41.69	43.27	41.58	37.16	37.54	36.71
	(8.76)	(9.78)	(13.9)	(15.78)	(16.87)	(18.11)	(18.58)	(15.65)	(16.42)	(14.87)
NV	44.02	47.09	50.01	53.15	57.39	61.4	58.3	54.11	57.2	53.63
	(18.14)	(19.52)	(20.54)	(19.3)	(20.18)	(26.53)	(20.76)	(17.9)	(19.64)	(20.28)
NY	19.29	21.95	23.69	25.33	26.65	28.11	26.78	24.47	23.18	24.38
	(7.59)	(8.43)	(9.22)	(9.73)	(10.27)	(10.6)	(10.73)	(10.7)	(10.42)	(9.75)
OH	31.83	36.39	40.01	43.68	45.64	47.5	46.2	43.97	42.85	42.01
	(16.28)	(17.32)	(16.15)	(16.64)	(16.21)	(15.67)	(15.22)	(14.62)	(14.41)	(15.84)
OK	39.88	45.77	50.25	54.64	58.1	63.17	64.57	63.12	61.24	55.64
	(14.98)	(16.05)	(17.61)	(19.25)	(20.57)	(22.05)	(23)	(22.26)	(21.47)	(19.69)
OR	39.44	43.52	47.14	48.4	52.78	54.87	53.48	50.79	49.38	48.87
	(14.09)	(14.45)	(15.54)	(18.42)	(20.30)	(21.16)	(21.81)	(20.89)	(20.22)	(18.54)
PA	26.18	29.89	32.9	35.53	37.34	40.62	41.11	39.65	38.95	35.8
	(7.67)	(8.69)	(9.68)	(10.18)	(10.90)	(11.85)	(12.03)	(11.38)	(10.84)	(10.36)
RI	27.13	32.1	33.55	35.36	36.04	39.16	38.32	34.26	31.16	34.12
	(7.16)	(8.78)	(9.51)	(10.58)	(11.28)	(11.9)	(11.45)	(10.33)	(8.89)	(9.99)
SC	30.77	34.44	37.23	41.34	44.55	48.95	50.51	49.37	48.02	42.8
	(14.02)	(15.32)	(16.08)	(17.92)	(19.54)	(20.46)	(21.2)	(21.7)	(21.04)	(18.59)
SD	15.1	17.83	19.89	22.24	24.17	26.96	27.57	28.07	28.79	23.4
	(6.26)	(6.88)	(8.59)	(9.30)	(10.00)	(11.94)	(13.58)	(15.68)	(14.22)	(10.72)
TN	43.82	48.35	52.43	58.01	62.83	67.61	65.57	61.54	60.19	57.82
	(22.81)	(25.15)	(26.28)	(28.5)	(30.45)	(32.43)	(31.89)	(31.46)	(30.1)	(28.79)
TX	25.80	30.67	29.93	31.62	32.89	34.84	33.41	32.54	29.57	31.25
	(13.76)	(15.43)	(15.13)	(16.18)	(16.57)	(17.36)	(17.95)	(16.92)	(15.63)	(16.1)
UT	33.27	34.11	34.87	36.13	38.25	39.02	39.72	38.96	38.65	37.00
	(16.86)	(15.81)	(16.23)	(16.39)	(18.96)	(17.4)	(17.63)	(18.23)	(19.99)	(17.5)
VA	22.55	24.93	26.44	28.67	30.10	32.85	33.11	31.85	30.78	29.03
	(30.8)	(34.56)	(37.14)	(42.54)	(44.33)	(48.86)	(48.05)	(48.47)	(48.88)	(42.63)
VT	23.81	26.65	27.6	33.47	29.04	29.25	28.51	27.9	26.42	28.07
	(6.66)	(7.59)	(8.03)	(10.54)	(8.21)	(10.62)	(10.02)	(10.17)	(9.58)	(9.05)
WA	34.4	37.09	39.24	39.64	41.05	41.36	40.21	38.86	38.76	38.96
	(12.32)	(13.99)	(14.72)	(14.93)	(16.39)	(16.64)	(16.63)	(17.54)	(17.68)	(15.65)
WI	25.71	28.24	30.71	32.59	35.07	37.44	38.09	36.39	36.06	33.37
	(8.84)	(9.54)	(10.04)	(10.45)	(10.95)	(11.62)	(11.81)	(11.25)	(11.08)	(10.62)
WV	51.6	59.97	67.01	70.34	68.12	71.61	71.31	68.08	65.29	65.93
	(31.21)	(41.03)	(50.78)	(42.01)	(31.27)	(33.39)	(32.54)	(30.10)	(27.94)	(35.59)
WY	27.30	29.22	29.2	30.02	33.38	35.14	37.06	36.78	37.12	32.8
	(9.49)	(11.32)	(11.34)	(11.91)	(12.73)	(13.73)	(14.76)	(14.83)	(14.5)	(12.73)
U.S.	12.72	13.94	15.19	16.19	16.21	16.95	17.12	17.46	18.11	18.19

Note: "All Years" values calculates the mean of the annual averages for all counties per state.
Data represents doses distributed. Standard deviations in parenthesis.
Source: ARCOS, The Washington Post. Julien Lewin analysis.

leading to severe or mild psychological or physical dependence.[12] While the theoretical assumption is that Schedule II drugs will lead to worsening economic conditions, as a result of those drugs' high potential for abuse, with use leading to severe dependence, I subset the drug-level summary dataset to include both Schedule II and III drugs because research suggests that both schedule classes can have adverse effects on labor market conditions (Aliprantis et al., 2019; Aliprantis & Chen, 2017; Currie et al., 2018; Harris et al., 2019).[13]

Of the total unique Schedule II and III drugs, 77 percent of the specified drugs in the list fall into the Schedule II category and more than 90 percent of the raw data observations fall into the Schedule II category.

With these data, I replicate the methodology employed in Harris et al. (2019), by identifying the number of unique practitioners — as referred to as NPIs — in each county in the top-five and top-one percent of opioid prescribers in the U.S., as measured by the number of opioid prescriptions written (i.e., total claim count) and the number of doses prescribed (i.e., total day supply), respectively. I transform the top-five and top-one percent variables to per capita, per-county, per-year figures, in order to locate abnormally high-prescribers in a given county relative to those across the country. These two variables — later used as instrumental variables — are used to identify the causal effects of per capita opioid prescriptions on labor market outcomes (i.e., unemployment rate, labor force participation rate, and employment-to-population ratio) (Harris et al., 2019).

Research has shown that a small subset of prescribers are responsible for prescribing the majority of opioids (Chang et al., 2016; Department of Health and Human Services, 2013; Dhalla et al., 2011). According to Oregon Health Authority (2012), Oregon's prescription drug monitoring program (PDMP) reported that 60 percent of all controlled substance Schedule II-IV prescriptions were written by the top 4.1 percent of prescribers in a six month period. In another study, which evaluated the link between opioid prescribing tendencies and opioid-related deaths, the authors found that the 20 percent of family physicians in the sample who prescribed opioids most often approved opioid prescriptions 55 times more frequently than the 20 percent who prescribed opioids least frequently (Dhalla et al., 2011). Furthermore, in 2009, the top 20 percent of prescribers in Kentucky issued 82 percent of the controlled substance prescriptions (Wixson et al., 2015).

In addition to calculating the two instrumental variables, these datasets, in conjunction with county-level population data from the U.S. Census Bureau, are used to calculate opioid prescriptions per capita. In the CMS Provider dataset, short-acting (SA) and long-acting (LA) opioids are reported in two separate categories. To encapsulate both SA and LA opioids in my opioid prescriptions per capita calculation, I specify one combined SA-LA total. First, to calculate this measure, I

[12] https://www.dea.gov/drug-scheduling

[13] Drugs include: Acetaminophen/Caff/Dihydrocodeine, Morphine Sulfate, Codeine/Butalbital/Asa/Caffein, Aspirin/Caffein/Dihydrocodeine, Buprenorphine HCL, Opium/Belladonna Alkaloids, Buprenorphine, Butalbit/Acetamin/Caff/Codeine, Codeine Sulfate, Meperidine HCL, Hydromorphone HCL, Methadone HCL, Fentanyl, Morphine Sulfate/Naltrexone, Oxycodone HCL/Acetaminophen, Hydrocodone/Acetaminophen, Hydrocodone/Ibuprofen, Hydrocodone Bitartrate, Levorphanol, Tartrate, Tapentadol HCL, Oxymorphone HCL, Oxycodone HCL, Oxycodone HCL/Aspirin, Ibuprofen/Oxycodone HCL, Oxycodone Myristate. Acetaminophen with Codeine is dropped because the drug falls into both Schedule II and Schedule V drugs depending on the dosage, which is not specified in the dataset.

Table 4: State Profiles, 2013-2017

State	Population[a]	Unemployment Rate[b]	Labor Force Participation Rate[b]	Opioid Prescriptions Per Capita (CMS)[c]	Opioid Prescriptions Per Capita (CDC)[d]
AK	633,531	0.065	0.622	0.32	0.64
AL	4,591,755	0.071	0.516	0.57	1.25
AR	2,697,638	0.061	0.520	0.71	1.13
AZ	6,821,368	0.087	0.519	0.62	0.72
CA	38,883,428	0.079	0.573	0.56	0.72
CO	5,320,842	0.046	0.627	0.71	0.69
CT	3,585,952	0.059	0.642	0.41	0.63
DE	940,788	0.054	0.575	0.71	0.87
FL	17,498,055	0.059	0.516	0.49	0.83
GA	9,591,138	0.071	0.544	0.59	1.01
HI	1,419,533	0.040	0.592	0.47	0.56
IA	3,043,612	0.039	0.668	0.78	0.61
ID	1,620,784	0.050	0.608	0.62	0.81
IL	12,799,412	0.066	0.593	0.63	0.71
IN	6,585,264	0.053	0.606	0.63	0.91
KS	2,792,032	0.041	0.651	0.81	0.70
KY	3,886,390	0.069	0.529	0.69	1.14
LA	4,499,441	0.070	0.532	0.56	0.94
MA	6,792,551	0.054	0.639	0.37	0.58
MD	5,973,205	0.058	0.626	0.57	0.77
ME	1,330,775	0.053	0.598	0.43	0.73
MI	9,923,927	0.072	0.552	0.78	0.93
MN	5,466,920	0.047	0.674	0.74	0.55
MO	5,784,347	0.059	0.575	0.62	0.82
MS	2,708,945	0.079	0.505	0.66	1.08
MT	994,879	0.047	0.595	0.67	0.59
NC	9,860,954	0.066	0.544	0.76	0.94
ND	715,808	0.033	0.677	0.69	0.48
NE	1,812,669	0.031	0.676	0.74	0.62
NH	1,337,613	0.036	0.637	0.55	0.74
NJ	8,871,814	0.065	0.616	0.41	0.60
NM	1,831,716	0.071	0.526	0.64	0.71
NV	2,861,018	0.070	0.563	0.56	0.95
NY	19,630,978	0.059	0.566	0.65	0.54
OH	11,608,299	0.061	0.588	0.66	0.79
OK	3,785,228	0.050	0.572	0.56	0.87
OR	4,015,265	0.068	0.566	0.94	0.99
PA	12,777,122	0.061	0.585	0.86	0.75
RI	1,056,172	0.061	0.634	0.30	0.64
SC	4,786,679	0.071	0.530	0.67	0.93
SD	777,653	0.035	0.647	0.73	0.52
TN	6,271,360	0.067	0.535	0.83	1.33
TX	26,993,985	0.052	0.569	0.48	0.65
UT	2,964,148	0.046	0.625	0.41	0.83
VA	7,957,621	0.054	0.581	0.94	1.01
VT	621,081	0.040	0.642	0.33	0.51
WA	7,167,142	0.071	0.550	0.69	0.76
WI	5,754,195	0.052	0.644	0.75	0.58
WV	1,722,622	0.071	0.498	0.76	1.05
WY	579,357	0.044	0.645	0.47	0.68
U.S.	6,238,940	0.058	0.588	0.62	0.79

Note: Opioid metrics per capita calculates the mean of the total distributions across nine years for all counties per state.

[a] Source: U.S. Census Bureau and National Bureau of Economic Research

[b] Source: Bureau of Labor Statistics

[c] Source: U.S. Centers for Medicare and Medicaid Services (Provider dataset). Julien Lewin analysis.

[d] Source: Centers for Disease Control and Prevention, National Center for Injury Prevention and Control

remove the NPI specification, which identifies individual practitioners. Second, I aggregate the raw opioid claims (i.e., prescriptions) by county-state FIPS-code and year. Third, I merge the opioid prescriptions datasets with the population dataset at the county-state FIPS-code and year level to identify opioid prescriptions by capita.[14]

Tables 5 and 6 report the two county-level data on the average number of high-volume opioid-prescribing physicians per 100,000 people at the county level in each state — the two instrumental variables. Both the CMS Provider and Drugs datasets are included, to draw out differences between the two variables. The CMS Provider data in these tables are often greater than that of the CMS Drugs data because the Provider data accounts for Schedule II-IV controlled substance opioids. In the U.S., the average number of prescribers per county that fall into the nation's top-5 percent of total opioid prescriptions per county is 3.97 and 8.21, for the Drugs and Provider datasets, respectively. The average number of prescribers per county that fall into the nation's top-1 percent of total opioid doses per county is 0.73 and 1.63, for the Drugs and Provider datasets, respectively. From 2013 to 2015, Oregon reported the highest average number of prescribers per county that fall into the top-5 percent of opioid prescriptions per county, 7.85 in the Drugs dataset and 13.82 in the Provider dataset.

Table 4, similar to that of Table 1, reports state-level data as evidenced by the representativeness, economic status, and the mean of the total prescriptions of opioids per capita from 2013 to 2017 for all counties per state. Notably, Rhode Island reported an average of 0.30 opioid prescriptions per capita (the lowest state), whereas Oregon and Virginia reported an average of 0.94 (the highest states). Similarly, in the states that have the highest prescriptions per capita, as observed in both the CMS and CDC columns, are accompanied by the highest rates of average annual unemployment.

2.3 Opioid Prescriptions, CDC

County-level prescription rate data are collected annual from 2006 to 2014, from the Centers for Disease Control and Prevention's (CDC) National Center for Injury Prevention and Control database.[15] This source captures both prescription opioid statistics and illicit narcotic overdose rates. These annual data show single-year U.S. retail opioid prescriptions dispensed per 100 persons, from 2006 to 2018, at both state and county levels. These data are merely representative as they are not raw values, but rather sample estimates. The CDC acquired these prescribing data from IQVIA Xponent — a dataset based on a sample of approximately 49,900 retail (non-hospital) pharmacies, which dispense nearly 92 percent of all retail prescriptions in the U.S. Inherently, these CDC opioid prescriptions estimates will be marginally larger than those from the Medicare Part D database because prescriptions in the CDC sample dataset are counted as either an initial or refill prescription dispensed at a retail pharmacy and paid for by commercial insurance, Medicaid, Medicare, cash or its equivalent. One caveat is that this database excludes all mail order prescriptions. Opi-

[14]The calculation for opioid prescriptions per capita is: (total claim count per-county, per-year) / (population per-county, per-year).

[15]https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html

Table 5: Part 1 - Summary Statistics: Concentration of High-Volume Prescribers by State

State	Top 5 Claim (Drugs)	Top 5 Claim (Provider)	Top 1 Supply (Drugs)	Top 1 Supply (Provider)
AK	2.73	3.72	0.19	0.29
	(2.25)	(3.25)	(0.24)	(0.56)
AL	4.78	6.27	1.19	4.74
	(4.12)	(3.6)	(1.45)	(4.11)
AR	3.57	9.15	0.70	3.30
	(3.34)	(5.63)	(1.2)	(3.78)
AZ	4.84	9.68	1.24	1.69
	(2.6)	(5.64)	(1.3)	(1.31)
CA	4.86	8.27	0.88	1.81
	(3.96)	(5.28)	(0.96)	(1.86)
CO	5.08	9.98	0.98	1.09
	(5.53)	(9.02)	(1.62)	(1.52)
CT	2.43	4.92	0.45	0.48
	(1.5)	(1.88)	(0.46)	(0.34)
DE	5.35	8.37	0.97	1.59
	(2.17)	(1.86)	(0.19)	(0.55)
FL	3.09	5.60	0.74	1.93
	(2.14)	(2.83)	(0.71)	(1.32)
GA	3.00	6.96	0.72	2.81
	(3.13)	(5.93)	(1.16)	(2.65)
HI	2.84	5.60	0.82	0.36
	(0.87)	(0.88)	(0.71)	(0.21)
IA	2.97	12.35	0.55	0.77
	(3.77)	(7.69)	(1.52)	(1.73)
ID	4.95	9.41	0.61	1.14
	(5.72)	(8.5)	(1.25)	(1.83)
IL	2.60	8.69	0.47	1.35
	(3)	(5.29)	(0.91)	(1.81)
IN	3.92	8.73	0.68	2.32
	(3.16)	(4.47)	(1.1)	(2.23)
KS	5.30	12.88	1.22	1.76
	(6.46)	(10.13)	(2.44)	(3.86)
KY	3.50	8.37	0.71	3.49
	(3)	(5.22)	(1.1)	(2.95)
LA	2.00	6.08	0.32	1.74
	(1.91)	(3.82)	(0.65)	(1.97)
MA	2.17	4.29	0.34	0.40
	(1.57)	(3.16)	(0.34)	(0.44)
MD	4.60	6.68	0.89	1.05
	(2.6)	(3.85)	(0.82)	(0.93)
ME	1.86	5.60	0.33	0.45
	(2.65)	(6.22)	(0.7)	(0.68)
MI	5.97	11.26	1.31	2.82
	(5.11)	(6.86)	(2.44)	(2.71)
MN	3.93	9.14	0.37	0.33
	(4.9)	(6.75)	(0.94)	(0.72)
MO	5.67	8.87	1.16	2.72
	(5.34)	(6.2)	(2.06)	(2.83)
MS	2.37	6.91	0.53	2.91
	(2.7)	(5.37)	(1.03)	(3.09)
U.S.	3.97	8.21	0.73	1.62

Note: Drugs and Provider are two different datasets. For a given county, Top 5 Claim is calculated as the number of prescribers in the top-5 percent of Part D opioid claims per 100,000 people. Top 1 Supply is the number of prescribers in the top-1 percent of opioid doses supplied per 100,000 people. Specific calculation: top-X percent / (county population / 100,000)
Source: CMS Part D Prescriber Public Use File Datasets. Julien Lewin analysis.

Table 6: Part 2 - Summary Statistics: Concentration of High-Volume Prescribers by State

State	Top 5 Claim (Drugs)	Top 5 Claim (Provider)	Top 1 Supply (Drugs)	Top 1 Supply (Provider)
MT	4.73	7.80	0.62	0.95
	(4.79)	(7.07)	(1.13)	(1.79)
NC	5.19	10.17	1.14	2.67
	(3.45)	(5.31)	(1.43)	(1.95)
ND	2.46	9.75	0.33	0.12
	(4.52)	(10.71)	(1.15)	(0.43)
NE	4.70	12.16	0.50	0.59
	(6.86)	(11.92)	(1.59)	(1.25)
NH	4.77	6.32	0.66	0.84
	(2.91)	(3.6)	(1.11)	(0.95)
NJ	2.88	4.79	0.48	0.59
	(1.51)	(2.44)	(0.37)	(0.53)
NM	5.05	8.94	0.98	1.77
	(5.87)	(5.04)	(1.69)	(1.98)
NV	4.18	10.54	1.13	1.29
	(3.09)	(9.87)	(1.1)	(1.87)
NY	3.23	8.08	0.57	0.88
	(1.74)	(3.86)	(0.57)	(0.84)
OH	3.84	8.53	0.73	1.57
	(2.41)	(4.05)	(0.68)	(1.47)
OK	3.98	6.69	0.96	2.74
	(4.41)	(4.9)	(1.99)	(2.78)
OR	7.85	13.82	1.49	1.80
	(4.53)	(5.69)	(1.35)	(1.45)
PA	5.65	12.03	0.97	1.83
	(3.84)	(8.63)	(0.81)	(1.34)
RI	1.22	2.86	0.16	0.29
	(1.68)	(3.5)	(0.21)	(0.41)
SC	3.17	8.01	0.60	2.31
	(2.5)	(5.03)	(0.69)	(1.88)
SD	3.23	9.84	0.47	0.64
	(5.93)	(8.41)	(1.29)	(1.53)
TN	5.53	10.20	0.86	4.35
	(4.26)	(5.9)	(1.01)	(4.14)
TX	1.14	6.08	0.17	1.28
	(2.1)	(5.33)	(0.5)	(1.85)
UT	3.60	5.54	0.66	1.15
	(3.27)	(4.73)	(1.03)	(2.05)
VA	5.57	11.22	0.94	3.13
	(8.98)	(15.76)	(2.03)	(8.59)
VT	3.09	4.03	0.43	0.40
	(3.27)	(4.96)	(0.64)	(0.51)
WA	6.77	10.50	1.43	1.43
	(5.41)	(6.84)	(2.64)	(2.05)
WI	4.43	9.31	0.58	0.76
	(2.79)	(4.81)	(0.8)	(1.02)
WV	4.06	8.97	0.81	3.39
	(3.93)	(6.52)	(1.3)	(3.43)
WY	3.93	6.34	0.54	0.96
	(4.67)	(5.04)	(1.04)	(1.81)
U.S.	3.97	8.21	0.73	1.62

Note: Drugs and Provider are two different datasets. For a given county, Top 5 Claim is calculated as the number of prescribers in the top-5 percent of Part D opioid claims per 100,000 people. Top 1 Supply is the number of prescribers in the top-1 percent of opioid doses supplied per 100,000 people. Specific calculation: top-X percent / (county population / 100,000)
Source: CMS Part D Prescriber Public Use File Datasets. Julien Lewin analysis.

oid prescriptions are identified using National Drug Codes.[16] In many cases — most commonly in the state of Alaska — there are missing data per county. As noted by the CDC, missing data values can be attributed to a lack of both physical retail pharmacies or sampling. Additionally, errors in assigning the data to the correct county might have occurred, as the sampling rules tended to disproportionately favor more populous counties (Centers for Disease Control and Prevention, 2020).

In order to compare the CDC and Medicare Part D datasets as fundamentally the same, I divide the CDC estimates by 100, in order to get opioid prescriptions per capita per-county, per-year. Thus, in both analyses, I estimate the impact of opioids per capita on county labor market outcomes.

Tables 7 and 8 report summary statistics for the ARCOS sample, years 2006 to 2014, the replication sample, years 2013 to 2015 (i.e., to model the empirical specifications of (Harris et al., 2019), and the analytic sample, years 2013 to 2017. In both tables, across the three groups of year ranges, they remain quite consistent, with no unexpected variation in variables. The unemployment rate is reasonably higher in the ARCOS sample, which is not surprising given that the ARCOS sample contains data that run through the Great Recession. This high unemployment rate persists marginally in the replication sample, as the economy was slowly recovering from the recession. In the ARCOS sample there were 23,012 county-level observations, 8,144 in the replication sample, and 12,987 in the analytic sample. Each sample makes up an unbalanced panel of data as some county-level observations are missed across years due to reporting errors from the downloaded sources or institutions.

2.4 Overdose Death Rates

Raw overdose death numbers and rates at the national-level are collected annually from 1999 to 2018, from the National Institute on Drug Abuse (NIDA) and the CDC WONDER databse.[17,18] These data include deaths with underlying causes of unintentional drug poisoning, suicide drug poisoning, homocide drug poisoning, or drug poisoning of undetermined intent, as coded in the International Classification of Diseases, 10th Revision (ICD-10). These data provide overdose death statistics of legal and illicit drugs —any opioids (i.e., legal and illicit), prescription opioids, fentanyl, heroin, cocaine, methamphetamine, benzodiazepines, and antidepressants. More detailed statistics of these data include gender and race demographics. These descriptive summary data are used to show the consistent upward trend of drug overdose deaths since 1999 and highlight the increase in *substitute* drugs to prescription opioids. For example, in a three-year average from 2009 to 2011, 80 percent of heroin users reported using prescription opioids prior to using heroin (Jones, 2013; Muhuri et al., 2013).

[16]The CDC sample dataset includes the count of "tramadol" prescriptions, a Schedule IV substance. This drug is intentionally excluded from the Medicare Part D Drugs dataset, as that dataset is comprised of only Schedule II and III drugs.

[17]NIDA: https://www.drugabuse.gov/related-topics/trends-statistics/overdose-death-rates

[18]CDC WONDER: https://wonder.cdc.gov/mcd.html

Table 7: Summary Statistics: CMS Part D Prescriber Public Use File (Drugs Dataset)

Variable	Replication Sample (2013-2015) (Drugs)	Analytic Sample (2013-2017) (Drugs)
Opioids Per Capita	2.969	3.098
	(2.206)	(2.319)
Employment-to-Population Ratio	0.546	0.550
	(0.088)	(0.086)
Unemployment Rate	0.064	0.058
	(0.023)	(0.022)
Labor Force Participation Rate	0.582	0.583
	(0.084)	(0.083)
Percent Male	0.499	0.499
	(0.020)	(0.020)
Percent Female	0.501	0.501
	(0.020)	(0.020)
Percent Black	0.094	0.092
	(0.144)	(0.142)
Percent Hispanic	0.092	0.094
	(0.131)	(0.132)
Percent Rural	0.539	0.528
	(0.300)	(0.300)
Percent Under 15	0.187	0.186
	(0.028)	(0.028)
Percent 15 to 19	0.065	0.065
	(0.011)	(0.011)
Percent 20 to 24	0.066	0.066
	(0.025)	(0.025)
Percent 25 to 34	0.119	0.119
	(0.014)	(0.014)
Percent 35 to 44	0.117	0.116
	(0.014)	(0.014)
Percent 45 to 54	0.135	0.133
	(0.014)	(0.014)
Percent 55 to 64	0.138	0.139
	(0.020)	(0.020)
Percent Aged 65+	0.173	0.176
	(0.043)	(0.043)
Total Population	112,647	120,359
	(337,720)	(353,803)
Number of PCPs and NPs per 1,000 People	1.00	1.05
	(0.58)	(0.61)
Number of Cancer Deaths per 100,000 People	166.61	
	(14.35)	
Top 1 Supply per 100,000 Population	0.75	0.68
	(2.12)	(1.89)
Top 5 Claim per 100,000 Population	4.05	3.94
	(5.81)	(5.65)
Number of Liquor Stores, Alc. Bev. Locations and Bars	99.99	107.55
	(308.67)	(328.97)
Number of Marijuana-Related Arrests (Sales)	28.13	
	(140.97)	
Number of Marijuana-Related Arrests (Possession)	229.71	
	(1,258.48)	
Number of Observations	8,144	12,987

Note: Standard deviations in parenthesis.

Table 8: Summary Statistics - ARCOS and CMS Part D Prescriber Public Use File (Provider Dataset)

Variable	Replication Sample (2013-2015) (Provider)	Analytic Sample (2013-2017) (Provider)	ARCOS Sample (2006-2014)
Opioids Per Capita	0.659	0.667	40.527
	(0.492)	(0.503)	(23.859)
Employment-to-Population Ratio	0.546	0.550	0.558
	(0.088)	(0.086)	(0.085)
Unemployment Rate	0.064	0.058	0.072
	(0.023)	(0.022)	(0.030)
Labor Force Participation Rate	0.582	0.583	0.600
	(0.084)	(0.083)	(0.080)
Percent Male	0.499	0.499	0.498
	(0.020)	(0.020)	(0.019)
Percent Female	0.501	0.501	0.502
	(0.020)	(0.020)	(0.019)
Percent Black	0.094	0.092	0.091
	(0.144)	(0.142)	(0.143)
Percent Hispanic	0.092	0.094	0.083
	(0.131)	(0.132)	(0.124)
Percent Rural	0.539	0.528	0.529
	(0.300)	(0.300)	(0.296)
Percent Under 15	0.187	0.186	0.192
	(0.028)	(0.028)	(0.028)
Percent 15 to 19	0.065	0.065	0.069
	(0.011)	(0.011)	(0.011)
Percent 20 to 24	0.066	0.066	0.064
	(0.025)	(0.025)	(0.027)
Percent 25 to 34	0.119	0.119	0.117
	(0.014)	(0.014)	(0.016)
Percent 35 to 44	0.117	0.116	0.124
	(0.014)	(0.014)	(0.016)
Percent 45 to 54	0.135	0.133	0.145
	(0.014)	(0.014)	(0.015)
Percent 55 to 64	0.138	0.139	0.130
	(0.020)	(0.020)	(0.021)
Percent Aged 65+	0.173	0.176	0.159
	(0.043)	(0.043)	(0.041)
Total Population	112,647	120,359	113,391
	(337,720)	(353,803)	(335,101)
Number of PCPs and NPs per 1,000 People	1.00	1.05	0.93
	(0.58)	(0.61)	(0.54)
Number of Cancer Deaths per 100,000 People	166.61		175.53
	(14.35)		(15.41)
Top 1 Supply per 100,000 Population	1.97	2.07	
	(3.99)	(4.07)	
Top 5 Claim per 100,000 Population	8.92	9.06	
	(8.86)	(8.99)	
Number of Liquor Stores, Alc. Bev. Locations and Bars	99.99	107.55	103.12
	(308.67)	(328.97)	(308.23)
Number of Marijuana-Related Arrests (Sales)	28.13		31.68
	(140.97)		(135.50)
Number of Marijuana-Related Arrests (Possession)	229.71		248.10
	(1,258.48)		(969.34)
Number of Observations	8,144	12,987	23,012

Note: Data for ARCOS Sample "Number of PCPs and NPs per 1,000 People" are from 2010 to 2014. Standard deviations in parenthesis.

2.5 Demographic Composition & Population

Demographic composition (i.e., age, gender, race and ethnicity) data and each subgroup's respective population estimates are collected from 2006 to 2017, from the U.S. Census Bureau, Population Division and downloaded from both the National Bureau of Economic Research (NBER) and the U.S. Census Bureau.[19,20] Population statistics come from decennial censuses, which count the entire U.S. population every ten years. In between these decades, annual population statistics are estimated and reported. Annual county-level estimates in this data series assist in per capita calculations for many variables. In order to match the two datasets (i.e., NBER, 2006-2009 and Census, 2010-2017), I transform the encoded descriptive variables in R. First, in the NBER dataset, I remove all years from 2000 to 2005, and remove both the resident 2010 Census population and the resident 2010 population estimates. Second, I re-encode the two age grouping buckets, age zero and ages one through four, in one bucket, age zero through four. In the Census dataset, I remove both of the resident 2010 population estimates — one of which is calculated in April and the other in July — and year 2018. After identifying the variables to keep in both, such as year, county, state, and all single race information (i.e., White, Black, Asian, Hispanic, American Indian), I merge the two datasets together to have one fully exhaustive 2006-2017 dataset. Lastly, unique counties and states are replaced with unique county-state FIPS-codes.

2.6 Cancer Death Rates

Cancer death data — raw counts and rate per 100,000 — are collected annually from 2006 to 2016, from the CDC's United States Cancer Statistics (USCS) database.[21] Public-use county-level data are only available for a 5-year time period, 2012-2016. Thus, I utilize state-level data which include rates of death per 100,000 people, age-adjusted to the 2000 U.S. standard population (19 age groups – Census P25–1130).[22]

In order to maintain county-level estimates across other variables in this paper, each distinct annual cancer death rate county-level observation is equal to respective year and state observation rate. Thus, there is no cross-county differences in cancer death rates in any given year. For greater detail, data recording county-level cancer death rates can be purchased through private institutions. These data are imported into a MS Excel spreadsheet to clean — leading and ending apostrophes — and, subsequently, loaded into R to be merged with the other regression variables.

[19] NBER (2006-2009 data):
https://data.nber.org/data/census-intercensal-county-population-age-sex-race-hispanic.html

[20] U.S. Census Bureau (2010-2017 data):
https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-detail.html#par_textimage_1383669527

[21] https://gis.cdc.gov/Cancer/USCS/DataViz.html

[22] Death data are from the CDC's National Center for Health Statistics National Vital Statistics System and cover 100 percent of U.S. population. Rates and counts are suppressed if fewer than 16 cases (deaths) were reported in a specific category, such as cancer type, race, ethnicity, age and state.

2.7 Drug Arrests & Possession

County-level detailed arrest and offense data are collected annually from 2006 to 2016, from the Inter-university Consortium for Political and Social Research's (ICPSR) Uniform Crime Reporting (UCR) Program.[23] There are a number of flaws in the imputation process to make these county-level files as a result of major gaps in county-level crime data Kaplan (2019).[24] This dataset aggregates agency-level crime and arrest data into county-level counts — agency locations are based on the matching county-state FIPS-code. This paper explores county-level counts of sales and possession arrests drug abuse violations.[25]

Processing these data require first importing each yearly file into SPSS, using an SPSS setup package in order to export the file as an R readable datafile (i.e., a comma-separated value file). Second, identification of the variables (i.e., drug sale and possession) to analyze are subsetted from the master file. Third, these data are merged with the other regression variables. Figure 2 shows the national drug arrest rates of drugs, from 2000 to 2016. This figure highlights the overly high arrest rate from the sale of synthetic narcotics relative to other drugs.

[23]Separate annual datafiles: https://www.icpsr.umich.edu/icpsrweb/. The public-use data files are maintained and distributed by the National Archive of Criminal Justice Data (NACJD). The Principal investigator for this study is the U.S. Department of Justice Federal Bureau of Investigation (FBI). Aggregated annual datafile:
https://www.openicpsr.org/openicpsr/project/108164/version/V3/view.

[24]To learn more about these imputation methods, please visit:
https://www.openicpsr.org/openicpsr/project/108164/version/V3/view

[25]Drugs include: marijuana, heroin, synthetic narcotics, and other drugs.

Figure 2: National Drug Arrests Rate Among All Ages, by Sales and Possession, 2000-2016

Note: This data aggregates agency-level crime and arrest data into county-level counts. County-level crime data have major gaps, and the imputation schemes for filling in the gaps are inadequate and inconsistent.
Source: ICPSR, UCR, FBI, Julien Lewin analysis.

2.8 Liquor Store, Alcoholic Beverage, and Bar Business Patterns

Liquor store, alcoholic beverage, and bar business patterns data are collected from 2006 to 2017, from the U.S. Census Bureau's County Business Patterns (CBP) database.[26] These statistics are available at the county-level for all 50 states in the U.S.

From the raw detailed data, the important series include: year, FIPS codes, North American Industry Classification System (NAICS) descriptions, and total number of establishments. The NAICS numeric values that corresponded with liquor store, alcoholic beverage, and bar businesses

[26] https://www.census.gov/programs-surveys/cbp/data/datasets.html

are subsetted as defined in each dataset's respective NAICS reference descriptions text file. Each annual dataset is downloaded individually in R, then combined together into one complete dataset after cleaning and subsetting to the needed specifications for analysis. Lastly, this dataset is merged with the other regression variables.

2.9 Primary Care Physicians & Nurse Practitioners

Albeit the high percentage of publicly funded medical expenses, hospital, medical, and insurance public-use data is highly sensitive and difficult to retrieve. Area Health Resource File (AHRF) data are collected from 2010 to 2017, from the U.S. Department of Health & Human Services' National Practitioner Data Bank's (NPDB) Public Use Data File.[27] This data series is updated four times a year, and the series contains selected variables from medical malpractice payment and adverse licensure, clinical privileges, professional society membership, and DEA reports (i.e., adverse actions) received by the NPDB concerning physicians, dentists, and other licensed health care practitioners.

To extract information relating to the total number of primary care physicians (PCP) and nurse practitioners (NP) from this ASCII text file in R, there is an attached User Documentation Contents (UDC) file, post-download. To save the correct values for the specified variables, I subset the variables per unique variable, county, and year, based on the classification of PCPs and NPs from the UDC file. These final numbers are adjusted to rate per 100,000, using the demographics composition and population dataset.[28] Once the dataset is at the correct grain (i.e., year, FIPS-code, number of combined PCP and NPs), the dataset is merged with other regression variables.

2.10 Labor Force Statistics

Labor force statistics — unemployment, employment, and labor force — are collected annually from 2006 to 2017, from the U.S. Bureau of Labor Statistics (BLS).[29] These data are obtained by county for all 50 states in the U.S.

In order to perform analyses on these statistics, I transform the figures to represent unemployment rate, labor force participation rate, and employment-to-population ratio. Unemployment rate per-county per-year is calculated by dividing unemployment by the respective labor force in that same county and year. The labor force is the number of economically active population (i.e., unemployed and employed). Labor force participation rate per-county per-year is calculated by the total number of unemployed and employed persons (i.e., labor force) divided by the eligible population (i.e., the civilian non-institutional population, which are people who are ages 16 and older). The employment-to-population ratio per-county per-year is calculated by the total number of employed persons divided by the eligible population. The eligible population is the sum of all ages 16 years old

[27] https://www.npdb.hrsa.gov/resources/publicData.jsp

[28] The calculation for rate per X is: (total count of combined PCP and NPs per-county, per-year) / (county-year population / 100,000).

[29] https://www.bls.gov/lau/#cntyaa

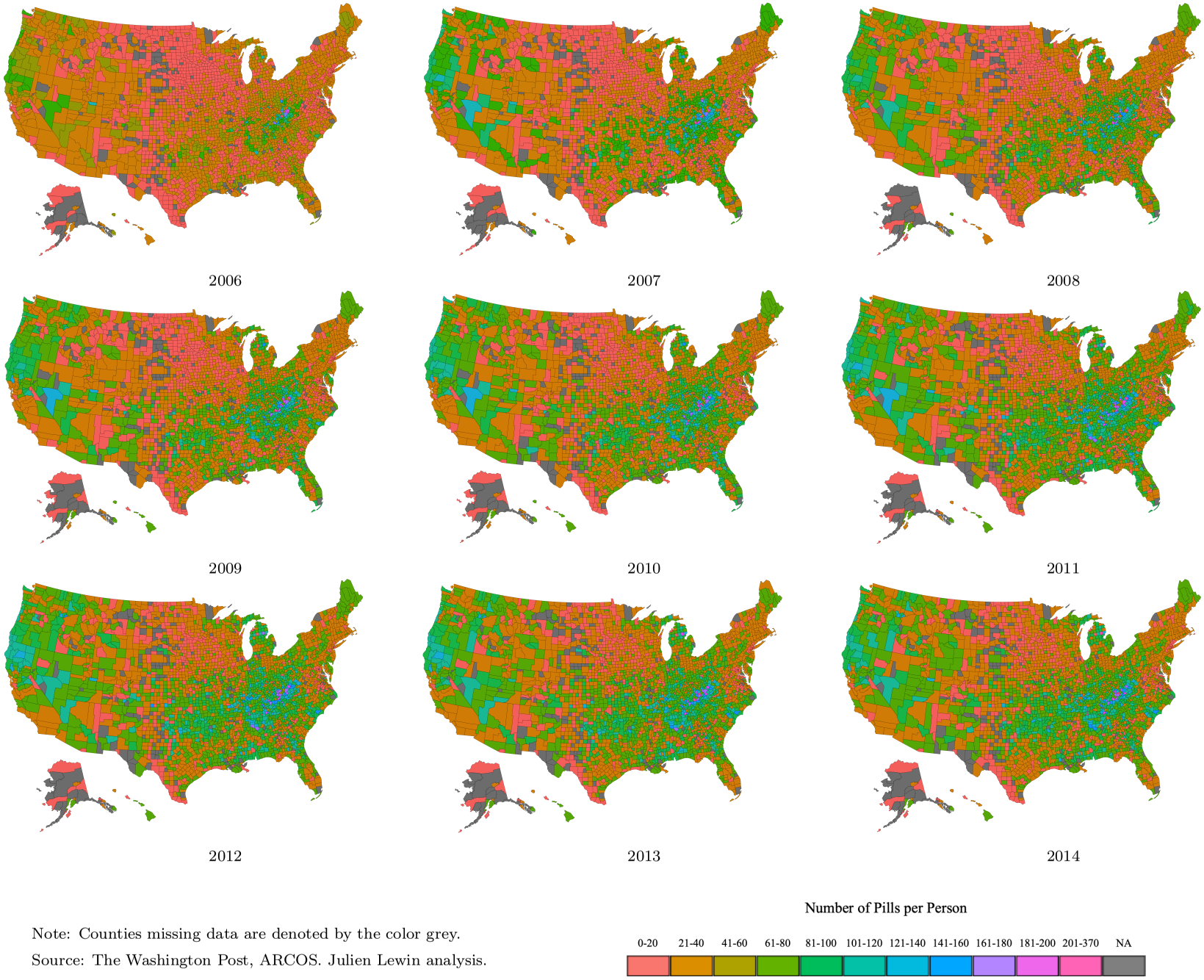
and above based on bucketed age group reporting dimensions from the demographics composition and population dataset (Bureau of Labor Statistics, 2012).[30]

Figures 3 and 4 represent visually the opioid distributions per capita at the county-level, which are presented in Tables 2 and 3. As observed in these tables, the standard deviations underneath each mean per year at the state-level are often larger than the mean itself. This is a result of unprecedented variation in the number of pills per person across counties in that state. In Figure 3 , the color pallet transitions from a light salmon color, then to a green range, then to a blue range, and finally to a hot pink range. In 2006, the majority of the map is filled with the light salmon and green colors. However, each year, select counties, regions, and states will become both darker and brighter — representing an increase in the average number of pills distributed per capita in those counties. With respect to this map, the most concerning rates arise from counties that are outside of large metropolitan cities.

In Figure 4 , I showcase year 2014, as it is halfway between the start and end of the replication sample. In many counties, such as Wheeler, Oregon, Saguache, Colorado, and Hamilton, New York, opioid pills per person are below 1, and even in the ranges of 0.004. However, the most alarming takeaways from this map are in select regions in the Midwest, such as Norton City, Virginia, Mingo, West Virginia, and Martinsville City, Virginia, where the annual average pills per person rates are 368.44, 364.81, and 303.11, respectively. To be clear, this rate suggests that each person in the county, of all ages, has an average of close to or above one pill per day for an entire year. These data show that for high-volume opioid distribution counties in the U.S., the average amount of pills per person, in one calendar year, for the top 10 percent of counties is 91 pills, for the top 5 percent of counties is 107.99 pills, and for the top 1 percent of counties is 156.83 pills. In the top-1 percent of high-volume opioid distribution counties in the dataset, there exist only 57 unique counties out of the total 265, indicating that 22 percent of that top-1 percent accounts for the same counties. Therefore, I strongly conjecture that "pill mills" exist during the times of these reported figures, suggesting that opioid-prescribing physicians in these "hot areas" are disregarding dispensing requirements, overprescribing, neglecting to accurately and reliably assess patient pain, and poorly assessing proper use of the medication from patients and patient addiction predisposition.

[30]This eligible population working age variable is overestimated because the variables includes 15 year olds. This happens as a result of the bucketing dimension from the U.S. Census Bureau — the lowest range bucket included was 15 to 19 years old.

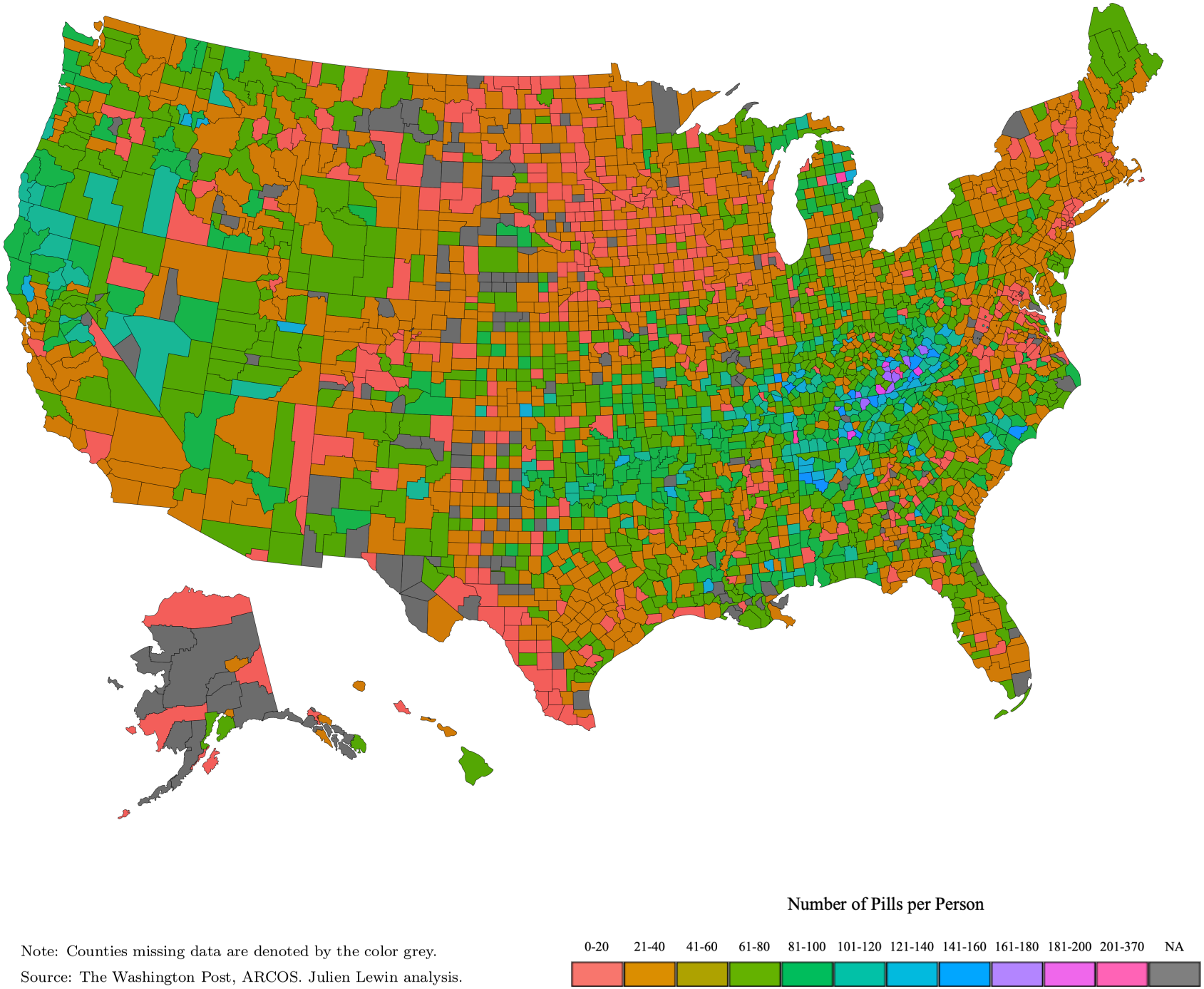
Figure 3: Total Per Capita Distributed Oxycodone and Hydrocodone Pills



Note: Counties missing data are denoted by the color grey.

Source: The Washington Post, ARCOS. Julien Lewin analysis.

Figure 4: Total Per Capita Distributed Oxycodone and Hydrocodone Pills, 2014



Note: Counties missing data are denoted by the color grey.

Source: The Washington Post, ARCOS. Julien Lewin analysis.

3 Methodology

Literature in the field of economics that focus on the causal impact of prescription opioids and labor market outcomes primarily focus on four econometric estimation techniques. The first approach is a standard linear regression, regressing macroeconomic conditions on drug use, as seen in Hollingsworth et al. (2017). The second method employed involves regressing the dependent variables of interest on lagged values of the independent variables, as seen in Aliprantis et al. (2019); Currie et al. (2018); Harris et al. (2019); Krueger (2017). Next, the third approach relies on the difference-in-differences framework comparing outcomes in non-triplicate states relative to triplicate states before and after the launch of OxyContin, as seen in Alpert et al. (2019). Finally, the fourth approach consists of the fixed-effects instrumental variable (FE-IV) regression which has a dependent variable of labor market conditions and instrument for per capita opioid prescriptions based on select variables, as seen in (Currie et al., 2018; Harris et al., 2019).

3.1 Regression Framework

In order to identify a causal relationship between either the distribution or prescriptions of opioids on employment outcomes, one must first assume that there exists an endogenous relationship between prescription opioids and labor market conditions (Currie et al., 2018; Harris et al., 2019; Krueger, 2017). A spurious correlation between opioid prescriptions and other unobserved factors in the economy could potentially impact national labor outcomes, which might bias the coefficient estimates from Equation 3. For this reason, it is important to analyze the possible factors that might drive the connection between the increase in opioid prescriptions and worsening labor market outcomes, which include but are not limited to:

1. The downward pressure on labor force participation as a result of an aging population and gender-age-specific participation trends that precede the Great Recession (Krueger, 2017).

2. The decline in labor force participation rates across the manufacturing industry, as a result of newly demanded skills, competition, and declined mobility, since 2000 (Hernandez, 2018; Richter et al., 2018).

3. The simultaneous decline in population health, as observed by increases in the rates of psychological distress, cancer, diseases of the heart, cerebral hemorrhage, and nephritis (Muennig et al., 2018; Perrott & Holland, 2005).

4. The increase in alcohol consumption, which has been notably linked to non-medical use of prescription drugs (Dawson et al., 2015; McCabe et al., 2006).

5. The potential decline in county-level economic opportunities (Harris et al., 2019; Hollingsworth et al., 2017; Richter et al., 2018).

In each of these examples, the prospect of reverse causality is evident, such that estimates on β_1 will be biased. All four scenarios would lead us to observe individuals both having a greater

predisposition to using drugs and engaging in increased patterns of substance abuse. Thus, in which direction does the causality lie? This prompts two opposing questions:

1. Does more opioid prescribing in a county cause people to lose their jobs?
2. Does a lack of employment opportunities cause people to turn to prescription opioids?

To answer this question, I implement the FE-IVs approach used in Harris et al. (2019) to instrument the per capita concentration of high-volume prescribers on opioid prescriptions. In theory, IVs are designed to allow for the estimation of casual relationships in a non-experimental setting (Nichols et al., 2006). Effectively, IVs are implemented in order to account for unexpected behavior between variables. In practice, IV regressions separate the explanatory variables into two parts:

- Part 1 – The explanatory variable could be correlated with error term ϵ,
- Part 2 – The estimated explanatory variable likely is not correlated with ϵ (Wooldridge, 2009).

Part 1 and Part 2 represent the first-stage and second-stage of the Two-Stage Least Squares (2SLS) regression, respectively. This 2SLS approach allows for consistent estimation when an explanatory variable (covariate) of interest — such as opioid prescriptions — is correlated with the error term in a regression model. Examples of such correlation may occur in scenarios, like:

- Non-random measurement error,
- Omitted variable bias,
- Confounding variables,
- Simultaneity,
- Reverse Causality (Staiger & Stock, 1994; Wooldridge, 2009).

All of these examples threaten the internal validity of a regression model. For example, in using standard ordinary least squares (OLS) regression — referred to as a linear regression — the estimator's results would be biased.[31] However, in empirical research, while OLS regression often lead to bias results, these regressions help to first identify whether a possibly causal relationship exists between two variables, such that the researcher can employ other sound econometric approaches.

With regard to this paper, the FE-IV approach is the most econometrically sound approach, given the aforementioned various possibilities of spurious correlation. Theoretically, a valid instrument modifies the explanatory variable, but has no independent effect on the dependent variable (Angrist & Imbens, 1995; Staiger & Stock, 1994). Thus, one can uncover the hidden causal effect of the explanatory variable (e.g., opioid prescriptions) on the response (dependent) variable (e.g., county labor market outcomes).

According to Harris et al. (2019); Nichols et al. (2006); Staiger & Stock (1994); Wooldridge (2009), prior to implementing an IV approach in a linear model, the following requirements and exclusion restrictions must be satisfied:

[31] OLS regressions are synonymous with reduced form regressions: $y = X\beta + \varepsilon$

1. The instrument (e.g., providers in top 1 percent opioid doses per 100,000 population and providers in top 5 percent opioid prescriptions per 100,000 population) must be correlated with the endogenous explanatory variables (e.g., opioid prescriptions), conditionally on the other covariates. If this correlation is strong, with a level of statistical significance less than 0.1, then the instrument is considered to have a strong first-stage (e.g., Equation 2) in the 2SLS equation. Alternatively, a weak correlation, with a level of statistical significance greater than 0.1, may lead to erroneous conclusions about parameter estimates and standard errors.

2. The instrument cannot be correlated with the error term in the second-stage of the 2SLS equation (e.g., Equation 3), conditionally on the other covariates. That is, the instrument must be relevant and orthogonal to the errors, (i.e., $E[Z'\epsilon] = 0$) (Harris et al., 2019; Wooldridge, 2009).

In this paper, I employ a 2SLS linear regression, such that I use:

- OLS to regress O on Z and get $\hat{O} = Z(Z'Z)^{-1}Z'O$,
- Then, OLS to regress Y on $\hat{O}$ to get $\hat{\beta}_{IV}$.

After evaluating both first- and second-stage results, I find no evidence that my instruments are invalid. In the present state, the regression model is overidentified. Thus, in future work, I would test the validity of my orthogonality assumption using tests developed by Hansen (1982) and Sargan (1958). Additionally, to ensure that my findings are robust, I would instrument for opioid prescriptions with prescriptions of non-opioids, as performed in Harris et al. (2019), from the CMS Provider dataset. By instrumenting for non-opioid prescriptions, Harris et al. (2019) find that variation in individual-level prescribing tendencies, as measured in their identification strategies, stems from heterogeneity in provider practices. Lastly, I would replicate the quantile regression specification designed and employed in Firpo et al. (2009) and Harris et al. (2019), respectively, to analyze the effects of prescriptions opioids across the distributions of county labor market outcomes.

Per the available reporting dimensions of the data, I cannot control for cross-county drug flows. Thus, in the context of this paper, I assume that each county experiences no spillover effects of opioids and, as such, it operates as its own entity or "opioid facility". To assume this as true, the econometric approach is both stronger and more sound, and the analysis of results can be interpreted as a direct effect of opioids in a given county on that same county's labor market conditions.

3.2 Empirical Specification

The following empirical specification regressions are based on the econometric methodologies implemented in Harris et al. (2019). These regressions are applied to both CMS Medicare Part D datasets – Provider and Drugs (as referenced in Section 2.2). To reiterate, the CMS Provider dataset is comprised of all opioids, excluding those in the Schedule I category, while the CMS Drug dataset involves only Schedule II and III classified opioids. In each of the following regressions, covariate subscripts i and t represent county and year, respectively.

Reduced Form Linear Regression

In the reduced form regression, I calculate the effect of opioid prescriptions on county labor market conditions. However, in this approach, estimates can only be econometrically interpreted via correlation, not causation. The reduced form equation species the estimated relationship between opioid prescriptions and county labor market outcomes as follows:

$$Y_{it} = \phi_0 + \phi_1 Z_{it} + \phi_1 X_{it} + \phi_2 P_{it} + \phi_3 C_{it} + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} measures the outcome variable (i.e., the unemployment rate, labor force participation rate and employment-to-population ratio). Z_{it} represents a vector of instrumental variables, both of which measure the number of high-volume opioid prescribing practitioners in a county:

1. The per capita number of practitioners in a county that are in the nation's top-five percent of opioid prescriptions written,

2. The per capita number of practitioners in a county that are in the nation's top-one percent of opioid doses prescribed.

There are three types of explanatory variables used in my series of regressions — X_{it}, P_{it}, and C_{it}. X_{it} represents a vector of explanatory variables including measures of the county's demographic composition (i.e., age, gender, race, and ethnicity). P_{it} counts the number of primary care physicians (PCP) per 1,000 people. C_{it} counts the number of cancer deaths per 100,000 people. Both P_{it} and C_{it} are necessary to include as they are proxies for the overall amount of care being provided and the health status of the county, respectively. Finally, γ_i and δ_t represent county and year fixed effects, respectively.

First-Stage 2SLS

As discussed earlier, in order to econometrically understand the direction of causation through unbiased parameter estimates, IVs are necessary. The first-stage estimate equation specifies the number of opioid prescriptions per capita (the IV instrument) as follows:

$$O_{it} = \alpha_0 + \alpha_1 Z_{it} + \alpha_3 X_{it} + \alpha_2 P_{it} + \alpha_3 C_{it} + \gamma_i^1 + \delta_t^1 + \epsilon_{it}^1 \tag{2}$$

where O_{it} measures the number of opioid prescriptions — both all prescription opioids and selectively Schedule II and III prescription opioids — per capita written by practitioners in the same county. Lastly, the superscript 1 in γ_i^1 and δ_t^1 represent county and year fixed effects for the specific regression, respectively.[32]

[32] In the first- and second-stage regressions performed by Harris et al. (2019), their regressions include R_{it} — the percentage of the county's population that is denoted as rural in the 2010 Census. However, this approach is not possible in my identification strategy as this rural status is a mostly time-invariant variable (i.e., there exists a constant share of the rural population from 2010 to 2015).

Second-Stage 2SLS

In this final stage, I identify causality through the estimation of the relationship between opioid prescriptions and county labor market outcomes as follows:

$$Y_{it} = \beta_0 + \beta_1 \hat{O}_{it} + \beta_2 X_{it} + \beta_3 P_{it} + \beta_4 C_{it} + \gamma_i^2 + \delta_t^2 + \epsilon_{it}^2 \tag{3}$$

where $\hat{O}_{it}$ is the estimated number of opioid prescriptions per capita written by practitioners in the same county.

4 Results

This paper employs the use of three datasets to optimize preferred empirical specification models. The first and second datasets are derived from the CMS Medicare Part D database. To reiterate, I separate the two CMS Medicare Part D datasets, discussed in Section 2.2, into distinct categories, one specifying all prescriptions opioids — CMS Provider dataset — and one specifying only Schedule II and III prescription opioids — CMS Drugs dataset. The third dataset, which can be found in Section 2.3, is the opioid prescriptions per capita dataset from the CDC — CDC dataset. Below, Table 9 represents the mean of opioid distributions and prescriptions per capita, which are used in later sections for analysis of the β_1 estimates' effects on county labor market outcomes.

Table 9: Average Opioids Per Capita

Years	ARCOS	CMS Provider	CMS Drugs	CDC
Reduced Form Variables				
2006-2014	40.527			0.860
2010-2014	45.085			0.921
2SLS Variables				
2013-2015		0.659	2.969	0.870
2013-2016		0.667	3.062	0.845
2013-2017		0.667	3.098	0.820
Omitted Top 10 Percent Variables				
2013-2015		0.550	2.476	0.837
2013-2016		0.554	2.539	0.814
2013-2017		0.557	2.582	0.790

Oneway vs. Twoway Regression

Additionally, this paper utilizes two regression functions from the plm package in R to calculate the effects of opioids on labor outcomes.[33] For each of the preferred empirical specification model datasets, I perform reduced form (Equation 1) , first-stage (Equation 2) and second-stage (Equation 3) regressions using the following two functions:

- **Function 1: Plm without Effect** – The default effect is an "individual" effect, also referred to as a oneway (individual) effect FE model,
- **Function 2: Plm with Effect "Twoways"** – The user-specific effect is a "twoways" effect, also referred to as a two-ways (individual and time) effects FE model.

[33]For more information on how to use the plm package in R, please visit: https://cran.r-project.org/web/packages/plm/vignettes/plmPackage.html.

These two FE functions have limitations when used individually, thus, I employ both when running my various regressions. Function 1 can be specified by two distinct measurements: (1) "time", which measures variation in time-specific confounders, and (2) "individual", which measures variation between unit-specific cases (e.g., counties). The first measurement comes from the use of time FE coefficients, while the latter uses case FE coefficients. One motivation for focusing on the second measurement, "individual" effect, in Function 1 is that my regression coefficients account for cross-sectional variation in opioids per capita by county. In this approach, I report coefficients and robust standard errors that are clustered by county.

Function 2 calculates a complex amalgamation of the cross-sectional and over-time effects in the data (Croissant et al., 2008; Kropko & Kubinec, 2018). One motivation for selecting a two-way FE model is that the regression "addresses omitted variable bias by removing unobserved confounders that are fixed over time or across cases" (Kropko & Kubinec, 2018). Arguably, the two-way FE approach is preferable to that of the one-way FE because the regression excludes more omitted variables, as it includes additional intercepts. As such, while Function 2 reports a singularly identified combination of cross-sectional and over-time effects in the data, this approach has received criticism in academia. The debate about this econometric tool hinges upon the approach's simultaneous adjustment of confounders, validity of results due to an over-reliance on modeling assumptions, and complex interpretation of coefficients in a linear model (Imai & Kim, 2019; Kropko & Kubinec, 2018). Despite this, I employ Function 2 in order to ensure that I consider all possible variation in FE coefficient and robust standard error clustering and testing.

These two different functions are clearly demarcated in the second-stage regression tables, as Panel A represents Function 1 and Panel B represents Function 2. I utilized the two different functions in order to measure both cross-sectional variation in unit-specific cases (i.e., counties) and cross-sectional variation unit-specific cases and time-specific confounders (i.e., year).

Instrument Validity

As previously discussed in Section 3.1, the results in this paper support that my chosen instruments are consistent and unbiased estimators, and, as such, are valid instruments. Across the board, first-stage (Equation 2) estimates of my two instrumental variables, which are designed to capture the pool of high-prescribing practitioners, top-1 supply and top-5 claim, are both positive and statistically significant, with coefficient p-values ranging from less than 0.01 to 0.05. According to Staiger & Stock (1994), a joint significance test of the IVs must yield a benchmark F statistic value of 10 or greater in order to be considered valid instruments. In each first- and second-stage regression, despite that of Table 12 Column 2, which specifies opioid prescriptions per capita from the CDC dataset, the reported F statistics well-exceed the baseline criteria value of 10. Additionally, because all of my first-stage estimates for my IVs in Column 1, which specify opioid prescriptions per capita from the CMS Medicare Part D datasets, are econometrically strong, and in many cases my first-stage estimates for my IVs in Column 2 are not, I am scrupulous about which first-stage results are stronger so that I can analyze one of the two datasets as my preferred IV specification in

the second-stage (Section 4.1.2). As follows, for the preferred IV specification models in the second-stage regressions, the reported p-values associated with my F statistics are consistently below that of 0.05. As such, I can conclude that both my instrumental and independent variables reliably predict the dependent variable.

ARCOS Reduced Form Regressions

Before performing any regressions on the three aforementioned data sets, I examine the ARCOS dataset, discussed in Section 2.1, to gain a baseline understanding of the relationship between opioids and labor markets. Intuitively, I first regress labor outcomes on opioid distributions per capita from the ARCOS dataset, using Equation 1 in order to see whether there exists a relationship between these two variables.[34] Table 10 reports these estimates, and, in both Panel A and B, the model yields strong, positive, and statistically significant results. These results show that as opioid distributions increase in a county, labor market conditions worsen, as observed in Harris et al. (2019).[35]

In Panel A, the data show that a one unit increase in opioids per capita leads to a 0.03 and 0.06 percentage point rise in the unemployment rate, *ceteris paribus*, as based on the ARCOS and CDC datasets, respectively. However, the data show that a one unit increase in opioid distributions is equivalent to over a 100 percent increase in opioid distributions. Thus, alternatively, to estimate a more modest increase in opioid distributions per capita, a 10 percent increase in opioid distributions per capita should be examined. When looking at the same two data sets, a 10 percent increase in opioid distributions per capita results in a 0.12 and 0.08 percentage point rise in the unemployment rate when all other variable in the model are held constant.[36]

In Panel B, the data show nearly identical effects. The hypothesized effects of opioids per capita on the labor force participation rate are validated in Columns 3 and 4 of Table 10, as represented by negative and statistically significant coefficients. Respective to the datasets analyzed in Panel A, the data show that a one unit increase in opioid distributions per capita leads to a 0.1 and 3.4 percentage point drop in the labor force participation rate. Again, to predict a less dramatic rise in opioids per capita, a 10 percent increase in opioid distributions per capita results in a 0.41 and 0.29 percentage point fall in the labor force participation rate when all other variable in the model are held constant.

Lastly, in Panel A, an increase of opioids per capita increase by one unit leads to a 0.1 and 3.7 percentage point drop in the employment–to-population ratio, *ceteris paribus*. A 10 percent increase in opioids per capita results in a 0.41 and 0.32 percentage point drop in the employment–to-population ratio when all other variable in the model are held constant. Panel B results are consistent in both signage and magnitude to those in Panel A and remain strongly statistically significant.

[34] Refer to Appendix Tables A8 and A9 for the full reduced form regressions, including all covariates.

[35] Harris et al. (2019) draw analysis from provider-level ARCOS data. As such, our approaches to this estimation were fundamentally different in terms of econometrics, but the models yield the same conclusions.

[36] The calculation for user specified percentage increases in opioid distributions and prescriptions (see Sections 4.1 and 4.2) per capita is as follows: (B_1 coefficient estimate $\times$ mean of opioids per capita $\times$ p). p denotes the percentage increase, such that if one estimates the effect of a 10 percent increase in opioids per capita, p is 10. The mean of opioids per capita can be found in Table 9.

Table 10: Reduced Form: Effects of Opioid Distributions and Prescriptions per Capita on Labor Market Conditions

DEA's ARCOS Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect (2006-2014)	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Distributions Per Capita (ARCOS)	0.0003***		−0.001***		−0.001***	
	(0.00002)		(0.00004)		(0.00004)	
Opioid Prescriptions Per Capita (CDC)		0.009***		−0.034***		−0.037***
		(0.001)		(0.002)		(0.002)
Observations	23,012	23,012	23,012	23,012	23,012	23,012
R^2	0.287	0.262	0.502	0.463	0.500	0.459
Adjusted R^2	0.286	0.261	0.502	0.463	0.500	0.459
F Statistic (df = 12; 22,991)	771.264***	679.787***	1,932.725***	1,653.008***	1,918.742***	1,627.883***
Panel B: Plm without Effect (2010-2014)	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Distributions Per Capita (ARCOS)	0.0003***		−0.001***		−0.001***	
	(0.00001)		(0.00005)		(0.00004)	
Opioid Prescriptions Per Capita (CDC)		0.012***		−0.040***		−0.044***
		(0.001)		(0.002)		(0.002)
Observations	12,875	12,875	12,875	12,875	12,875	12,875
R^2	0.359	0.327	0.529	0.487	0.528	0.484
Adjusted R^2	0.358	0.326	0.528	0.486	0.527	0.483
F Statistic (df = 13; 12,857)	554.104***	480.454***	1,109.197***	939.134***	1,106.463***	925.872***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
Pabel A ARCOS (2006-2014) dataset is incomplete (i.e., missing Number of PCPs and NPs per 1,000 Population).
Pabel B ARCOS (2010-2014) dataset is complete with all control variables.

It is important to note that Table 10 reports the ARCOS dataset in opioid distributions per capita (i.e., pills per person), whereas the CDC dataset is reported by opioid prescriptions per capita (i.e., prescriptions per person). Thus, my analysis cannot be directly compared until I make an assumption about the number of pills in a prescription bottle. In the U.S., from 2006 to 2014, Table 1 shows that the average amount of distributed opioid pills per capita was 39.21 and the average amount of opioid prescriptions per capita was 0.86. Therefore, I make the assumption that the average amount of pills in a prescription is 45.59, which is logically sound given that most prescriptions are designed to be taken either once- or twice-a-day on a monthly basis. This assumption is supported by scientific research studies. In examining the relationship between the number of doses prescribed per day and the actual patient dose-intake compliance rates, Claxton et al. (2001) found that one- and two-doses per day accounted for the largest share of prescriptions. Moreover, in another study conducted by Hill et al. (2017), when looking at the average of opioid pills prescribed for 5 different outpatient procedures, the mean was approximately 43 pills per prescription. Now that the unit of measure has been equalized, there is a clearer comparison of these results in terms of prescriptions per capita.

Although I cannot draw the same analysis via a 2SLS (IV) approach using the ARCOS dataset, as I do not instrument for high-volume opioid-prescribing practitioners because of a lack of provider-level data, the analysis provides the framework to evaluate the CMS Provider, CMS Drugs, and CDC datasets via the 2SLS approach. After confidently establishing a correlative relationship between opioids per capita and county labor market outcomes, I set out to prove a causal relationship between the two through replicating the work of Harris et al. (2019).

CMS & CDC Reduced Form Regressions

Prior to performing each 2SLS regression on the three datasets, I analyzed each dataset's respective reduced form linear regression (Equation 1) in order to gain preliminary results about the relationship between opioids per capita and labor market.[37] In many cases, the labor outcome variables do not show strong or statistically significant signs when regressed on the two instruments. Regardless of the poor performance, with wide-ranging R^2, adjusted R^2, and F statistic values, I continue with the 2SLS approach to see if my empirical specification outperforms the reduced form model.

The results of this preliminary regression suggest a strong relationship and, thus, enable me to employ the 2SLS approach (see Equations 2 and 3 for the econometric methodologies). Before delving into the results of Replication (4.1) and Extension (4.2) sections, there appears to be a causal effect of opioid prescriptions per capita on county labor market outcomes. Across all second-stage models in Panel A, reporting the one-way (individual) effect FE model, as observed in Tables 15, 16, 21, 22, the β_1 estimates of the effect of opioid prescription per capita on county labor market outcomes remain consistent: the unemployment rate increases, the labor force participation rate decreases, and the employment-to-population ratio decreases.

[37] Refer to Appendix Tables A2, A3, A4, and A5 to see the relationship between the IVs and county labor market outcomes variables through a strictly correlative lens.

4.1 Harris et al. (2019) Replication, 2013-2015

4.1.1 First-Stage 2SLS

CMS Provider & CDC Datasets

This section estimates the combined effects of my IV specification strategy on opioid prescriptions per capita by using the CMS Provider dataset opioid measurements. Table 11 reports the estimates of Equation 2 using Function 1, oneway (individual) effect.

These first-stage results show a positive correlation between high-volume opioid-prescribing practitioners in a county and opioid prescriptions per capita, as observed in (Harris et al., 2019). In both the CMS Provider and CDC datasets, the estimated coefficients on the two IVs designed to capture the pool of high-prescribing practitioners, top-1 supply and top-5 claim, are both positive and statistically significant at the 99 percent level. For both datasets, the two instruments produce F statistics greater than 250. The CMS Provider dataset appears to have a much stronger R^2 value than that of the CDC dataset, 75.7 percent and 31.5 percent, respectively. These values show that both the CMS Provider instruments and additional regressors predict opioids per capita better than those of the CDC dataset. Regardless, both sets of results indicate that the IVs are valid and can both be interpreted meaningfully in the second-stage regression.

Table 12 reports the estimates of Equation 2 using Function 2, two-ways (individual and time) effects. For the CMS Provider dataset, the estimated coefficients on the two IVs are both positive and statistically significant, at the 99 percent level — consistent to the results in Table 11. However, the instruments for the CDC dataset are inconsistent (i.e., the top-5 claim is negative) and statistically insignificant with respect to the results of the IVs in Table 11. More so, the R^2 is roughly 20 percentage points higher in the Medicare data Function 1 regression, relative to that of the Medicare data Function 2 regression. The low F statistic (less than 10), low R^2, and inconclusive IV results from the CDC dataset in Table 15 lead me to focus on the CMS Provider dataset instead in Section 4.1.2, specifically Table 15 Panel A.

CMS Drugs & CDC Datasets

This section estimates the combined effects of my IV specification strategy on opioid prescriptions per capita by using the CMS Drugs dataset opioid measurements. Tables 13 and 14 report the estimates of Equation 2 using Functions 1 and 2, respectively. Across both tables, the performance of the Medicare dataset's IVs and covariates is much stronger than those from the CDC's dataset. The CMS Drugs dataset reports higher R^2 values, higher F statistics, and stronger statistical significance, especially in that of the Function 1 regression (Table 13). Therefore, all analyses in the second-stage equation in Section 4.1.2 will focus on the Medicare data in Table 16 Panel A, which are derived from the first-stage's best performing instruments (i.e., Table 13 Column 1).

Table 11: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2015) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.014***	0.035***
	(0.001)	(0.003)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.038***	0.009***
	(0.0003)	(0.002)
Percent Female	0.488***	3.673***
	(0.061)	(0.350)
Percent Black	0.073***	0.063**
	(0.016)	(0.026)
Percent Hispanic	0.024	−0.082**
	(0.015)	(0.032)
Percent under 15	−0.184	−0.030
	(0.151)	(1.296)
Percent 15 to 19	−0.949***	−2.396**
	(0.189)	(0.995)
Percent 20 to 24	−0.248	2.041
	(0.258)	(1.626)
Percent 35 to 44	−1.467***	8.111***
	(0.408)	(1.871)
Percent 45 to 54	−1.147***	−4.266***
	(0.092)	(0.310)
Percent 55 to 64	−1.076***	0.019
	(0.325)	(1.052)
Percent Aged 65+	0.171	1.978**
	(0.115)	(0.946)
Number of PCPs and NPs per 1,000 Population	0.242***	0.063***
	(0.015)	(0.009)
Number of Cancer Deaths per 100,000 Population	0.001***	0.006***
	(0.0001)	(0.001)
Observations	8,114	8,114
R^2	0.757	0.315
Adjusted R^2	0.756	0.314
F Statistic (df = 14; 8,097)	1,800.316***	266.372***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 12: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2015) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.006***	0.0003
	(0.0004)	(0.002)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.028***	−0.0001
	(0.0004)	(0.00004)
Percent Female	−1.838	−1.522*
	(1.259)	(0.826)
Percent Black	0.422	−1.810***
	(0.467)	(0.128)
Percent Hispanic	0.900	−0.110
	(0.800)	(0.516)
Percent under 15	2.428**	−1.228
	(0.987)	(1.150)
Percent 15 to 19	−0.526	−3.312***
	(1.305)	(1.171)
Percent 20 to 24	0.915	2.729***
	(1.462)	(0.150)
Percent 35 to 44	1.503	0.524
	(1.132)	(0.400)
Percent 45 to 54	5.059***	−0.095
	(1.107)	(0.766)
Percent 55 to 64	1.181	1.770***
	(1.394)	(0.390)
Percent Aged 65+	4.370***	1.905***
	(1.471)	(0.698)
Number of PCPs and NPs per 1,000 Population	0.058***	−0.038***
	(0.009)	(0.006)
Number of Cancer Deaths per 100,000 Population	−0.001***	−0.001
	(0.0001)	(0.001)
Observations	8,114	8,114
R^2	0.553	0.020
Adjusted R^2	0.314	−0.504
F Statistic (df = 14; 5,287)	466.857***	7.652***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 13: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2015) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.035***	0.010
	(0.012)	(0.007)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.217***	0.020***
	(0.006)	(0.004)
Percent Female	0.031	3.770***
	(1.257)	(0.297)
Percent Black	−0.069	0.113***
	(0.081)	(0.020)
Percent Hispanic	−0.459**	−0.025**
	(0.186)	(0.013)
Percent under 15	2.963**	0.525
	(1.421)	(1.117)
Percent 15 to 19	−1.814	−2.905***
	(3.059)	(0.859)
Percent 20 to 24	−1.569***	2.737**
	(0.176)	(1.322)
Percent 35 to 44	−5.571***	8.912***
	(1.227)	(1.133)
Percent 45 to 54	−13.863***	−4.006***
	(1.957)	(0.173)
Percent 55 to 64	−2.862	0.032
	(1.775)	(1.175)
Percent Aged 65+	4.633***	2.666***
	(1.552)	(0.614)
Number of PCPs and NPs per 1,000 Population	1.545***	0.087***
	(0.152)	(0.003)
Number of Cancer Deaths per 100,000 Population	0.001	0.008***
	(0.001)	(0.0002)
Observations	8,114	8,114
R^2	0.659	0.258
Adjusted R^2	0.658	0.256
F Statistic (df = 14; 8,097)	1,117.394***	200.607***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 14: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2015) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.032***	0.002*
	(0.009)	(0.001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.113***	0.001*
	(0.013)	(0.001)
Percent Female	−16.924***	−1.525**
	(2.290)	(0.747)
Percent Black	5.422	−1.779***
	(4.727)	(0.139)
Percent Hispanic	−5.741***	−0.208
	(1.257)	(0.510)
Percent under 15	25.563***	−1.163
	(8.555)	(1.054)
Percent 15 to 19	16.054***	−3.236***
	(3.015)	(1.145)
Percent 20 to 24	2.701	2.580***
	(9.649)	(0.230)
Percent 35 to 44	24.234***	0.680**
	(7.443)	(0.309)
Percent 45 to 54	11.800**	−0.249
	(5.723)	(0.830)
Percent 55 to 64	11.067***	1.611***
	(3.787)	(0.469)
Percent Aged 65+	23.198**	1.824***
	(10.632)	(0.667)
Number of PCPs and NPs per 1,000 Population	0.394***	−0.038***
	(0.109)	(0.005)
Number of Cancer Deaths per 100,000 Population	0.010***	−0.001
	(0.004)	(0.001)
Observations	8,114	8,114
R^2	0.324	0.030
Adjusted R^2	−0.038	−0.489
F Statistic (df = 14; 5,287)	180.877***	11.504***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

4.1.2 Second-Stage 2SLS

CMS Provider & CDC Datasets

Table 15 reports the estimates of the second-stage regression for the CMS Provider and CDC datasets. As discussed in Section 4.1.1, the results from both Function 1 and the Medicare data (slightly) were more robust. Thus, we focus our attention to Panel A, which draws more insightful statistics on the causal effects of opioids on labor outcomes. Across Panel A, in each of the columns, the B_1 estimates are consistent with the hypothesis that an increase in opioid prescriptions per capita results in more adverse county labor market conditions.

We see that a one unit increase in opioid prescriptions per capita leads to a 0.4 and 1.4 percentage point rise in the unemployment rate, *ceteris paribus*, as based on the CMS Provider and CDC datasets, respectively. In this case, a one unit increase in opioid prescriptions implies more than doubling the number of opioids in the average county in the sample. Thus, alternatively, to estimate a more realistic increase in opioid prescriptions per capita, I investigate the effect of a 10 percent increase in opioid prescriptions per capita. When looking at the same two data sets, a 10 percent increase in opioid prescriptions per capita results in a 0.03 and 0.09 percentage point rise in the unemployment rate when all other variable in the model are held constant.

Respective to the datasets mentioned above, a one unit increase in opioid prescriptions per capita leads to a 0.8 and 5.6 percentage point drop in the labor force participation rate, all else equal. Again, to estimate a more modest increase in opioid prescriptions per capita, a 10 percent increase in opioid prescriptions results in a 0.05 and 0.37 percentage point drop in the labor force participation rate.

During this same time period, from 2013 to 2015, the average labor force participation rate across the U.S. was 58.18 percent (see Table 7 for value).[38] In using both the CMS Provider and CDC dataset estimates, in assuming that opioid prescriptions per capita will increase by 10 percent, this would mean that the labor force participation rate would fall from 58.18 percent to 58.13 and 57.81 percent, respectively. This decline in the labor force participation rate is equivalent to 28 and 205 persons leaving the labor force per county, respectively. The CMS Provider and CDC dataset yield wide-ranging results, yet both indicate that opioids have a strongly adverse effect on county labor market conditions.

In terms of the two datasets' effect on the employment-to-population ratio, a one unit increase in opioid prescriptions per capita leads to a 0.9 and 6.0 percentage point drop in this ratio, *ceteris paribus*. Scaling the magnitude of the increase in opioid prescriptions per capita, a 10 percent increase in opioids results in a 0.06 and 0.40 percentage point drop in the employment-to-population ratio. Again, these results support the main hypothesis strongly.

In Table 15 Panel B, the effects of opioid prescriptions on county labor market outcomes are both less impactful and less statistically significant. This can be explained by the different econometric approaches involved in Function 2, as outlined in Imai & Kim (2019) and Kropko & Kubinec (2018).

[38] This statistic is based on my data gathered from the BLS in Section 2.10.

Table 15: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2015)

CMS Medicare Part D Provider Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.004***		−0.008***		−0.009***	
	(0.0002)		(0.002)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.014***		−0.056***		−0.060***
		(0.001)		(0.007)		(0.007)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.271	0.312	0.402	0.457	0.396	0.453
Adjusted R^2	0.270	0.311	0.401	0.456	0.395	0.452
F Statistic	3,022.301***	3,300.853***	5,457.132***	6,166.405***	5,311.758***	6,037.223***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	−0.0002		−0.001***		−0.001***	
	(0.0002)		(0.0004)		(0.0003)	
Opioid Prescriptions Per Capita (CDC)		0.055		0.389		0.356
		(0.136)		(1.914)		(1.808)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.127	0.030	0.035	0.003	0.030	0.002
Adjusted R^2	−0.339	−0.488	−0.481	−0.530	−0.489	−0.531
F Statistic	768.343***	492.006***	190.201***	20.229*	161.786***	20.693*

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

CMS Drugs & CDC Datasets

Table 16 shows the results of the second-stage regression for the CMS Drugs and CDC datasets. Consistent with my findings from the CMS Provider and CDC second-stage regressions (Section 4.1.2), the labor market outcomes yield an increase in the unemployment rate and a decline in both the labor force participation rate and the employment-to-population ratio as opioids per capita increase. As discussed in Section 4.1.1, the results from both Function 1 and the Medicare data were considerably stronger. Thus, Panel A produces the strongest results from the first-stage results with regard to IVs. Again, in each of the columns, the B_1 estimates suggest that the current levels of opioid prescriptions per capita yield adverse county labor market outcomes.

As such, the CMS Provider and CDC datasets report that a one unit increase in opioid prescriptions per capita leads to a 0.2 and 1.6 percentage point rise in the unemployment rate, *ceteris paribus*, respectively. However, a more suitable estimate of the increase in opioids per capita might be anyway from 5 to 10 percent. Thus, a 10 percent increase in opioid prescriptions per capita results in a 0.06 and 0.14 percentage point rise in the unemployment rate when all other variable in the model are held constant.

During this same time period, from 2013 to 2015, the average labor force participation rate across the U.S. was 6.36 percent (see Table 7 for value).[39] In using both the CMS Provider and CDC dataset estimates, in assuming that opioid prescriptions per capita will increase by 10 percent, this would mean that the unemployment rate would fall from 6.36 percent to 6.30 and 6.22 percent, respectively. This percentage point decline is equivalent to 2 and 5 persons becoming unemployed per county, respectively. Altogether, if we scale the effect of 2 or 5 people per county to all counties in the U.S. becoming unemployed as a result of opioid misuse, we observe that thousands of individuals are affected by the increase in opioid prescriptions.

Respective to the datasets mentioned above, a one unit increase in opioid prescriptions per capita leads to a 0.5 and 4.7 percentage point drop in the labor force participation rate, all else equal. Again, to estimate a more modest increase in opioid prescriptions per capita, a 10 percent increase in opioid prescriptions results in a 0.15 and 0.41 percentage point drop in the labor force participation rate.

In terms of the two datasets' effect on the employment-to-population ratio, a one unit increase in opioid prescriptions per capita leads to a 0.5 and 5.4 percentage point drop in this ratio, *ceteris paribus*. Scaling the magnitude of the increase in opioid prescriptions per capita, a 10 percent increase in opioid prescriptions results in a 0.15 and 0.47 percentage point drop in the employment-to-population ratio. These results strongly suggest that increasing opioid prescriptions per capita are linked with worsening county labor market outcomes.

I neglect to analyze the effects of the estimates Table 16 Panel B because both the IVs in the first-stage regression are invalid and inconclusive and the second-stage lacks statistical significance. Overall, the results in both second-stage estimate regression, Tables 15 and 16, indicate that high levels of opioid prescriptions per capita have strong adverse county labor market effects, and this is

[39] This statistic is based on my data gathered from the BLS in Section 2.10.

Table 16: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2015)

CMS Medicare Part D Drugs Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.002***		−0.005***		−0.005***	
	(0.0002)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.016***		−0.047***		−0.054***
		(0.001)		(0.008)		(0.009)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.272	0.307	0.403	0.458	0.397	0.455
Adjusted R^2	0.271	0.306	0.402	0.457	0.396	0.454
F Statistic	3,087.096***	3,229.166***	5,512.543***	6,076.627***	5,377.192***	5,948.787***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.0001		−0.0003***		−0.0004***	
	(0.0001)		(0.0001)		(0.0001)	
Opioid Prescriptions Per Capita (CDC)		0.019***		−0.025**		−0.033***
		(0.001)		(0.011)		(0.011)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.127	0.091	0.033	0.011	0.028	0.005
Adjusted R^2	−0.340	−0.395	−0.483	−0.518	−0.491	−0.526
F Statistic	768.524***	726.944***	188.874***	180.390***	161.611***	151.246***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

mostly driven through workers leaving the labor force.

4.2 Harris et al. (2019) Extension, 2013-2017

As previously outlined Section 2, in 2017, there is missing data for 3 variables — Cancer Death Rates per 100,000 People (Cancer), Marijuana-related Arrests (Sales), and Marijuana-related Arrests (Possession). In order to test whether the Cancer data skewed the results due to omitted variable bias, I run identical regressions as those performed in Section 4.1 for the years in which there is a complete dataset (2013-2016) with no missing variables, as shown in the Robustness Checks Section (5). This section represents the extension of the work done by Harris et al. (2019), including 2 extra years of data. With no reason to assume the initial hypothesis no longer holds, I expect to find strong causal effects that increased opioid prescriptions per capita lead to adverse labor market outcomes.

4.2.1 First-Stage 2SLS

CMS Provider Dataset

Table 17 reports the estimates of Equation 2 using Function 1, oneway (individual) effect. This section estimates the combined effects of my IV specification strategy on opioid prescriptions per capita by using the CMS Drugs dataset opioid measurements. Tables 17 and 18 report the estimates of Equation 2 using Functions 1 and 2, respectively. Across both tables, the performance of the Medicare dataset's IVs and covariates is much stronger than those from the CDC's dataset. The CMS Provider's dataset reports higher R^2 values, higher F statistics, and stronger statistical significance, especially in that of the Function 2 regression (Table 18). Therefore, the second-stage regression analyses in Section 4.2.2 will focus on the Medicare data in Table 21 Panel A, which are derived from the first-stage's best performing instruments (i.e., Tables 17 and 18 Column 1).

CMS Drugs Dataset

Table 19 reports the estimates of the first-stage regression using Function 1. Table 20 reports the estimates of the first-stage regression using Function 2. Table 19 yields significantly stronger results than than of Table 20, showing, in both Column 1 and 2, moderately robust R^2 values, above benchmark F statistics, and statistical significance at the 95 and 99 percent levels. Moving forward, the second-stage regression analyses in Section 4.2.2 will uncover the effects of opioids per capita on labor market conditions on both the Medicare and CDC data in Table 22 Panel A.

4.2.2 Second-Stage 2SLS

CMS Provider Dataset

Table 21 reports the estimates of the second-stage regression for the CMS Provider and CDC datasets. As discussed in Section 4.2.1, the results from Function 1, specifically the Medicare data

Table 17: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2017) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.015***	0.034***
	(0.002)	(0.004)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.039***	0.009***
	(0.001)	(0.002)
Percent Female	0.250*	3.773***
	(0.136)	(0.321)
Percent Black	0.080***	0.195***
	(0.014)	(0.041)
Percent Hispanic	−0.016	−0.339***
	(0.012)	(0.009)
Percent under 15	0.365**	0.085
	(0.152)	(1.193)
Percent 15 to 19	−0.568*	−1.725*
	(0.344)	(0.968)
Percent 20 to 24	0.241	1.836
	(0.155)	(1.957)
Percent 35 to 44	−1.194***	7.494***
	(0.390)	(2.823)
Percent 45 to 54	−0.530**	−1.846***
	(0.209)	(0.601)
Percent 55 to 64	−0.736***	−2.022
	(0.235)	(1.560)
Percent Aged 65+	0.375**	2.372**
	(0.159)	(0.971)
Number of PCPs and NPs per 1,000 Population	0.233***	0.036***
	(0.009)	(0.009)
Observations	12,987	12,987
R^2	0.772	0.276
Adjusted R^2	0.772	0.275
F Statistic (df = 13; 12,969)	3,384.635***	380.871***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table 18: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2017) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.007***	0.002
	(0.001)	(0.002)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.029***	−0.0002
	(0.0002)	(0.0001)
Percent Female	0.325	0.222
	(2.137)	(0.525)
Percent Black	−0.271	−1.064**
	(0.555)	(0.426)
Percent Hispanic	−0.517	1.223**
	(0.544)	(0.486)
Percent under 15	0.834	−0.438
	(1.418)	(0.369)
Percent 15 to 19	−0.048	−1.590
	(1.173)	(1.214)
Percent 20 to 24	−0.707	4.343***
	(0.543)	(0.726)
Percent 35 to 44	0.338	3.056***
	(0.883)	(0.789)
Percent 45 to 54	1.466	−0.124
	(1.783)	(0.295)
Percent 55 to 64	1.611***	3.989***
	(0.451)	(0.291)
Percent Aged 65+	1.377	2.143***
	(1.732)	(0.363)
Number of PCPs and NPs per 1,000 Population	0.094***	−0.072***
	(0.017)	(0.011)
Observations	12,987	12,987
R^2	0.543	0.035
Adjusted R^2	0.414	−0.237
F Statistic (df = 13; 10129)	926.770***	28.556***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table 19: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2017) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.042**	0.018***
	(0.018)	(0.006)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.242***	0.017***
	(0.005)	(0.002)
Percent Female	−0.108	4.063***
	(0.925)	(0.201)
Percent Black	−0.037	0.260***
	(0.098)	(0.020)
Percent Hispanic	−0.543***	−0.374***
	(0.111)	(0.018)
Percent under 15	5.240***	0.960
	(1.047)	(1.225)
Percent 15 to 19	0.010	−2.052**
	(1.954)	(1.026)
Percent 20 to 24	0.737	2.956
	(1.080)	(1.942)
Percent 35 to 44	−3.586***	8.885***
	(1.168)	(2.532)
Percent 45 to 54	−11.722***	−1.171**
	(1.388)	(0.488)
Percent 55 to 64	−1.667	−2.165
	(1.321)	(1.710)
Percent Aged 65+	6.147***	3.450***
	(0.751)	(0.854)
Number of PCPs and NPs per 1,000 Population	1.527***	0.062***
	(0.106)	(0.013)
Observations	12,987	12,987
R^2	0.670	0.193
Adjusted R^2	0.670	0.192
F Statistic (df = 13; 12,969)	2,027.183***	237.959***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table 20: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2017) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.017*	0.003
	(0.010)	(0.002)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.147***	0.001
	(0.017)	(0.0005)
Percent Female	5.204	0.179
	(7.172)	(0.520)
Percent Black	0.658	−1.027**
	(3.564)	(0.445)
Percent Hispanic	−4.983***	1.297***
	(1.214)	(0.491)
Percent under 15	1.143	−0.509
	(7.657)	(0.384)
Percent 15 to 19	9.217	−1.624
	(5.818)	(1.251)
Percent 20 to 24	−4.052	4.280***
	(4.678)	(0.737)
Percent 35 to 44	11.463***	3.110***
	(3.932)	(0.833)
Percent 45 to 54	7.063***	−0.142
	(1.665)	(0.304)
Percent 55 to 64	−0.137	3.989***
	(3.931)	(0.296)
Percent Aged 65+	6.104	2.145***
	(4.674)	(0.283)
Number of PCPs and NPs per 1,000 Population	0.516***	−0.072***
	(0.160)	(0.013)
Observations	12,987	12,987
R^2	0.395	0.036
Adjusted R^2	0.224	−0.236
F Statistic (df = 13; 10129)	508.041***	28.924***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

(slightly), were more robust. Thus, we focus our attention to Panel A, which draw more insightful statistics on the causal effects of opioids on labor outcomes. Across Panel A, in each of the columns, the B_1 estimates are consistent with the hypothesis that an increase in opioid prescriptions per capita results in more adverse county labor market conditions.

We see that a one unit increase in opioid prescriptions per capita leads to a 0.4 and 1.6 percentage point rise in the unemployment rate, *ceteris paribus*, as based on the CMS Provider and CDC datasets, respectively. Similar to the situation in Section 4.1.2, a one unit increase in opioid prescriptions implies more than doubling the number of opioids in the average county in the sample. Thus, when looking at the same two data sets, a more respectable 10 percent increase in opioid prescriptions per capita results in a 0.03 and 0.13 percentage point rise in the unemployment rate when all other variable in the model are held constant.

Respective to the datasets mentioned above, a one unit increase in opioid prescriptions per capita leads to a 1.1 and 6.7 percentage point drop in the labor force participation rate, all else equal. Again, to estimate a more modest increase in opioid prescriptions per capita, a 10 percent increase in opioid prescriptions results in a 0.07 and 0.55 percentage point drop in the labor force participation rate, the latter value moving the rate relatively significantly.

During this same time period, from 2013 to 2017, the average labor force participation rate across the U.S. was 58.30 percent (see Table 7 for value).[40] In using both the CMS Provider and CDC dataset estimates, in assuming that opioid prescriptions per capita will increase by 10 percent, this indicates that the labor force participation rate would fall from 58.30 percent to 58.23 and 57.75 percent, respectively. This decline in the labor force participation rate is equivalent to 42 and 326 persons leaving the labor force per county, respectively. Despite the range of these values, a minimum of 42 persons per county leaving the labor force each year has negative impacts on local economies. The CMS Provider and CDC dataset yield wide-ranging results, yet both indicate that opioids have a strongly adverse effect on county labor market conditions.

In terms of the two datasets' effect on the employment-to-population ratio, a one unit increase in opioid prescriptions per capita leads to a 1.2 and 7.2 percentage point drop in this ratio, *ceteris paribus*. Scaling the magnitude of the increase in opioid prescriptions per capita, a 10 percent increase in opioids results in a 0.08 and 0.59 percentage point drop in the employment-to-population ratio. Again, these results are statistically strong and continue to support the narrative that the increase in opioid prescriptions per capita have detrimental effects on county-level markets.

In Table 21 Panel B, the effects of opioid prescriptions on county labor market outcomes are both less impactful and less statistically significant. This can be explained by the poorly performing IVs in the first-stage regression.

CMS Drugs Dataset

Table 22 reports the estimates of the second-stage regression for the CMS Provider and CDC datasets. As discussed in Section 4.2.1, the results from Function 1, both the CMS and CDC

[40] This statistic is based on my data gathered from the BLS in Section 2.10.

datasets (Column 1 and 2) were the most robust. Thus, the coefficient estimates in Panel A are fundamentally more valid and econometrically fit for analysis. Again, across Panel A, in each of the columns, the B_1 estimates continue to suggest that opioid prescription per capita are heavily tied to county-level employment statistics. Both of the CMS Provider and Drugs datasets for the extension analysis draw the same conclusions, and are consistent with the findings of in Section 4.1 and those of Harris et al. (2019) — that the increase in opioid prescriptions per capita causally and adversely impacts county labor market outcomes. Specifically, as opioid prescriptions increase, the unemployment rate rises and the labor force participation rates and employment-to-population fall, indicators that the economy could be performing behind its expected and true potential.

The remaining steps are to evaluate the robustness checks models, which provide more insight into whether or not my findings are accurate, econometrically sound, and viable.

Table 21: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2017)

CMS Medicare Part D Provider Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.004***		−0.011***		−0.012***	
	(0.0003)		(0.002)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.016***		−0.067***		−0.072***
		(0.001)		(0.008)		(0.008)
Observations	12,987	12,987	12,987	12,987	12,987	12,987
R^2	0.201	0.258	0.334	0.424	0.325	0.417
Adjusted R^2	0.200	0.257	0.334	0.423	0.324	0.417
F Statistic	3,269.863***	3,742.139***	6,501.766***	7,865.806***	6,233.698***	7,591.087***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	−0.0003		0.0002		0.0003	
	(0.0003)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.058***		−0.021		−0.046
		(0.016)		(0.047)		(0.052)
Observations	12,987	12,987	12,987	12,987	12,987	12,987
R^2	0.136	0.039	0.022	0.012	0.035	0.012
Adjusted R^2	−0.107	−0.232	−0.254	−0.267	−0.237	−0.266
F Statistic	1,597.816***	990.816***	229.697***	225.370***	370.273***	342.897***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table 22: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2017)

CMS Medicare Part D Drugs Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.001***		−0.004***		−0.004***	
	(0.0003)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.015***		−0.049***		−0.055***
		(0.002)		(0.008)		(0.008)
Observations	12,987	12,987	12,987	12,987	12,987	12,987
R^2	0.200	0.259	0.334	0.421	0.325	0.416
Adjusted R^2	0.199	0.258	0.333	0.420	0.324	0.415
F Statistic	3,308.736***	3,566.723***	6,530.557***	7,507.215***	6,268.472***	7,253.655***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	−0.00000		0.0004		0.0004	
	(0.0002)		(0.0004)		(0.0005)	
Opioid Prescriptions Per Capita (CDC)		0.016***		−0.0003		−0.008
		(0.006)		(0.022)		(0.022)
Observations	12,987	12,987	12,987	12,987	12,987	12,987
R^2	0.136	0.115	0.022	0.022	0.035	0.034
Adjusted R^2	−0.107	−0.134	−0.254	−0.253	−0.237	−0.238
F Statistic	1,596.958***	1,546.494***	233.050***	229.658***	373.022***	369.800***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

5 Robustness Checks

I employ robustness check strategies to my preferred IV specification models, most of which derived from the CMS Provider and Drugs datasets. In a few select cases, I elect to use the CDC dataset as my preferred IV specification model, dependent on its performance relative to those of the CMS datasets. Robustness checks operate through the second-stage level of final results.[41]

Tables 23, 24, 25, and 26 I estimate first-stage regressions coefficients on both the CMS Provider and Drugs datasets, using Functions 1 and 2, in order to test the validity of my instruments. I check the strength of the IVs in these following regressions differently, because these datasets are complete with all variables. As a reference, in the 2013 to 2017 Extension Section (4.2), the datasets did not include "Number of Cancer Deaths per 100,000 Population" as the data was unavailable for that year. Consistent to the results in the main Results Section (4), the CMS Provider and Drugs datasets appear to have both strongly positive and valid instruments, when using Function 1, plm with oneway "individual" effect. All but coefficient for the CMS datasets are statistically significant and positive, the outlier (top-1 supply in Table 26 Column 1) still positive but not statistically significant above the 90 percent level. Regardless, both the R^2 and F statistics and other CMS results are strong enough to assume instrumental validity of the second-stage results.

In Tables 27 and 28 Panel A, the CMS Provider and Drugs and CDC second-stage estimates are positive, strong, and consistent with my other results and intuition about the effect of opioids on labor markets. Thus, we can assume that the 2013 to 2017 Extension Section (4.2) results are robust and valid.

Additionally, I evaluate a series of regressions, one for each year-group (i.e., 2013-2015, 2013-2016, and 2013-2017), omitting the top 10 percent of high-volume prescribing counties. This approach tests to verify that my results are not solely driven by between-county heterogeneity in data reporting or the aggregation of opioids. Consistently, in each of these year-groups, the β_1 estimates, in Tables 29, 30, and 31, seemingly strengthened in magnitude, both indicating a larger rise in unemployment and greater fall in the labor force participation rate and employment-to-population ratio. However, in the grand scheme of the analysis, this approach did not substantively change the results. I expect to obtain these results, which reinforce the claim that all of the counties are driving this movement in county labor market outcomes, and that movement of the outcomes variables are not centered around strictly heavy-opioid prescribing counties.

Furthermore, in Tables 32 and 33 Panel A, which represents the CMS Provider dataset, and Panel B, which represents the CMS Drugs dataset, I report the results of an IV specification that includes controls for the number of liquor stores, alcohol-related businesses, and bars (as outlined in Section 2.8) and marijuana-related arrests per county, which include specification by sales and possession (as outlined in Section 2.7). This approach is undergone is Harris et al. (2019) in order to include as evidence that the preferred IV specification findings are attributable to opioid use specifically, instead of a consistent pattern of substance use. Albeit the estimate results in Tables 32 and 33

[41] Refer to Appendix Tables A6 and A7 to see the relationship between the IVs and county labor market outcomes variables through a strictly correlative lens — this is the reduced form linear regression (i.e., Equation 1) approach .

are strongly positive and statistically significant, the seemingly endogenous connection between marijuana-arrests and opioid use reassures me that my main 2SLS (IV) preferred specification from Equation 3, which I perform in both Sections 4.1 and 4.2, is still the best option.

Table 23: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2016) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.014***	0.032***
	(0.002)	(0.004)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.038***	0.008***
	(0.001)	(0.001)
Percent Female	0.361***	3.616***
	(0.111)	(0.288)
Percent Black	0.065***	0.078***
	(0.013)	(0.025)
Percent Hispanic	0.017	−0.070**
	(0.010)	(0.029)
Percent under 15	−0.093	−1.185
	(0.202)	(1.199)
Percent 15 to 19	−0.911***	−2.123***
	(0.156)	(0.746)
Percent 20 to 24	−0.197	0.445
	(0.232)	(1.723)
Percent 35 to 44	−1.502***	6.093***
	(0.365)	(2.293)
Percent 45 to 54	−1.034***	−4.088***
	(0.206)	(0.296)
Percent 55 to 64	−0.822***	−1.344
	(0.304)	(1.350)
Percent Aged 65+	0.019	1.099
	(0.117)	(0.936)
Number of PCPs and NPs per 1,000 Population	0.238***	0.052***
	(0.010)	(0.010)
Number of Cancer Deaths per 100,000 Population	0.001***	0.006***
	(0.0001)	(0.001)
Observations	10,883	10,883
R^2	0.775	0.321
Adjusted R^2	0.775	0.320
F Statistic (df = 14; 10865)	2,672.289***	366.473***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 24: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2016) - Provider Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.007***	0.0004
	(0.001)	(0.001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.029***	−0.0002*
	(0.0003)	(0.0001)
Percent Female	0.523	−0.401
	(2.617)	(0.509)
Percent Black	0.539*	−1.666***
	(0.275)	(0.188)
Percent Hispanic	−0.984**	0.574
	(0.485)	(0.416)
Percent under 15	1.093	−0.034
	(1.759)	(0.519)
Percent 15 to 19	−0.714	−1.422
	(1.510)	(1.412)
Percent 20 to 24	−1.140	3.853***
	(0.852)	(0.565)
Percent 35 to 44	1.579*	1.756***
	(0.856)	(0.533)
Percent 45 to 54	1.973	0.095
	(2.570)	(0.148)
Percent 55 to 64	1.168	3.784***
	(0.853)	(0.694)
Percent Aged 65+	3.244**	2.570***
	(1.595)	(0.256)
Number of PCPs and NPs per 1,000 Population	0.112***	−0.055***
	(0.022)	(0.011)
Number of Cancer Deaths per 100,000 Population	0.0002	−0.003**
	(0.001)	(0.001)
Observations	10,883	10,883
R^2	0.550	0.025
Adjusted R^2	0.390	−0.321
F Statistic (df = 14; 8030)	699.746***	14.996***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 25: First Stage (Plm without Effect): Effects of Variables on Opioid Prescriptions (2013-2016) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.023**	0.017**
	(0.009)	(0.007)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.240***	0.017***
	(0.005)	(0.003)
Percent Female	0.240	3.805***
	(1.066)	(0.158)
Percent Black	−0.038	0.127***
	(0.100)	(0.016)
Percent Hispanic	−0.546***	−0.035**
	(0.147)	(0.014)
Percent under 15	2.773***	−0.804
	(0.887)	(1.284)
Percent 15 to 19	−1.167	−2.230***
	(2.105)	(0.834)
Percent 20 to 24	−1.768**	0.855
	(0.716)	(1.789)
Percent 35 to 44	−5.827***	6.618***
	(0.343)	(2.008)
Percent 45 to 54	−13.820***	−3.806***
	(1.369)	(0.229)
Percent 55 to 64	−3.637***	−1.716
	(1.250)	(1.624)
Percent Aged 65+	4.736***	1.800**
	(1.043)	(0.840)
Number of PCPs and NPs per 1,000 Population	1.575***	0.083***
	(0.117)	(0.010)
Number of Cancer Deaths per 100,000 Population	0.0002	0.008***
	(0.001)	(0.0002)
Observations	10,883	10,883
R^2	0.665	0.246
Adjusted R^2	0.664	0.245
F Statistic (df = 14; 10,865)	1,538.921***	253.370***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 26: First Stage (Plm with Effect): Effects of Variables on Opioid Prescriptions (2013-2016) - Drugs Dataset

	Opioids Per Capita (Medicare)	Opioids Per Capita (CDC)
	(1)	(2)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.006	0.005***
	(0.008)	(0.002)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.146***	0.001
	(0.018)	(0.0005)
Percent Female	5.795	−0.403
	(7.568)	(0.546)
Percent Black	−0.623	−1.644***
	(4.801)	(0.187)
Percent Hispanic	−4.997***	0.579
	(1.292)	(0.427)
Percent under 15	7.521	−0.076
	(11.158)	(0.491)
Percent 15 to 19	15.325***	−1.455
	(5.925)	(1.388)
Percent 20 to 24	−0.769	3.679***
	(1.999)	(0.587)
Percent 35 to 44	18.674***	1.757***
	(3.843)	(0.553)
Percent 45 to 54	6.936***	0.052
	(1.980)	(0.168)
Percent 55 to 64	0.456	3.619***
	(5.540)	(0.661)
Percent Aged 65+	6.862	2.494***
	(7.922)	(0.253)
Number of PCPs and NPs per 1,000 Population	0.531***	−0.053***
	(0.135)	(0.009)
Number of Cancer Deaths per 100,000 Population	0.005	−0.003**
	(0.007)	(0.001)
Observations	10,883	10,883
R^2	0.396	0.033
Adjusted R^2	0.181	−0.310
F Statistic (df = 14; 8,030)	375.554***	19.629***

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

Table 27: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2016)

CMS Medicare Part D Provider Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.003***		−0.006***		−0.007***	
	(0.0003)		(0.002)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.014***		−0.056***		−0.061***
		(0.001)		(0.008)		(0.008)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.251	0.292	0.396	0.455	0.388	0.450
Adjusted R^2	0.250	0.291	0.395	0.454	0.387	0.449
F Statistic	3,642.154***	3,996.287***	7,110.802***	8,112.427***	6,890.004***	7,905.043***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	−0.0004		−0.0002		0.00003	
	(0.0003)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.074		−0.003		−0.041
		(0.083)		(0.108)		(0.126)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.141	0.023	0.031	0.030	0.038	0.012
Adjusted R^2	−0.164	−0.324	−0.314	−0.315	−0.304	−0.339
F Statistic	1,319.219***	636.030***	252.886***	252.578***	315.947***	292.146***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 28: Second Stage: Effects of Opioid Precriptions on County Labor Market Conditions (2013-2016)

CMS Medicare Part D Drugs Dataset

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Plm without Effect	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.001***		−0.003***		−0.004***	
	(0.0003)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.015***		−0.042***		−0.049***
		(0.002)		(0.006)		(0.007)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.251	0.290	0.396	0.454	0.389	0.450
Adjusted R^2	0.250	0.289	0.395	0.453	0.388	0.450
F Statistic	3,692.693***	3,888.933***	7,157.981***	7,915.231***	6,945.255***	7,724.262***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	−0.0001		0.001*		0.001	
	(0.0002)		(0.0003)		(0.0004)	
Opioid Prescriptions Per Capita (CDC)		0.025***		−0.012		−0.024**
		(0.002)		(0.010)		(0.010)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.141	0.088	0.029	0.023	0.037	0.022
Adjusted R^2	−0.164	−0.236	−0.315	−0.323	−0.305	−0.325
F Statistic	1,318.764***	1,195.885***	260.438***	251.005***	323.781***	309.283***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table 29: Effects of Opioid Precriptions Per Capita on County Labor Market Conditions (2013-2015) - Excl. Top 10 Percent

CMS Medicare Part D Datasets

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Provider Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.012***		−0.025***		−0.031***	
	(0.001)		(0.007)		(0.007)	
Opioid Prescriptions Per Capita (CDC)		0.024***		−0.089***		−0.098***
		(0.002)		(0.015)		(0.014)
Observations	6,571	6,571	6,571	6,571	6,571	6,571
R^2	0.269	0.277	0.419	0.456	0.413	0.448
Adjusted R^2	0.267	0.275	0.418	0.454	0.411	0.446
F Statistic	2,416.217***	2,440.109***	4,716.764***	5,110.077***	4,582.995***	4,940.508***
Panel B: Drugs Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.004***		−0.010***		−0.012***	
	(0.0002)		(0.001)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.035***		−0.084***		−0.101***
		(0.002)		(0.007)		(0.006)
Observations	6,571	6,571	6,571	6,571	6,571	6,571
R^2	0.274	0.245	0.416	0.454	0.411	0.441
Adjusted R^2	0.273	0.243	0.415	0.452	0.410	0.439
F Statistic	2,557.842***	2,211.572***	4,710.206***	4,991.421***	4,617.794***	4,776.459***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
Panel A and Panel B FE-IV plm regressions (without effects) exclude the top 10 percent of counties with the highest average per capita opioid prescriptions.

Table 30: Effects of Opioid Precriptions Per Capita on County Labor Market Conditions (2013-2016) - Excl. Top 10 Percent

CMS Medicare Part D Datasets

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Provider Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.008***		−0.017***		−0.021***	
	(0.001)		(0.005)		(0.004)	
Opioid Prescriptions Per Capita (CDC)		0.020***		−0.079***		−0.086***
		(0.002)		(0.011)		(0.011)
Observations	9,794	9,794	9,794	9,794	9,794	9,794
R^2	0.253	0.278	0.405	0.459	0.397	0.453
Adjusted R^2	0.252	0.276	0.404	0.459	0.396	0.452
F Statistic	3,294.606***	3,477.841***	6,618.558***	7,476.829***	6,421.475***	7,257.814***
Panel B: Drugs Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.003***		−0.008***		−0.009***	
	(0.0004)		(0.001)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.028***		−0.072***		−0.085***
		(0.0003)		(0.008)		(0.008)
Observations	9,794	9,794	9,794	9,794	9,794	9,794
R^2	0.260	0.259	0.411	0.470	0.405	0.461
Adjusted R^2	0.259	0.258	0.411	0.469	0.404	0.460
F Statistic	3,497.989***	3,305.369***	6,861.393***	7,606.667***	6,693.370***	7,352.481***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
Panel A and Panel B FE-IV plm regressions (without effects) exclude the top 10 percent of counties with the highest average per capita opioid prescriptions.

Table 31: Effects of Opioid Precriptions Per Capita on County Labor Market Conditions (2013-2017) - Excl. Top 10 Percent

CMS Medicare Part D Datasets

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Provider Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.012***		−0.034***		−0.040***	
	(0.001)		(0.006)		(0.006)	
Opioid Prescriptions Per Capita (CDC)		0.025***		−0.101***		−0.109***
		(0.003)		(0.010)		(0.011)
Observations	10,519	10,519	10,519	10,519	10,519	10,519
R^2	0.213	0.239	0.362	0.434	0.354	0.424
Adjusted R^2	0.212	0.238	0.361	0.433	0.353	0.424
F Statistic	2,826.816***	2,985.184***	5,895.184***	6,868.101***	5,670.597***	6,586.905***
Panel B: Drugs Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.004***		−0.010***		−0.012***	
	(0.001)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.031***		−0.089***		−0.103***
		(0.003)		(0.004)		(0.003)
Observations	10,519	10,519	10,519	10,519	10,519	10,519
R^2	0.215	0.225	0.357	0.435	0.349	0.424
Adjusted R^2	0.214	0.224	0.356	0.434	0.348	0.423
F Statistic	2,912.161***	2,737.065***	5,836.075***	6,615.852***	5,647.103***	6,316.904***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
Panel A and Panel B FE-IV plm regressions (without effects) exclude the top 10 percent of counties with the highest average per capita opioid prescriptions. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table 32: Second Stage: Effects of Opioid Precriptions Per Capita on Labor Market Conditions (2013-2015) - Incl. Drugs/Alcohol

CMS Medicare Part D Datasets

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Provider Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.004***		−0.007***		−0.009***	
	(0.0001)		(0.002)		(0.002)	
Opioid Prescriptions Per Capita (CDC)		0.015***		−0.056***		−0.061***
		(0.001)		(0.007)		(0.007)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.272	0.314	0.404	0.457	0.397	0.453
Adjusted R^2	0.270	0.312	0.403	0.456	0.396	0.452
F Statistic	3,031.557***	3,318.140***	5,500.948***	6,187.899***	5,343.241***	6,051.158***
Panel B: Drugs Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.002***		−0.005***		−0.005***	
	(0.0002)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.017***		−0.047***		−0.054***
		(0.001)		(0.008)		(0.009)
Observations	8,114	8,114	8,114	8,114	8,114	8,114
R^2	0.273	0.309	0.405	0.459	0.398	0.455
Adjusted R^2	0.271	0.308	0.403	0.457	0.397	0.454
F Statistic	3,097.039***	3,244.535***	5,552.374***	6,104.854***	5,405.289***	5,968.974***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
This FE-IV plm regression (without effects) includes additional control variables (i.e., Marijuana Sales, Marijuana Possession, and Liquor Stores and Bars).

Table 33: Second Stage: Effects of Opioid Precriptions on Labor Market Conditions (2013-2016) - Incl. Drugs/Alcohol

CMS Medicare Part D Datasets

	U-Rate		LFP-Rate		E-P-Ratio	
Panel A: Provider Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.001***		0.001		0.001	
	(0.0002)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.009***		−0.038***		−0.041***
		(0.002)		(0.008)		(0.009)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.240	0.279	0.393	0.441	0.384	0.435
Adjusted R^2	0.239	0.278	0.392	0.441	0.383	0.434
F Statistic	3,446.512***	3,719.799***	7,035.607***	7,762.140***	6,766.893***	7,504.318***
Panel B: Drugs Dataset	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Prescriptions Per Capita (Medicare)	0.001**		−0.002**		−0.002**	
	(0.0003)		(0.001)		(0.001)	
Opioid Prescriptions Per Capita (CDC)		0.009***		−0.022***		−0.026***
		(0.002)		(0.007)		(0.008)
Observations	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.237	0.279	0.391	0.430	0.381	0.425
Adjusted R^2	0.236	0.278	0.390	0.429	0.380	0.424
F Statistic	3,462.882***	3,664.917***	7,025.463***	7,496.415***	6,759.132***	7,270.641***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.
This FE-IV plm regression (without effects) includes additional control variables (i.e., Marijuana Sales, Marijuana Possession, and Liquor Stores and Bars).

6 Conclusion

This paper examines the causal effects of opioid prescriptions per capita on salient county labor market outcomes. I employ a 2SLS (IV) approach that instruments for opioid prescription per capita with high-volume opioid prescribers, as measured by the number of providers in the top-1 percent of doses prescribed and the number of providers in the top-5 percent of prescriptions written. The IV approach plausibly identifies the causal effects of opioid prescriptions on labor market conditions, which is not possible using a standard OLS regression. My findings show that the current level of prescription opioids dispensed to both pharmacies and individuals strongly, negatively, and statistically significantly affect the unemployment rate, labor force participation rate, and employment-to-population ratio. While this research is limited to the recorded effect of county-level prescription opioids, my analyses show that the subsequent and frequent transition from prescription opioids to illicit opioids and narcotics has strong adverse effects on county labor market conditions as well.

In an extension of my research, I would perform a redundancy test based on Breusch et al. (1999) and Baum et al. (2007) to ensure that my chosen instruments were both contributing to the estimation, as they are similar to one another. Additionally, I would analyze the difference in effects of opioids in rural versus urban status counties or metropolitan statistical areas. Furthermore, I suggest that future contribution should focus on the examination of industry-level effects, namely those that exhibit and report on average higher levels of injury and depression or mental illness, as well as those that focus on the elderly population.

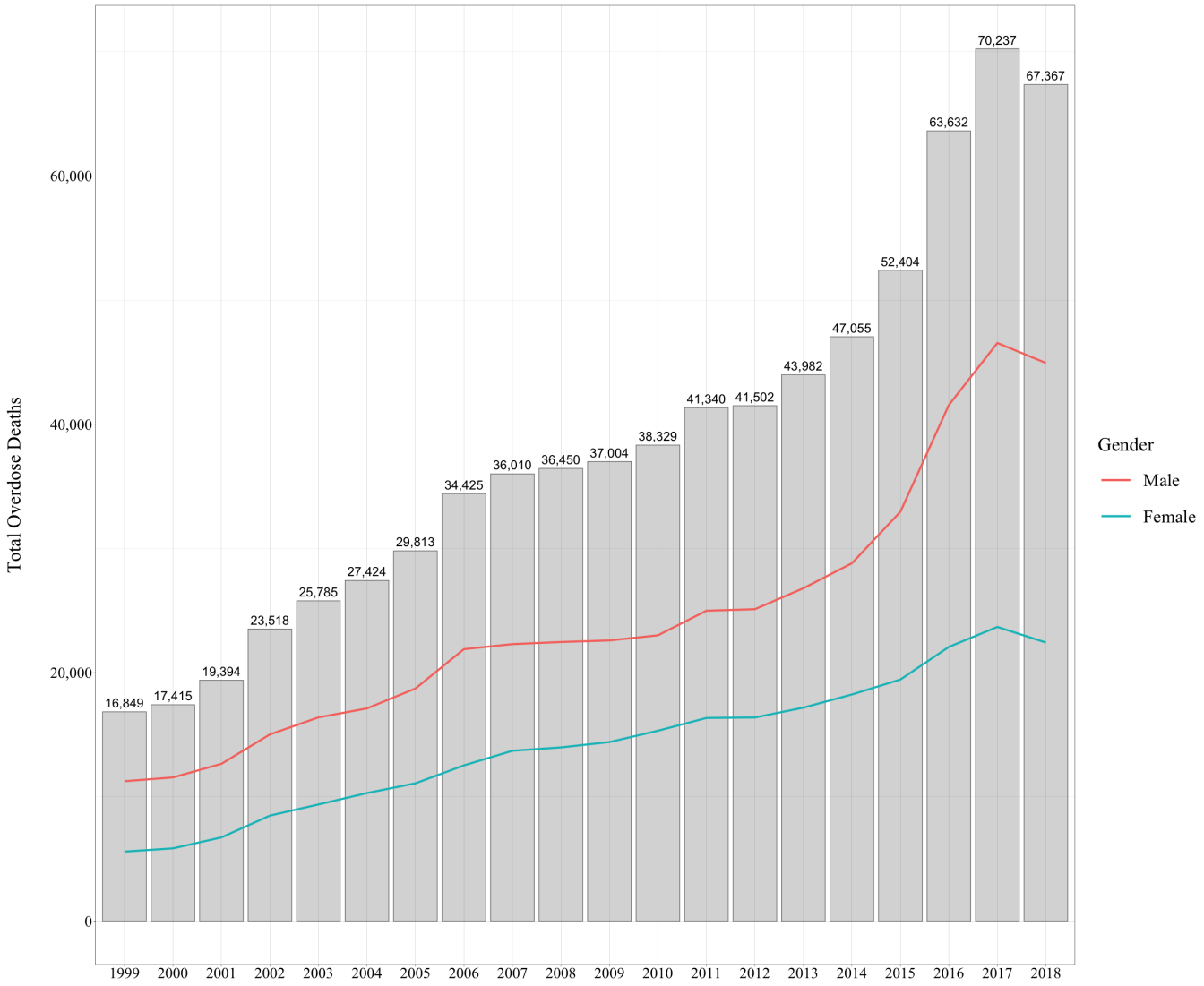
According to Blanchflower & Oswald (2019), Americans appear to experience greater *pain* as compared to citizens from other countries, and since the 1970s, happiness levels have trended downwards. As of 2015, between 21 and 29 percent of patients misuse their chronic pain prescription opioids (Vowles et al., 2015). Thus, while individuals might reap the medical benefits of pain medication prescriptions when first prescribed, it is clear that a large share of these individuals become irreversibly addicted to and therefore show the adverse impact of their formerly needed opioid prescription. Opioids have been regarded as the most effective treatment for pain, when prescribed properly, however, since the 1990s when large pharmaceutical companies began to rapidly grow in size, advertising online and targeting clinics, the trends in both overprescription by physicians and misuse by legal receivers has only continued to worsen (Alpert et al., 2019; Chang et al., 2016; Paulozzi et al., 2015; Rosenblum et al., 2008). Proven strategies are available to relieve both general and chronic pain without the use of opioids. The next step in addressing the opioid overdose and misuse crisis is modifying prescribing practices, and hopefully this will lead us in the direction of beginning to reverse the current adverse effects on U.S. communities.

Through reporting these findings, I do not intend to imply that all opioid prescriptions are illegitimate and that limiting the supply of prescriptions will lead to more prosperous county labor market conditions. However, alongside other research conducted in this field of study (e.g., Aliprantis & Chen (2017); Aliprantis et al. (2019); Alpert et al. (2019); Currie et al. (2018); Harris et al. (2019); National Academies of Sciences, Engineering, and Medicine (2017)), strong evidence

holds in support of the negative effects of today's distribution of Schedule II-IV controlled substance prescriptions and the malpractice associated with physicians' improperly prescribing dangerously addictive drugs. More so, this research is intended to help target physicians who are prescribing drugs to individuals who either might be already suffering from drug misuse, have a genetic or environmental predisposition to drug addiction, or do not fully understand the pending risks prior to the use of these substances. I hope that this research drives awareness of the ongoing three-decade long catastrophe of the opioid crisis, and incentivizes both local community organizations and public policy officials to identify and eliminate "opioid pill mills" and halt the malpractice of improperly prescribing physicians.

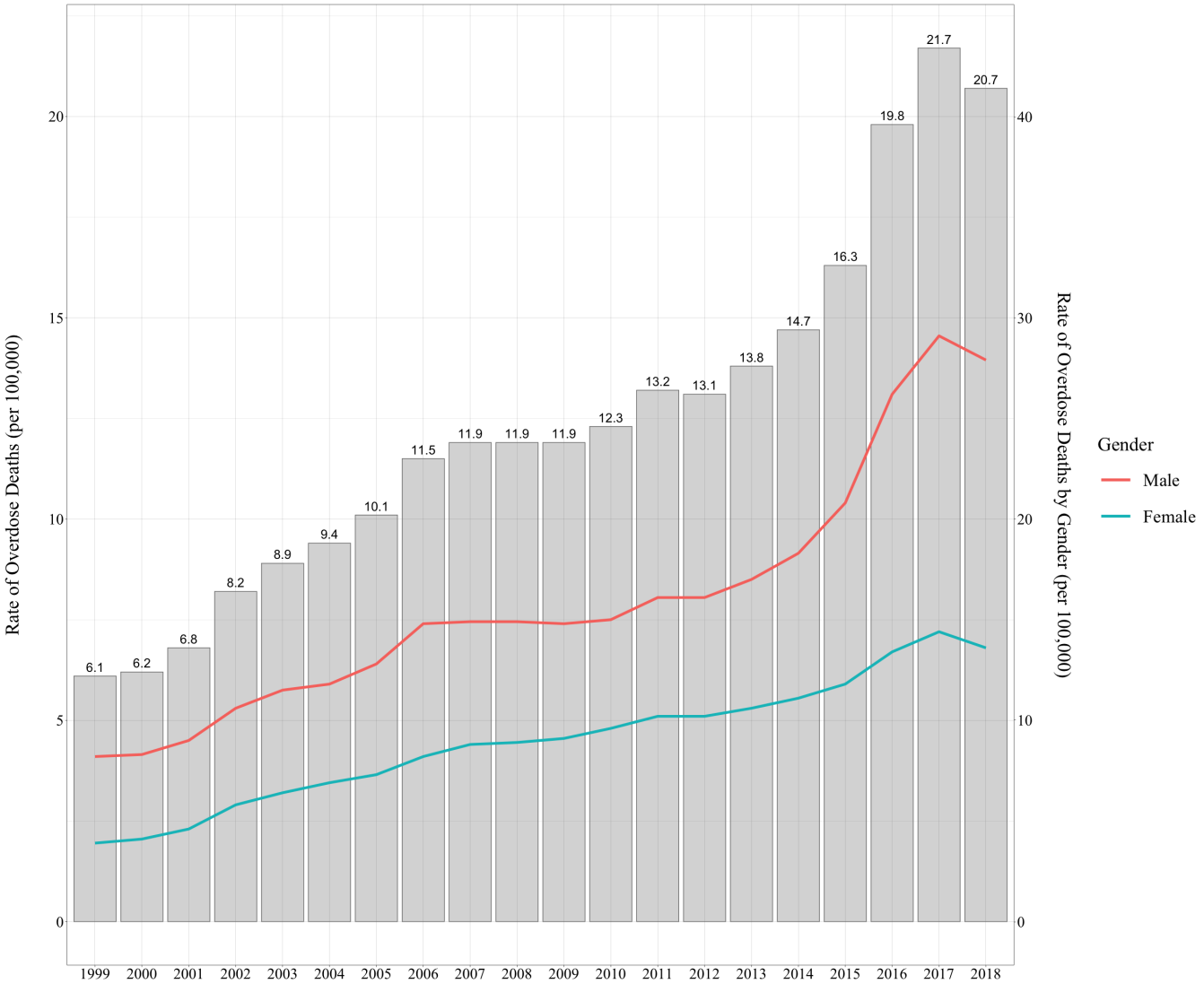
7 Appendix

Figure A1: National Drug Overdose Deaths Number Among All Ages, by Gender, 1999-2018



Note: Rate for Gender variables denoted by secondary axis. Data for 1999-2018 uses ICD-10 codes.
Source: CDC WONDER, Julien Lewin analysis.

Figure A2: National Drug Overdose Deaths Rate Among All Ages, by Gender, 1999-2018



Note: Rate for Gender variables denoted by secondary axis. Data for 1999-2018 uses ICD-10 codes.
Source: CDC WONDER, Julien Lewin analysis.

Table A1: National Drug Overdose Deaths Among All Ages, 1999-2018

Year	Total Overdose Deaths	Female	Male	Any Opioid	Prescription Opioids	Fentanyl	Heroin	Cocaine	M.	B.	A.
1999	16,849	5,591	11,258	8,048	3,442	730	1,960	3,822	547	1,135	1,749
2000	17,415	5,852	11,563	8,407	3,785	782	1,842	3,544	578	1,298	1,798
2001	19,394	6,736	12,658	9,492	4,770	957	1,779	3,833	563	1,594	2,017
2002	23,518	8,490	15,028	11,917	6,483	1,295	2,089	4,599	941	2,022	2,370
2003	25,785	9,386	16,399	12,939	7,461	1,400	2,080	5,199	1,179	2,248	2,512
2004	27,424	10,304	17,120	13,755	8,577	1,664	1,878	5,443	1,305	2,627	2,758
2005	29,813	11,089	18,724	14,917	9,612	1,742	2,009	6,208	1,608	3,084	2,861
2006	34,425	12,532	21,893	17,545	11,589	2,707	2,088	7,448	1,462	3,835	3,133
2007	36,010	13,712	22,298	18,515	12,796	2,213	2,399	6,512	1,378	4,500	3,425
2008	36,450	13,982	22,468	19,582	13,149	2,306	3,041	5,129	1,302	5,010	3,610
2009	37,004	14,411	22,593	20,422	13,523	2,946	3,278	4,350	1,632	5,567	3,768
2010	38,329	15,323	23,006	21,088	14,583	3,007	3,036	4,183	1,854	6,497	3,889
2011	41,340	16,352	24,988	22,784	15,140	2,666	4,397	4,681	2,266	6,872	4,113
2012	41,502	16,390	25,112	23,164	14,240	2,628	5,925	4,404	2,635	6,524	4,259
2013	43,982	17,183	26,799	25,050	14,145	3,105	8,257	4,944	3,627	6,973	4,458
2014	47,055	18,243	28,812	28,647	14,838	5,544	10,574	5,415	4,298	7,945	4,768
2015	52,404	19,447	32,957	33,091	15,281	9,580	12,989	6,784	5,716	8,791	4,894
2016	63,632	22,074	41,558	42,249	17,087	19,413	15,469	10,375	7,542	10,684	4,812
2017	70,237	23,685	46,552	47,600	17,029	28,466	15,482	13,942	10,333	11,537	5,269
2018	67,367	22,426	44,941	46,802	14,975	31,335	14,996	14,666	12,676	10,724	5,064
Total	769,935	283,208	486,727	446,014	232,505	124,486	115,568	125,481	63,442	109,467	71,527

Note: "M." denotes Methamphetamine. "B." denotes Benzodiazepine. "A." denotes Antidepressants.
The sum of the different drug deaths do not equal the total rate of overdose deaths due to overlap in counting. Each death rate by drug is not mutually exclusive. Data for 1999-2018 use ICD-10 codes.
Source: CDC WONDER, Julien Lewin analysis.

Table A2: Reduced Form: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes (2013-2015)

CMS Medicare Part D Provider Dataset

	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0006***	−0.0030***	−0.0032***
	(0.0001)	(0.0005)	(0.0005)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.00003	0.0002	0.0002
	(0.00005)	(0.0002)	(0.0002)
Observations	8,114	8,114	8,114
R^2	0.2825	0.4194	0.4133
Adjusted R^2	0.2811	0.4183	0.4122
F Statistic (df = 14; 8,097)	227.6968***	417.8102***	407.4622***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.00001	0.0001*	0.0001**
	(0.0001)	(0.0001)	(0.00003)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00001	−0.00004***	−0.00004***
	(0.00001)	(0.00001)	(0.00001)
Observations	8,114	8,114	8,114
R^2	0.1269	0.0355	0.0303
Adjusted R^2	−0.3398	−0.4800	−0.4880
F Statistic (df = 14; 5,287)	54.8812***	13.8998***	11.8136***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table A3: Reduced Form: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes (2013-2015)

CMS Medicare Part D Drugs Dataset

	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0001	−0.0001	−0.0001
	(0.0001)	(0.0005)	(0.0006)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.0003***	−0.0010***	−0.0012***
	(0.0001)	(0.0003)	(0.0003)
Observations	8,114	8,114	8,114
R^2	0.2775	0.4065	0.4007
Adjusted R^2	0.2761	0.4053	0.3995
F Statistic (df = 14; 8,097)	222.1302***	396.0790***	386.6939***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0001**	−0.0001***	−0.0001***
	(0.0001)	(0.00001)	(0.00004)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00001*	−0.00003***	−0.00002***
	(0.00001)	(0.00001)	(0.000004)
Observations	8,114	8,114	8,114
R^2	0.1283	0.0346	0.0300
Adjusted R^2	−0.3377	−0.4814	−0.4885
F Statistic (df = 14; 5,287)	55.5774***	13.5347***	11.6817***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table A4: Reduced Form: Effects of Opioid Prescriptions Per Capita on Labor Market Outcomes (2013-2017)

CMS Medicare Part D Provider Dataset

	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0007***	−0.0034***	−0.0036***
	(0.0001)	(0.0006)	(0.0007)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.00002	0.0002	0.0002
	(0.00005)	(0.0002)	(0.0002)
Observations	12,987	12,987	12,987
R^2	0.2171	0.3566	0.3479
Adjusted R^2	0.2161	0.3557	0.3471
F Statistic (df = 13; 12,969)	276.6118***	552.8145***	532.2773***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0001	−0.00004	−0.0001
	(0.0001)	(0.0001)	(0.0001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00002**	0.00001	0.00002
	(0.00001)	(0.00002)	(0.00002)
Observations	12,987	12,987	12,987
R^2	0.1381	0.0222	0.0356
Adjusted R^2	−0.1049	−0.2535	−0.2365
F Statistic (df = 13; 10,129)	124.8900***	17.7271***	28.7271***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table A5: Reduced Form: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes (2013-2017)

CMS Medicare Part D Drugs Dataset			
	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0002	−0.0010*	−0.0011*
	(0.0001)	(0.0006)	(0.0006)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.0003***	−0.0008***	−0.0009***
	(0.0001)	(0.0003)	(0.0003)
Observations	12,987	12,987	12,987
R^2	0.2042	0.3357	0.3267
Adjusted R^2	0.2031	0.3348	0.3258
F Statistic (df = 13; 12,969)	255.9264***	504.0316***	484.0936***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0001	−0.0001*	−0.0002
	(0.0001)	(0.0001)	(0.0001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00001	0.0001	0.0001
	(0.00003)	(0.0001)	(0.0001)
Observations	12,987	12,987	12,987
R^2	0.1365	0.0229	0.0360
Adjusted R^2	−0.1070	−0.2528	−0.2359
F Statistic (df = 13; 10,129)	123.1986***	18.2204***	29.0957***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis. Dataset excludes "Number of Cancer Deaths per 100,000 Population" as data is unavailable for 2017.

Table A6: Reduced Form: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes (2013-2016)

CMS Medicare Part D Provider Dataset

	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0006***	−0.0029***	−0.0031***
	(0.0001)	(0.0006)	(0.0006)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.000005	0.0003**	0.0003**
	(0.00004)	(0.0001)	(0.0002)
Observations	10,883	10,883	10,883
R^2	0.2628	0.4142	0.4071
Adjusted R^2	0.2616	0.4133	0.4062
F Statistic (df = 14; 10,865)	276.6143***	548.7329***	532.8951***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.00004	−0.00001	−0.00003
	(0.0001)	(0.0001)	(0.0001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00001*	−0.000004	0.000004
	(0.00001)	(0.00002)	(0.00002)
Observations	10,883	10,883	10,883
R^2	0.1414	0.0305	0.0379
Adjusted R^2	−0.1635	−0.3138	−0.3038
F Statistic (df = 14; 8,030)	94.4778***	18.0660***	22.6009***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table A7: Reduced Form: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes (2013-2016)

CMS Medicare Part D Drugs Dataset			
	U-Rate	LFP-Rate	E-P-Ratio
Panel A: Plm without Effect	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0002	−0.0007	−0.0007
	(0.0001)	(0.0006)	(0.0007)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	0.0003***	−0.0007***	−0.0009***
	(0.0001)	(0.0003)	(0.0003)
Observations	10,883	10,883	10,883
R^2	0.2546	0.3978	0.3907
Adjusted R^2	0.2534	0.3968	0.3898
F Statistic (df = 14; 10,865)	265.0540***	512.6371***	497.7019***
Panel B: Plm with Effect "Twoways"	(1)	(2)	(3)
Providers in Top 1 percent Opioid Doses/100,000 Population	0.0002***	−0.0002***	−0.0003***
	(0.0001)	(0.0001)	(0.0001)
Providers in Top 5 percent Opioid Prescriptions/100,000 Population	−0.00003	0.0001**	0.0001**
	(0.00002)	(0.0001)	(0.0001)
Observations	10,883	10,883	10,883
R^2	0.1427	0.0322	0.0401
Adjusted R^2	−0.1618	−0.3115	−0.3009
F Statistic (df = 14; 8,030)	95.4922***	19.0931***	23.9412***

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

Includes unique county and year fixed effects. Robust standard errors in parenthesis.

Table A8: Reduced Form: Effects of Opioid Distributions and Prescriptions Per Capita on Labor Market Conditions (2006-2014) - ARCOS

	U-Rate		LFP-Rate		E-P-Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Distributions Per Capita (ARCOS)	0.0003***		−0.001***		−0.001***	
	(0.00002)		(0.00004)		(0.00004)	
Opioid Prescriptions Per Capita (CDC)		0.009***		−0.034***		−0.037***
		(0.001)		(0.002)		(0.002)
Percent Female	−0.111***	−0.108***	1.462***	1.445***	1.407***	1.390***
	(0.020)	(0.020)	(0.061)	(0.058)	(0.071)	(0.068)
Percent Black	0.066***	0.062***	−0.241***	−0.227***	−0.260***	−0.244***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Percent Hispanic	0.032***	0.034***	−0.090***	−0.095***	−0.105***	−0.110***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.008)
Percent under 15	0.305***	0.309***	−0.535***	−0.543***	−0.665***	−0.675***
	(0.064)	(0.069)	(0.170)	(0.193)	(0.195)	(0.220)
Percent 15 to 19	0.425***	0.416***	−1.203***	−1.161***	−1.381***	−1.337***
	(0.082)	(0.086)	(0.166)	(0.180)	(0.191)	(0.208)
Percent 20 to 24	0.298***	0.306***	−0.864***	−0.893***	−0.977***	−1.009***
	(0.102)	(0.112)	(0.285)	(0.323)	(0.327)	(0.368)
Percent 35 to 44	0.652***	0.697***	−1.473***	−1.646***	−1.771***	−1.958***
	(0.146)	(0.159)	(0.330)	(0.373)	(0.387)	(0.434)
Percent 45 to 54	−0.010	−0.048	0.721***	0.878***	0.674***	0.842***
	(0.077)	(0.083)	(0.232)	(0.258)	(0.258)	(0.286)
Percent 55 to 64	0.626***	0.677***	−1.356***	−1.552***	−1.619***	−1.830***
	(0.107)	(0.113)	(0.197)	(0.208)	(0.226)	(0.239)
Percent Aged 65+	0.283***	0.289***	−1.257***	−1.276***	−1.335***	−1.356***
	(0.053)	(0.060)	(0.171)	(0.203)	(0.187)	(0.221)
Number of Cancer Deaths per 100,000 Population	0.0002***	0.0003***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00004)	(0.00004)	(0.0001)	(0.00004)	(0.0001)	(0.0001)
Observations	23,012	23,012	23,012	23,012	23,012	23,012
R^2	0.287	0.262	0.502	0.463	0.500	0.459
Adjusted R^2	0.286	0.261	0.502	0.463	0.500	0.459
F Statistic (df = 12; 22,991)	771.264***	679.787***	1,932.725***	1,653.008***	1,918.742***	1,627.883***

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

Table A9: Reduced Form: Effects of Opioid Distributions and Prescriptions Per Capita on Labor Market Conditions (2010-2014) - ARCOS

	U-Rate		LFP-Rate		E-P-Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Distributions Per Capita (ARCOS)	0.0003***		−0.001***		−0.001***	
	(0.00001)		(0.00005)		(0.00004)	
Opioid Prescriptions Per Capita (CDC)		0.012***		−0.040***		−0.044***
		(0.001)		(0.002)		(0.002)
Percent Female	0.002	−0.0001	1.165***	1.171***	1.048***	1.056***
	(0.015)	(0.016)	(0.082)	(0.083)	(0.079)	(0.081)
Percent Black	0.077***	0.073***	−0.230***	−0.217***	−0.253***	−0.239***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Percent Hispanic	0.041***	0.043***	−0.081***	−0.088***	−0.102***	−0.109***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Percent under 15	0.266***	0.294***	−0.474**	−0.569***	−0.595***	−0.698***
	(0.059)	(0.064)	(0.184)	(0.198)	(0.208)	(0.224)
Percent 15 to 19	0.268***	0.256***	−0.601***	−0.558***	−0.706***	−0.661***
	(0.088)	(0.094)	(0.094)	(0.112)	(0.124)	(0.146)
Percent 20 to 24	0.425***	0.459***	−1.307***	−1.423***	−1.483***	−1.610***
	(0.071)	(0.079)	(0.169)	(0.193)	(0.198)	(0.225)
Percent 35 to 44	0.778***	0.867***	−1.915***	−2.218***	−2.267***	−2.597***
	(0.112)	(0.121)	(0.142)	(0.156)	(0.179)	(0.200)
Percent 45 to 54	−0.001	−0.032	0.415***	0.520***	0.349**	0.463**
	(0.087)	(0.094)	(0.133)	(0.152)	(0.169)	(0.190)
Percent 55 to 64	0.715***	0.780***	−1.069***	−1.287***	−1.388***	−1.626***
	(0.101)	(0.113)	(0.302)	(0.333)	(0.342)	(0.377)
Percent Aged 65+	0.277***	0.309***	−1.409***	−1.517***	−1.478***	−1.596***
	(0.037)	(0.041)	(0.075)	(0.083)	(0.088)	(0.098)
Number of PCPs and NPs per 1,000 Population	−0.007***	−0.007***	0.019***	0.018***	0.022***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Cancer Deaths per 100,000 Population	0.0001***	0.0002***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00005)	(0.00004)	(0.00003)	(0.00003)	(0.00005)	(0.0001)
Observations	12,875	12,875	12,875	12,875	12,875	12,875
R^2	0.359	0.327	0.529	0.487	0.528	0.484
Adjusted R^2	0.358	0.326	0.528	0.486	0.527	0.483
F Statistic (df = 13; 12,857)	554.104***	480.454***	1,109.197***	939.134***	1,106.463***	925.872***

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

References

Aliprantis, D. & Chen, A. (2017). The opioid epidemic and the labor market. *Economic Commentary*, (2017-15).

Aliprantis, D., Fee, K., & Schweitzer, M. E. (2019). Opioids and the labor market.

Alpert, A. E., Evans, W. N., Lieber, E. M., & Powell, D. (2019). *Origins of the Opioid Crisis and Its Enduring Impacts*. Technical report, National Bureau of Economic Research.

Angrist, J. D. & Imbens, G. W. (1995). *Identification and estimation of local average treatment effects*. Technical report, National Bureau of Economic Research.

ARCOS (1997). *ARCOS Registrant Handbook*. Technical report, U.S. Department of Justice Drug Enforcement Administration.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2007). Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *The Stata Journal*, 7(4), 465–506.

Blanchflower, D. G. & Oswald, A. J. (2019). Unhappiness and pain in modern america: A review essay, and further evidence, on carol graham's happiness for all? *Journal of Economic Literature*, 57(2), 385–402.

Breusch, T., Qian, H., Schmidt, P., & Wyhowski, D. (1999). Redundancy of moment conditions. *Journal of econometrics*, 91(1), 89–111.

Bureau of Labor Statistics (2012). *International Comparisons of Annual Labor Force Statistics, 1970–2012*. Technical report, Bureau of Labor Statistics.

Califf, R. M., Woodcock, J., & Ostroff, S. (2016). A proactive response to prescription opioid abuse. *New England Journal of Medicine*, 374(15), 1480–1485.

Centers for Disease Control and Prevention (2020). *U.S. Opioid Prescribing Rate Maps*. Technical report, U.S. Department of Health & Human Services.

Chang, H.-Y., Lyapustina, T., Rutkow, L., Daubresse, M., Richey, M., Faul, M., Stuart, E. A., & Alexander, G. C. (2016). Impact of prescription drug monitoring programs and pill mill laws on high-risk opioid prescribers: a comparative interrupted time series analysis. *Drug and alcohol dependence*, 165, 1–8.

Claxton, A. J., Cramer, J., & Pierce, C. (2001). A systematic review of the associations between dose regimens and medication compliance. *Clinical therapeutics*, 23(8), 1296–1310.

Croissant, Y., Millo, G., et al. (2008). Panel data econometrics in r: The plm package. *Journal of statistical software*, 27(2), 1–43.

Currie, J., Jin, J. Y., & Schnell, M. (2018). *US employment and opioids: Is there a connection?* Technical report, National Bureau of Economic Research.

Dawson, D. A., Goldstein, R. B., Saha, T. D., & Grant, B. F. (2015). Changes in alcohol consumption: United states, 2001–2002 to 2012–2013. *Drug and alcohol dependence*, 148, 56–61.

Department of Health and Human Services (2013). Addressing prescription drug abuse in the united states: current activities and future opportunities. USDoHaH Services, Editor.

Dhalla, I. A., Mamdani, M. M., Gomes, T., & Juurlink, D. N. (2011). Clustering of opioid prescribing and opioid-related mortality among family physicians in ontario. *Canadian Family Physician*, 57(3), e92–e96.

Dineen, K. K. & DuBois, J. M. (2016). Between a rock and a hard place: can physicians prescribe opioids to treat pain adequately while avoiding legal sanction? *American journal of law & medicine*, 42(1), 7–52.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, 77(3), 953–973.

Florence, C., Luo, F., Xu, L., & Zhou, C. (2016). The economic burden of prescription opioid overdose, abuse and dependence in the united states, 2013. *Medical care*, 54(10), 901.

Hagemeier, N. E. (2018). Introduction to the opioid epidemic: the economic burden on the healthcare system and impact on quality of life. *Am J Manag Care*, 24(10, suppl), S200–S206.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, (pp. 1029–1054).

Hanson, T. (2019). Understanding the opioid epidemic: How pain management policy contributed to opioid mortality. Master's thesis, University of California, Berkeley.

Harris, M. C., Kessler, L. M., Murray, M. N., & Glenn, B. (2019). Prescription Opioids and Labor Market Pains: The Effect of Schedule II Opioids on Labor Force Participation and Unemployment. *Journal of Human Resources*, (pp. 1017–9093R2).

Hernandez, R. (2018). The fall of employment in the manufacturing sector. *Monthly Lab. Rev.*, 141, 1.

Hill, M. V., McMahon, M. L., Stucke, R. S., & Barth, R. J. (2017). Wide variation and excessive dosage of opioid prescriptions for common general surgical procedures. *Annals of surgery*, 265(4), 709–714.

Hollingsworth, A., Ruhm, C. J., & Simon, K. (2017). Macroeconomic conditions and opioid abuse. *Journal of health economics*, 56, 222–233.

Imai, K. & Kim, I. S. (2019). *On the use of two–way fixed effects regression models for causal inference with panel data*. Technical report, Harvard University IQSS Working Paper. Cambridge, MA.

Jones, C. M. (2013). Heroin use and heroin use risk behaviors among nonmedical users of prescription opioid pain relievers–united states, 2002–2004 and 2008–2010. *Drug and alcohol dependence*, 132(1-2), 95–100.

Kaplan, J. (2019). Uniform crime reporting (ucr) program data: County-level detailed arrest and offense data.

Kenan, K., Mack, K., & Paulozzi, L. (2012). Trends in prescriptions for oxycodone and other commonly used opioids in the united states, 2000–2010. *Open Medicine*, 6(2), e41.

Kertesz, S. G. & Gordon, A. J. (2019). A crisis of opioids and the limits of prescription control: United states. *Addiction*, 114(1), 169–180.

Kropko, J. & Kubinec, R. (2018). Why the two–way fixed effects model is difficult to interpret, and what to do about it. *Available at SSRN 3062619*.

Krueger, A. B. (2017). Where have all the workers gone? an inquiry into the decline of the us labor force participation rate. *Brookings papers on economic activity*, 2017(2), 1.

Laird, J. & Nielsen, T. (2016). The effects of physician prescribing behaviors on prescription drug use and labor supply: Evidence from movers in denmark. *Job market paper. http://scholar. harvard. edu/files/lairdja/files/Laird_ JMP. pdf*.

Leslie, D. L., Ba, D. M., Agbese, E., Xing, X., & Liu, G. (2019). The economic burden of the opioid epidemic on states: the case of medicaid. *Am J Manag Care*, 25, S243–S249.

Levine, M. & Fraser, M. (2018). Elements of a comprehensive public health response to the opioid crisis. *Annals of internal medicine*, 169(10), 712–715.

Mattson, C. L., Schieber, L., Scholl, L., Rudd, R. A., Seth, P., Xu, L., Wilson, N. O., & Paulozzi, L. J. (2017). Annual surveillance report of drug-related risks and outcomes–united states, 2017.

McCabe, S. E., Cranford, J. A., & Boyd, C. J. (2006). The relationship between past-year drinking behaviors and nonmedical use of prescription drugs: prevalence of co–occurrence in a national sample. *Drug and alcohol dependence*, 84(3), 281–288.

Muennig, P. A., Reynolds, M., Fink, D. S., Zafari, Z., & Geronimus, A. T. (2018). Americas declining well–being, health, and life expectancy: not just a white problem. *American journal of public health*, 108(12), 1626–1631.

Muhuri, P. K., Gfroerer, J. C., & Davies, M. C. (2013). Associations of Nonmedical Pain Reliever Use and Initiation of Heroin Use in the United States. *Center for Behavioral Health Statistics and Quality, SAMHSA*, 1, 17.

National Academies of Sciences, Engineering, and Medicine (2017). *Pain management and the opioid epidemic; balancing societal and individual benefits and risks of prescription opioid use.* National Academies Press.

National Safety Council (2020). Implications of Drug and Alcohol Use for Employers. National Safety Council.

Nichols, A. et al. (2006). Weak instruments: An overview and new techniques. In *Stata 5th North American Meeting Presentation.*

NIDA (2020). *Overdose Death Rates.* Technical report, National Institute on Drug Abuse.

OECD (2018). *OECD Economic Surveys: United States.* Technical report, OECD.

Oregon Health Authority (2012). *Prescription Drug Dispensing in Oregon October 1, 2011 – March 31, 2012.* Technical report, Oregon Health Authority.

Patrick, S. W., Schumacher, R. E., Benneyworth, B. D., Krans, E. E., McAllister, J. M., & Davis, M. M. (2012). Neonatal abstinence syndrome and associated health care expenditures: United states, 2000–2009. *Jama*, 307(18), 1934–1940.

Paulozzi, L. J., Strickler, G. K., Kreiner, P. W., & Koris, C. M. (2015). Controlled substance prescribing patterns–prescription behavior surveillance system, eight states, 2013. *Morbidity and Mortality Weekly Report: Surveillance Summaries*, 64(9), 1–14.

Perrott, G. S. J. & Holland, D. F. (2005). Population trends and problems of public health. *The Milbank Quarterly*, 83(4), 569.

Preuss, C. V., Kalava, A., & King, K. C. (2019). Prescription of controlled substances: benefits and risks. In *StatPearls [Internet]*. StatPearls Publishing.

RATE, P. (2014). The labor force participation rate since 2007.

Richter, A. W., Chapman, D., & Mihaylov, E. (2018). Declining us labor force participation rates stand out. *Economic Letter*, 13(6), 1–4.

Ropero-Miller, J. D. & Speaker, P. J. (2019). The hidden costs of the opioid crisis and the implications for financial management in the public sector. *Forensic Science International: Synergy*, 1, 227–238.

Rosenblum, A., Marsch, L. A., Joseph, H., & Portenoy, R. K. (2008). Opioids and the treatment of chronic pain: controversies, current status, and future directions. *Experimental and clinical psychopharmacology*, 16(5), 405.

SAMHSA (2013). Drug abuse warning network, 2011: national estimates of drug-related emergency department visits.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, (pp. 393–415).

Scavette, A. (2019). Exploring the economic effects of the opioid epidemic. *Economic Insights*, 4(2), 1–7.

Schieber, L. Z., Guy, G. P., Seth, P., Young, R., Mattson, C. L., Mikosz, C. A., & Schieber, R. A. (2019). Trends and patterns of geographic variation in opioid prescribing practices by state, united states, 2006–2017. *JAMA network open*, 2(3), e190665–e190665.

Sites, B. D., Beach, M. L., & Davis, M. A. (2014). Increases in the use of prescription opioid analgesics and the lack of improvement in disability metrics among users. *Regional Anesthesia & Pain Medicine*, 39(1), 6–12.

Staiger, D. & Stock, J. H. (1994). *Instrumental variables regression with weak instruments*. Technical report, National Bureau of Economic Research.

Substance Abuse and Mental Health Services Administration (2017). *Results from the 2016 National Survey on Drug Use and Health: National Findings*. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration.

The Washington Post (2019). Drilling into the dea's pain pill database.

Vowles, K. E., McEntee, M. L., Julnes, P. S., Frohe, T., Ney, J. P., & van der Goes, D. N. (2015). Rates of opioid misuse, abuse, and addiction in chronic pain: a systematic review and data synthesis. *Pain*, 156(4), 569–576.

Wilson, N. (2020). Drug and opioid-involved overdose deaths–united states, 2017–2018. *MMWR. Morbidity and Mortality Weekly Report*, 69.

Wixson, S. E., Blumenschein, K., Goodin, A. J., Talbert, J., & Freeman, P. R. (2015). Prescription drug monitoring program utilization in kentucky community pharmacies. *Pharmacy practice*, 13(2).

Wooldridge, J. (2009). Instrumental variables estimation and two stage least squares. *Introductory Econometrics: A Modern Approach. Nashville, TN: South-Western*.

Zhou, C., Yu, N. N., & Losby, J. L. (2018). The association between local economic conditions and opioid prescriptions among disabled medicare beneficiaries. *Medical care*, 56(1), 62.