

# Prescription Opioids and Labor Market Pains:

The Effect of Schedule II Opioids on Labor Force Participation and Unemployment\*

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## Abstract

We examine the effect of prescription opioids on county labor market outcomes, using data from the Prescription Drug Monitoring Programs of ten U.S. states and labor data from the Bureau of Labor Statistics. We achieve causal identification by exploiting plausibly exogenous variation in the concentration of high-volume prescribers as instruments (using Medicare Part D prescriber data). We find strong adverse effects on labor force participation rates, employment-to-population ratios, and unemployment rates. Notably, a 10 percent increase in prescriptions causes a 0.56 percentage point reduction in labor force participation, similar to the drop attributed to the 1984 liberalization of Disability Insurance.

**Keywords: Prescription Opioids, Unemployment, Regional Labor Markets**

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\*We are grateful to the states who shared data from their PDMP or CSMD. All errors are our own.

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# 1 Introduction

The use and abuse of prescription opioids in the United States has become sufficiently ubiquitous to be labeled an epidemic. The number of opioid prescriptions written and dispensed in the U.S. has grown more than three-fold from 76 million in 1991 to almost 245 million in 2014, roughly equivalent to one opioid prescription per adult in the U.S. (Volkow, 2014; Volkow and McLellan, 2016). Prescription growth has been accompanied by a host of adverse outcomes including higher rates of opioid overdose, abuse, addiction, diversion, emergency room visits, and neonatal abstinence syndrome (SAMHSA, 2011; Patrick et al., 2012; Nelson et al., 2015; Chou et al., 2015). While much of the focus on the opioid epidemic has centered on how opioid use affects users' health, their families, and communities, little is known about how the rise in opioid prescriptions has impacted labor outcomes at the individual or aggregate level.

In this paper we use variation in provider-prescribing behavior per county to estimate the causal effect of per capita opioid prescriptions on county labor market outcomes including unemployment rates, labor force participation rates, and employment-to-population ratios. While the vast majority of labor economics research is conducted using individual-level data, in our context county data yield three distinct advantages. First, diversion of prescriptions presents a significant challenge in evaluating the effects of prescription opioids. Most illegal opioids are not purchased from street corners, but received from friends and family. Similarly, a substantial share of prescribed opioids is diverted to friends, family, or illegal markets rather than being consumed by the patient who received the prescription.<sup>1</sup> In practice, diversion within immediate social circles would be impossible to track using individual-level prescription data, which is currently not available in the U.S. Therefore, county-level analysis better enables us to capture the net effects of all per capita opioid prescriptions (both legitimate and diverted) on labor force participation and employment. Second, counties represent a common region for policies to promote labor force engagement and mitigate problems associated with substance abuse. The former includes workforce development and training initiatives and the latter includes public health programs that seek to mitigate substance use and abuse. A third advantage is that aggregate data allow isolation of net impacts on the labor market.

Because opioids have both a therapeutic use in treating pain as well as a narcotic effect

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<sup>1</sup>In 2013 and 2014, on average 25.2 percent of misused prescription drugs (i.e. using a prescription drug that was not prescribed to you or taken solely for the euphoric feeling it caused) were from doctors, 66.3 percent were from a friend or relative (a category including drugs offered free, sold, or stolen), and only 8.5 percent were from drug dealers or other strangers (Lipari and Hughes, 2017). Other estimates on diversion rates range from 5 percent to 50 percent (Garnier et al., 2010; Surratt et al., 2014).

and high risk of dependency, prescription opioids may have both beneficial and adverse effects on labor force participation and unemployment rates. On the positive side, opioids have a therapeutic purpose for pain treatment and may help individuals continue or resume work. Garthwaite (2012) and Butikofer and Skira (2017) examine the effects of Cox-2 inhibitors (which also treat a specific sort of pain) and found positive effects on workplace attendance. However, Cox-2 inhibitors do not have the potential for dependence, addiction, or use as an intoxicant, all of which can lead to adverse labor market outcomes.

While most prior work on the relationship between intoxicants and labor market outcomes has focused on alcohol or illegal drug use, the relationship between prescription opioids and labor market outcomes may fundamentally differ from that of alcohol or illicit drugs (Cook and Moore, 1993; French and Zarkin, 1995; Mullahy and Sindelar, 1993, 1996; Buchmueller and Zuvekas, 1998; Zarkin et al., 1998; DeSimone, 2002; Auld, 2005; Bray, 2005). The aforementioned therapeutic potential implies that prescription opioids may positively affect employment outcomes in moderation, but negatively affect employment when taken for illegitimate purposes or in excess.<sup>2</sup> Additionally, the social context of prescription drug use differs fundamentally from alcohol and other illicit substances. Prescription opioids are initially dispensed by a health care provider, are legal, and are sanctioned by the health community for private use. While alcohol and prescription opioids are legal, the use of prescription opioids is arguably less acceptable in social settings. These contextual differences likely imply that individuals who select into prescription opioid use will differ in both observable and unobservable characteristics from those who select into heavy alcohol or illicit drug use.<sup>3</sup> These differences suggest that prescription opioids may affect labor market outcomes differently than alcohol or other illicit substances.

To empirically examine the relationship between prescription opioids and labor market outcomes, we use an unbalanced panel of county-year data on per capita opioid prescriptions from the prescription drug monitoring program (PDMP) databases of 10 U.S. states from 2010 to 2015 and county labor market data from the Bureau of Labor Statistics (BLS).<sup>4</sup> Because it is

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<sup>2</sup>Papers such as Mullahy and Sindelar (1993) have documented a similar phenomenon for alcohol. However, as alcohol has no medical therapeutic use, this is viewed as somewhat of a puzzle. Similar findings would be less surprising for opioids.

<sup>3</sup>Demographically, prescription opioid use may be more concentrated in different segments of the population than either alcohol or other illicit substances. For example, McCabe et al. (2007) finds that race/ethnicity was not a significant predictor of prescription drug misuse among college students, but was a significant predictor for illicit drug use (most common among White and Hispanic students). Alcohol use is also most common among Whites (Office of the Surgeon General, 2016). There is evidence to suggest that prescription opioid misuse is also significantly related to age. A 2014 report by the Substance Abuse and Mental Health Services Agency finds that the two younger age brackets, 18 to 24 year olds and 25 to 34 year olds, were the most likely to be admitted for prescription opioid abuse treatment. There were no gender differences except at the oldest age bracket (65 or older), where women were more likely than men to be admitted (SAMHSA, 2014).

<sup>4</sup>PDMPs are used to collect, monitor, and analyze prescribing and dispensing data submitted electronically by

impossible to distinguish between legitimate and illegitimate uses of prescription opioids, we interpret these results as a net effect of both types of use. We partially control for medical necessity by including controls for the supply of primary care doctors and cancer mortality rates.

Our model is identified through variation in provider practices between counties, specifically the number of high-volume opioid prescribers per capita in a given county. We merge data on opioid prescriptions by physician from the Medicare Part D summary claims database to identify the concentration of providers in each county in the nation’s top-five percent of opioid prescriptions written and the nation’s top-one percent of doses prescribed.<sup>5</sup> Previous research has used the top-five percent as a cut-off to define high-volume prescribers (Betses and Brennan, 2013; Daubresse et al., 2017), while the top-one percent was chosen as a secondary measure of even heavier prescribers. While Medicare Part D data do not cover all prescriptions, it covers most providers. According to a Kaiser Family Foundation survey of primary care doctors, 93 percent accept Medicare patients (Boccuti et al., 2015). Additionally, roughly two thirds of primary care physicians who accept Medicare patients report that less than half of their patients have Medicare, suggesting that the majority of prescribers in the Medicare Part D database have a mix of older and relatively younger patients. Essentially, the thought experiment behind our instruments is the following: suppose we subtract a high volume prescriber from a given county, while opioids per capita prescribed in that county will likely decrease, the unobservable factors that affect the labor market will not.

Prior work has found that providers have considerable autonomy in the way they conduct their practices. Therefore, a considerable share of the variation in medical practice is attributable directly to the provider (Davis et al., 2000; Grytten and Sorensen, 2003; Wang and Pauly, 2005).<sup>6</sup> Our identification strategy relies on the exogeneity of the heterogeneity in provider practices to labor market outcomes. While it is certainly true that patients’ demand affects the equilibrium number of prescriptions written, this is only an issue in our context if preferences among the patients of the heavy prescribers is correlated with the unobservable factors that affect county

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pharmacies and prescribing practitioners (e.g., physicians or nurse practitioners) in an effort to combat prescription drug misuse, abuse, and diversion. Currently all PDMPs are operated at the state level, and PDMPs have been authorized or established in all 50 states and Washington D.C.

<sup>5</sup>We use the national distribution so that our measure of per-capita heavy prescribers is comparable across states. We also verify that the performance of our instrumental variables and our second-stage results are not sensitive to the thresholds at the top-one and top-five percent. We verify that our results are similar in instrument strength, instrument validity, and estimated effect when using several delineations of ‘heavy prescribers.’ Results are available in Appendix Table A2.

<sup>6</sup>Recent work by Sacarny et al. (2017) suggests that high-volume prescribers are aware that they are heavy prescribers and may be reluctant to change.

labor outcomes. We address these concerns in two ways. First, any correlation between the concentration of heavy prescribers and unobservable factors related to county labor market outcomes (e.g., patient appropriateness for opioids, proportion of the population with legitimate pain problems, etc.) will result in violations of the orthogonality condition for our instruments. Because our model is over-identified, we are able to directly test our instruments using Hansen’s J-test, and find no evidence to support concerns regarding the orthogonality of our instruments to unobservable labor market factors. Second, we estimate the model with alternative instruments, including the number of prescriptions written for Schedule IV non-opioids written (per capita) by high-volume opioid prescribers and the number of high-volume Schedule IV prescribers in a county.<sup>7</sup> These instruments perform well and our results are unchanged under the alternative strategies. In demonstrating that our findings are robust when instrumenting for opioid prescriptions with prescriptions of non-opioids, we provide additional evidence that the variation behind our identification strategy stems from heterogeneity in provider practices.

We find that prescription opioids adversely impact county-level labor market indicators. Our preferred model indicates that a 10 percent increase in per capita opioid prescriptions leads to a 0.61 percentage point reduction in the employment-to-population ratio. For a given population, a decrease in the employment-to-population ratio could occur if more people leave their jobs either voluntarily or involuntarily. If these individuals continue looking for work, the unemployment rate will increase. Alternatively, if these individuals were to exit the labor force entirely, the labor force participation rate will decrease. We find that a 10 percent increase in per capita opioid prescriptions leads to a 0.56 percentage point drop in the labor force participation rate,<sup>8</sup> and a 0.1 percentage point increase in the county unemployment rate, though the latter is only marginally significant.

Finding that prescription opioids have a strong negative effect on the labor force participation rate but only a marginal adverse effect on the unemployment rate suggests that prescription opioids are primarily leading people to exit the labor force entirely. These results contrast sharply with the positive labor market effects found for Cox 2 inhibitors, which were also used to treat pain but not used for recreational purposes (Garthwaite, 2012; Butikofer and Skira, 2017).

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<sup>7</sup>Schedule IV drugs include benzodiazepines such as alprazolam (Xanax) and diazepam (Valium) as well as a number of sleeping pills such as zolpidem (Ambien) and eszopiclone (Lunesta). Our results are robust to the inclusion/exclusion of Schedule IV opioids (tramadol and dextropropoxyphene) of any analysis involving Schedule IV drugs. High-volume Schedule IV prescribers were defined in a similar fashion as the high-volume opioid prescribers – those in the nation’s top-five percent of Schedule IV prescriptions written and the nation’s top-one percent of doses supplied.

<sup>8</sup>This is comparable to the reduction in labor force participation among high school dropouts that is attributed to the 1984 liberalization of the federal Disability Insurance program (Autor and Duggan, 2003).

While prescription opioids may have therapeutic value which could help individuals suffering from pain to continue or return to work, our findings imply that for a regional labor market the adverse effects of opioids dominate any positive labor market effects from therapeutic use. These outcomes reflect both individual behavior and firm dynamics of hiring and termination.

To supplement the county-level analysis, we also examine the relationship between prescription opioids and labor force engagement at the regional level using data from the Drug Enforcement Administration’s Automated Reports and Consolidated Orders System (ARCOS), which contains data from 2000 to 2016 for all U.S. states and Washington D.C.. While the ARCOS data cover all 50 states and more years than our 10-state PDMP data, they are reported at the generally larger area defined by 3-digit zip codes.<sup>9</sup> Thus, while we view the county as the preferable unit of observation for labor market outcomes, we acknowledge that the ARCOS data may have more complete information on prescription opioids. Therefore, there is useful information in both the county PDMP and the regional ARCOS analysis. Our results are highly similar when using opioid data from either source, indicating that imperfections in either variable of interest are not responsible for our findings.

Using quantile regressions, we also investigate whether the labor market effects of prescription opioids vary by the vitality of the county labor market. Our results indicate that prescription opioids have the strongest measurable adverse effects in counties with higher labor force participation rates and employment-to-population ratios and lower unemployment rates. We also find that the marginal effects of prescription opioids on county labor market indicators do not substantively differ between relatively rural and non-rural counties.

To our knowledge, this is the first paper to examine the direct causal linkage between prescription opioids and labor market outcomes at the county level. The question of how opioid use affects labor market outcomes is relatively new in the economics literature, and the early evidence is somewhat mixed. Hollingsworth et al. (2017) show that higher unemployment rates are associated with higher opioid-related death and overdose rates. Laird and Neilson (2016) examine the effects of physician-prescribing behaviors on labor market outcomes in Denmark, and find that increases in physician prescribing rates are associated with a slight decrease in the probability of labor force participation. However, Laird and Neilson estimate the effect of changes in the prescriber environment rather than the direct effects of opioids prescribed on labor market outcomes. Conversely, Kilby (2015) finds evidence consistent with the therapeutic value of opioids: the introduction of PDMPs leads to a decrease in opioid prescriptions and an

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<sup>9</sup>For example, Tennessee has 95 counties, but only 15 3-digit zip code regions.

increase in absence rates for short-term disabled and injured workers. However, Kilby (2015) does not examine rates of labor force participation or unemployment.

The remainder of the paper is organized as follows: Section 2 provides background on the opioid epidemic. Section 3 describes both the county-level data that we have acquired from a number of U.S. states and the ARCOS regional-level data on all U.S. states, and Section 4 outlines the empirical framework. Section 5 presents the results, and Section 6 concludes with a brief discussion.

## 2 Background

Several factors have contributed to the increased prevalence of prescription opioid use, including changes in how opioids are viewed by the American medical community and the rapid development and Federal Drug Administration (FDA) approval of new types of opioids in the mid-1990s and 2000s.<sup>10</sup> In 1999 the National Pain Society launched a campaign to treat pain as a “fifth vital sign,” and minimizing pain through opioid use, without comprehensive evidence of either the effectiveness or consequences of long-term use became commonplace (Meldrum, 2003; Mularski et al., 2006).<sup>11</sup> This regime change in the rationale for opioid use dovetailed with the rollout of extended-release opioids, which can impart psychoactive effects for up to twelve hours from a single dose. When the first of these, MS Contin (morphine sulfate), was approved by the FDA in 1987, no significant increase in opioid misuse followed. In 1995 the third extended-release opioid, OxyContin (oxycodone controlled-release), was approved and marketed aggressively to physicians.<sup>12</sup> The rollout of OxyContin appears to have been a watershed moment in the emergence of the opioid epidemic, with emergency room visits from prescription drug misuse increasing substantially in the early 2000s (FDA, 2017b). Extended-release opioids, such as OxyContin, are associated with a higher risk of addiction and overdose, and two decades after OxyContin’s release there were 52 extended-release opioids with FDA approval on the market (FDA, 2017a). From 1999-2015, the percentage of drug overdoses involving opioids more

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<sup>10</sup>For a comprehensive overview of the way chronic pain has been treated by the American medical system from the 1970s to present, and how opioids fit into this history, see Tompkins et al. (2017).

<sup>11</sup>The ubiquitous pain metric scales in doctors offices which ask patients to rate their pain on a scale from 0 to 10 are the culmination of this campaign. Ballantyne and Sullivan (2015) note that “[for patients with chronic pain] maintaining low pain scores requires continuous or escalating doses of opioids at the expense of worsening function and quality of life” (p. 2098).

<sup>12</sup>OxyContin’s parent company, Purdue Pharmacy, was sent a warning letter by the FDA in 2003 because its medical journal advertisements neglected to mention addiction as a possible negative side effect of OxyContin use (FDA, 2017). In 2007 the company and three executives pleaded guilty to criminal charges that they misled regulators, doctors, and patients about the drug’s risk of addiction, and the company paid out \$600 million in fines and settlement payments (Meier, 2010).

than doubled from 30 to 63.1 percent, and in 2015 alone, opioids were involved in 33,091 drug overdose deaths in the U.S. (Department of Health and Human Services, 2013; Rudd, 2016).

In 2014 there were an estimated 2.5 million adults affected by opioid addiction in the U.S. (Volkow and McLellan, 2016). Boscarino et al. (2010) found evidence to suggest that 26 percent of patients who received long-term opioid therapy (four or more opioid prescriptions in a 12-month period) from a primary physician would struggle with opioid dependence. Furthermore, Shah et al. (2017) found that the probability of long-term opioid use increases most dramatically during the first days of therapy. Specifically, the likelihood of chronic opioid use increases with each additional day of medication supplied, but the sharpest increases occurred after the 5th and 31st day, or after receiving just one prescription refill. While the path to opioid dependence and/or chronic use differs across these two studies, both highlight the addictive nature of prescription opioids and the role of provider behavior (in the amount prescribed) in the risk of dependence.

The U.S. labor force participation rate has been on a steady decline since 2000, which coincides with large increases in prescription opioid use for both medical and non-medical reasons.<sup>13</sup> For earlier years, Zancy et al. (2003) show that the number of people using a prescription opioid for a non-medical reason increased five-fold from 400,000 people per year in the mid-1980s to roughly 2 million in 2000.<sup>14</sup> The authors also find evidence to suggest that the prevalence of non-medical prescription opioid use was steady from 1999 to 2000, but increased significantly from 2000 to 2001. Moreover, Compton et al. (2016) estimate that this figure has ballooned in recent years, with over 10.3 million Americans using prescription opioids for non-medical purposes in 2014. Similarly, Gilson et al. (2004) show that the total medical use of Oxycodone and Fentanyl, two popular prescription opioids, increased by over 402.9 percent and 226.7 percent respectively from 1997 to 2002. However, the extent to which prescription opioids have affected labor force engagement is unclear. Krueger (2015) finds that out of 571 nonworking men, close to one third reported taking prescription pain medication. Krueger also examined data from the American Time Use Survey Well-being Supplement (ATUS-WB) and found that 44 percent of prime-age men who were out of the labor force had reported taking pain medication the previous day, which was more than double the rates for employed and unemployed men. However, it is important to note that the survey did not differentiate between non-prescription (e.g. Tylenol,

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<sup>13</sup>The labor force participation rate of men has been in decline since the 1940s while the labor force participation rate of women peaked in 2000 and has since declined. There are many possible explanations for these trends. For example, see Autor (2015).

<sup>14</sup>Non-medical use was defined as using a prescription drug even once, that was not prescribed for you, or that you took only for the experience or feeling it caused (Zancy et al., 2003).



Advil, etc.) and prescription pain medication. It is also unclear from these surveys whether individuals are not employed because of pain medication use or whether they are unemployed and using pain medication because of a health condition.

Table I reports data from the 2014 National Survey of Drug Use and Health (NSDUH), a survey of 55,271 people aged 12 and over. The survey asks questions about drug use behavior as well as demographic data. We use this data to compare the observable characteristics of individuals who report ever using prescription opioids for a nonmedical reason to individuals who report ever using other intoxicants. We compare family income, race, age, gender, and education levels for both groups. Age is restricted to those 24 and over for the education comparison but unrestricted for other comparisons. Compared to other intoxicants, users of prescription opioids (non-medically) are a relatively young, male, working class subset of the population. They are less likely to have graduated college and less likely to earn at least \$75,000 per year compared to users of other substances (except heroin). Additionally, 47 percent of prescription opioid users are younger than age 35, while only 38 percent of marijuana users are under age 35.

In summary, the opioid epidemic has coincided with mounting concerns regarding declining economy-wide labor force participation, despite the absence of direct evidence. Importantly, prescription opioids represent a substance that differs socially, demographically, and pharmacologically from other substances whose impacts on the labor force have been previously documented. The limited evidence does not offer clarity on the extent to which opioid use may affect individual and aggregate engagement with the labor market. We therefore focus on county-level opioid prescriptions to determine whether dispensation has a material effect on economy-wide labor market outcomes, as measured by traditional and observable metrics like participation rates, unemployment rates and employment-to-population ratios. Our causally-identified estimates, based on data from 10 U.S. states, reveal large and statistically significant adverse impacts on the labor market.

### 3 Data

County-level data on opioid prescriptions were acquired directly from 10 U.S. states – Arkansas, California, Colorado, Florida, Massachusetts, Michigan, Ohio, Oregon, Tennessee and Texas – by request through their respective Controlled Substance Monitoring Database (CSMD) or PDMP database. These data form an unbalanced panel from 2010 to 2015. We use the total number of Schedule II opioid prescriptions filled per county in a given year as our

Table I: Summary Comparison of Prescription Drug Misuse and Use of Other Illicit Drugs

	Percent of Respondents Who Ever Use a Specific Drug (Non-medically)				
	Pain Relievers	Alcohol	Marijuana	Cocaine	Heroin
Education					
Less Than High School	13.34	10.86	9.61	11.94	20.22
High School	27.72	27.51	27.15	28.24	27.26
Some College	30.57	27.01	28.88	31.30	35.22
College Graduate	28.36	34.62	34.36	28.52	17.31
Family Income					
< \$20,000	20.77	16.59	17.32	18.94	32.94
\$20,000 - \$49,999	31.71	30.12	28.95	29.36	33.02
\$50,000 - \$74,999	16.28	17.22	16.72	16.63	13.36
≥ \$75,000	31.25	36.07	37.00	35.07	20.68
Race					
White	71.77	67.97	71.62	75.53	76.55
Black	9.96	11.02	11.47	7.58	9.95
Hispanic	12.77	14.45	11.68	11.97	8.43
Age					
12-17 Years	5.04	3.40	3.49	0.59	0.83
18-25 Years	19.19	13.40	15.85	9.92	14.53
26-34 Years	22.86	15.84	17.97	17.15	25.52
35-49 Years	25.76	24.90	25.79	29.33	24.62
50-64 Years	22.37	25.51	28.47	37.28	28.29
≥ 65 Years	4.77	16.95	8.42	5.73	6.21
Gender					
Male	56.66	49.91	54.23	61.44	71.60
Female	43.34	50.09	45.77	38.56	28.40

Authors' calculations from the National Survey on Drug Use and Health, 2014.

Age is restricted to 24 and over for the education comparison but unrestricted otherwise.

measure of ‘opioid prescriptions’. The Drug Enforcement Administration (DEA) classifies drugs into five categories based on the drug’s acceptable medical use and abuse potential.<sup>15</sup> Schedule I is reserved for drugs with no acceptable medical use and a high potential for abuse, such as heroin and lysergic acid diethylamide (LSD). Schedules II-V have accepted medical uses and decreasing potential for psychological or physical dependence. Most of the ongoing conversation about ‘prescription opioids’ focuses on Schedule II opioids (e.g., Hydrocodone, OxyContin, Oxycodone, Fentanyl), which have acceptable medical use but high potential for abuse. These drugs must be prescribed in writing and refills are prohibited in the absence of a new prescription from the provider. Our empirical analysis focuses on the dispensing of all Schedule II prescription opioids, as the goal of the paper is to model the effects of increased prescriptions in this pivotal class of drugs.<sup>16,17</sup> We convert prescriptions to per capita measures to facilitate comparisons across counties and states.

Table II reports state-level data as evidence of the representativeness of these ten states. (These are 2012 data, the only year for which state-level opioid prescription data are available for all states.) The ten states together accounted for 41.4 percent of the U.S. population in 2012. The average unemployment rate for the ten states is slightly higher than the national average (8.5% vs 8.1%) and the labor force participation rate is slightly lower (63.1% vs 63.8%). Average opioid prescriptions per capita for the U.S. were 0.82 compared to 0.78 for our ten states in 2012. Tennessee held the second-highest prescription rate in the nation while California had the lowest among all U.S. states.

We obtained data on prescribers from the 2013-2015 Medicare Part D Prescriber database housed by the Centers for Medicare and Medicaid Services. From these data, we identify the number of practitioners in each county in the top-five and top-one percent of opioid prescribers in the nation, as measured by the number of opioid prescriptions written and the number of doses prescribed, respectively. We use the number of high-volume prescribers per-capita in a county-year, to identify the causal effects of per capita opioid prescriptions on labor market outcomes. Previous work has shown that the majority of prescription drugs in a given state are prescribed by a small percentage of practitioners (Dhalla et al., 2011; Department of Health

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<sup>15</sup><https://www.dea.gov/druginfo/ds.shtml>

<sup>16</sup>A small number of prescription opioids are classified as Schedule III narcotics (drugs with acceptable medical use and low potential for dependence), including some cough syrups and Tylenol mixed with less than 90 milligrams of codeine per dosage.

<sup>17</sup>The prescription opioids data provided by Colorado and Ohio measured all opioid prescriptions and not just Schedule II opioids, thus over-counting the number of Schedule II opioid prescriptions coming from these two states. In the subsequent regression analysis, this is accounted for through unique metropolitan statistical area (MSA) fixed effects that differ across states.

and Human Services, 2013). For example, an analysis of Oregon’s PDMP indicated that the top 4.1 percent of prescribers were responsible for 60 percent of all Schedule II-IV controlled substances dispensed in a six month period (Oregon Health Authority, 2012). Similarly, data from California suggest that 3 percent of the prescribing physicians account for 55 percent of all Schedule II prescriptions (Swedlow et al., 2011). Furthermore, Powell et al. (2015) show that increases in opioid prescriptions are associated with diversions to non-medical uses, while Laird and Neilson (2016) find that a higher concentration of high-prescribing general practitioners leads to increases in individual opioid use. The intuition behind our identification strategy is that individuals who are in close proximity to one (or more) of these high-volume prescribers, by virtue of living in the same county, will face lower time and transportation costs and less difficulty in accessing prescription opioids within family and social circles.

Table III shows how opioid prescriptions per capita vary across states and time.<sup>18</sup> Because the data necessary for our identification strategy are only available from 2013-2015, we restrict our analytical sample to those years. Average per capita opioid prescriptions over the analytic sample are also presented as a map in Figure 1. Prescription opioids data were available for eight of the 10 states in all three years, and all 10 states in 2014 and 2015. In all three years, Tennessee had the highest average number of per capita opioid prescriptions, with roughly 1.4 prescriptions per person. If there is an average of 60 opioid doses per prescription, this is equivalent to prescribing 80 opioid doses to every man, woman, and child in Tennessee each year. Conversely, Texas and Massachusetts had the fewest per capita opioid prescriptions, averaging 0.4 and 0.5 prescriptions per person respectively. In the Analysis section, we perform a number of robustness checks to account for data reporting heterogeneity across the 10 states and examine whether our results are sensitive to the exclusion of certain states.

Table IV reports county-level data on the average number of high-volume opioid prescribers per 100,000 population at the county level in each state. Tennessee had the highest number of heavy opioid prescribers among the 10 states in our sample, averaging 18.0 prescribers per 100,000 population per county in the nation’s top-five percent and 4.3 per county in the top-one

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<sup>18</sup>In 2014 Hydrocodone, one of the most heavily prescribed opioids was rescheduled from Schedule III to the more restrictive Schedule II category (Laxmaiah Manchikanti et al., 2012; Drug Enforcement Administration, 2014). Most states in our dataset counted Hydrocodone prescriptions as a Schedule II opioid, even before the schedule change, as there was no uptick in Schedule II opioids after the schedule change (in 2014). Michigan was the exception, and as a result we have added Hydrocodone prescriptions to the Schedule II count for Michigan. Without this correction Michigan averaged only 0.26 prescription opioids per person in 2013, but in 2014, the year that Hydrocodone was rescheduled, per capita opioid prescriptions increased more than 3-fold to 0.93 prescriptions per person. Adding the Schedule III Hydrocodone prescriptions to the Michigan data completely removes this uptick, leads to much more stable prescription opioids per capita over time, and results in summary statistics that are more comparable to the other states in our sample (see Table III). In the Analysis section, we also perform robustness checks by excluding the Schedule III Hydrocodone prescriptions from the Michigan counties to see if this changes any of our results.

percent. In contrast, the counties in Colorado and Massachusetts averaged the fewest high-volume prescribers with only 2.9 and 3.0 practitioners per 100,000 people in the top-five percent of national prescribers respectively, and approximately 0.2 practitioners per 100,000 people in the top-one percent.

County-level labor force, employment, and unemployment rate data were collected from the Bureau of Labor Statistics (BLS), and county population and demographic data (age, gender, race, and ethnicity) were taken from U.S. Census Bureau. The percentage of the county population that is classified as rural is based on the 2010 U.S. Census. Additional health-related variables such as the number of cancer deaths and the number of primary care physicians per county were drawn from the Centers for Disease Control and Prevention (CDC) and the American Medical Associations (AMA) Physician Masterfile respectively. Each county is matched to a unique BLS-defined metropolitan statistical area (MSA) or regional nonmetropolitan area (e.g. East Tennessee nonmetropolitan area). County-level data on the number of marijuana-related arrests were collected from the U.S. Department of Justice’s Uniform Crime Reporting (USR) database. Data on the number of liquor stores and bars were gathered from the U.S. Census Bureau’s County Business Patterns database. Finally, data on the number of adults receiving disability benefits were taken from the Social Security Administration (SSA).

Table V reports summary statistics for the full sample (2010-2015) as well as the analytic sample (2013-2015), and shows that the two samples are fairly similar. The unemployment rate is higher in the full sample, which is not surprising given that the full sample contains more years closer to the Great Recession. In the analytic sample there were 2,167 county-level observations, with 505 counties observed in 2013, 830 in 2014, and 832 counties in 2015.<sup>19</sup> This increase in observations was due to the additions of Arkansas and Texas in 2014.

In addition to the county-level analysis, we also obtain regional-level opioid prescriptions data from the Drug Enforcement Administration’s Automated Reports and Consolidated Orders System (ARCOS) from 2000 to 2016 for all U.S. states and Washington D.C. ARCOS is an automated data system that tracks the flow of controlled substances starting at the drug manufacturer and ending at the point of sale or distribution (i.e. hospitals, retail pharmacies, practitioners, etc.). The ARCOS reports contain data on the total number of grams of all Schedule I and Schedule II substances, and select Schedule III narcotics sold or distributed.

For consistency with our county-level analysis, we examine prescriptions of Schedule II opioids

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<sup>19</sup>In the analytic sample 6 observations were dropped in 2014 and 2 were dropped in 2015, all from Texas, for having labor force participation rates greater than one: Loving County (2014 and 2015), King County (2014), McMullen County (2014 and 2015), and Kennedy County (2014).

Table II: State Profiles, 2012

State	Population <sup>a</sup>	Unemployment Rate <sup>b</sup>	Labor Force Participation Rate <sup>b</sup>	Opioid Prescriptions Per Capita <sup>c</sup>
Arkansas	2,950,685	0.076	0.594	1.16
California	38,011,074	0.104	0.629	0.57
Colorado	5,189,867	0.079	0.688	0.71
Florida	19,344,156	0.085	0.606	0.73
Massachusetts	6,658,008	0.067	0.651	0.71
Michigan	9,887,238	0.091	0.599	1.07
Ohio	11,550,839	0.074	0.632	1.00
Oregon	3,899,116	0.088	0.631	0.89
Tennessee	6,454,306	0.078	0.616	1.43
Texas	26,071,655	0.067	0.656	0.74
10 State Aggregate	130,016,940	0.085	0.631	0.78
U.S.	313,998,379	0.081	0.638	0.82

<sup>a</sup> Source: U.S. Census Bureau

<sup>b</sup> Source: Bureau of Labor Statistics

<sup>c</sup> Source: Paulozzi et al. (2014)

and hydrocodone. While the ARCOS data are measured in terms of grams, opioid doses are generally measured in milligrams (mg), for example hydrocodone dosages range from 5mg up to 10mg. Thus, a 60-pill prescription of 10mg hydrocodone would total 600mg or 0.6 grams. Therefore, in many cases, 1 gram of opioids is much larger than a full prescription.<sup>20</sup>

However, our PDMP data are measured in prescriptions, and in most cases we do not have sufficient information on dosages to convert to MME's (Morphine milligram equivalents). Therefore, it is difficult to make direct comparisons between the ARCOS data and the PDMP data. When we compare the magnitudes of our results from regressions using opioids as measured by PDMP or ARCOS data, we use the sample means for a common basis of comparison. As noted earlier, the ARCOS data cover a larger sample than the PDMP data described above (in both  $N$  and  $T$ ). However, the ARCOS data are reported at the more aggregated regional level, as measured by 3-digit zip codes and are not directly comparable to the BLS labor market data. In the subsequent ARCOS analysis, we convert the county-level labor force, employment, and unemployment data to the regional level using residential weights provided by the Department of Housing and Urban Development (HUD). Similar conversions are performed for the population, demographic, and health-related data as well. Appendix Table A1 presents summary statistics for the ARCOS full sample (2000-2016) and the analytic sample (2013-2015).

<sup>20</sup>This is not always the case with some of the stronger opioids such as oxycodone, with dosage ranges from 10mg up to 80mg. Here, a 60-pill prescription of 80mg oxycodone would equal 4,800mg or 4.8 grams.

Table III: Opioid Prescriptions Per Capita by State and Year

State	2010	2011	2012	2013	2014	2015	All Years
Arkansas					1.28 (0.22)	0.85 (0.16)	1.06 (0.29)
California	0.92 (0.36)	0.92 (0.36)	0.95 (0.37)	0.92 (0.36)	0.93 (0.35)	0.92 (0.33)	0.93 (0.35)
Colorado	0.82 (0.19)	0.87 (0.19)	0.86 (0.19)	0.83 (0.18)	0.82 (0.17)	0.79 (0.16)	0.83 (0.18)
Florida			0.83 (0.26)	0.81 (0.25)	0.78 (0.24)	0.75 (0.23)	0.80 (0.25)
Massachusetts	0.45 (0.11)	0.45 (0.10)	0.47 (0.10)	0.46 (0.10)	0.45 (0.10)	0.55 (0.11)	0.47 (0.10)
Michigan	0.83 (0.20)	0.91 (0.22)	0.96 (0.23)	0.96 (0.24)	0.93 (0.24)	0.87 (0.21)	0.91 (0.23)
Ohio	1.18 (0.36)	1.18 (0.34)	1.21 (0.33)	1.19 (0.32)	1.16 (0.32)	1.09 (0.30)	1.17 (0.33)
Oregon			1.01 (0.21)	1.06 (0.22)	1.02 (0.23)	0.96 (0.21)	1.01 (0.22)
Tennessee				1.42 (0.39)	1.38 (0.37)	1.32 (0.36)	1.37 (0.36)
Texas					0.26 (0.08)	0.50 (0.17)	0.38 (0.18)
Full Sample	0.93 (0.34)	0.96 (0.33)	0.96 (0.32)	1.04 (0.38)	0.81 (0.47)	0.82 (0.35)	0.89 (0.39)

A blank indicates no opioid data were available from that state year.

Standard deviations in parenthesis.

Data from CO and OH are on all opioid prescriptions and are now limited to Schedule II opioids. Ohio data were only available as the number of doses prescribed. The number of prescriptions were estimated as doses divided by 60.

Table IV: Summary Statistics: County-level Concentration of High-Volume Prescribers by State

State	Top 5 Claim	Top 1 Supply
Arkansas	13.31 (8.44)	2.11 (3.42)
California	7.06 (5.94)	1.00 (1.48)
Colorado	2.90 (4.96)	0.25 (0.91)
Florida	7.04 (4.42)	2.06 (1.97)
Massachusetts	3.00 (2.24)	0.21 (0.35)
Michigan	10.94 (8.38)	1.41 (2.70)
Ohio	7.43 (5.48)	1.00 (1.29)
Oregon	8.06 (5.74)	0.44 (0.95)
Tennessee	17.98 (11.09)	4.31 (4.92)
Texas	4.33 (6.54)	0.51 (1.15)

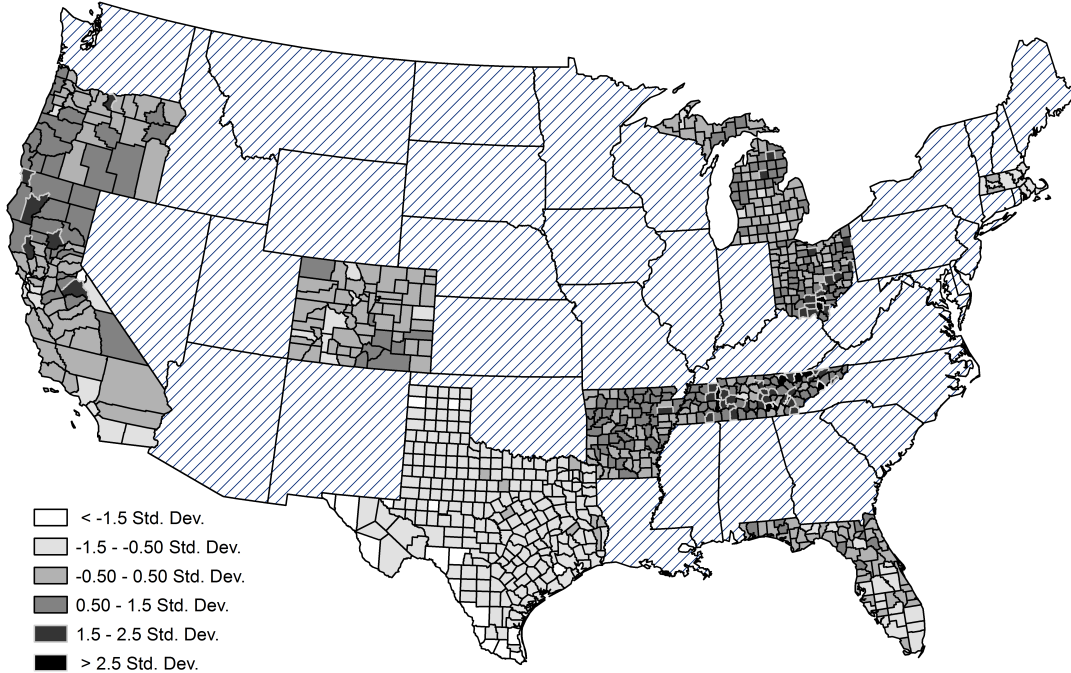
For a given county, Top 5 Claim is calculated as the number of prescribers in the top-5 percent of Part D opioid claims per 100,000 people. Top 1 Supply is the number of prescribers in the top-1 percent of opioid doses supplied per 100,000 people.  
Standard deviations in parenthesis.



Table V: Summary Statistics

Variable	Full Sample (2010-2015)	Analytic Sample (2013-2015)
Opioids Per Capita	0.894 (0.39)	0.867 (0.42)
Employment-to-Population Ratio	0.527 (0.08)	0.525 (0.08)
Unemployment Rate	0.078 (0.03)	0.067 (0.02)
Labor Force Participation Rate	0.571 (0.08)	0.562 (0.08)
Percent Male	0.504 (0.03)	0.504 (0.03)
Percent Female	0.496 (0.03)	0.496 (0.03)
Percent Black	0.087 (0.12)	0.088 (0.12)
Percent Hispanic	0.142 (0.18)	0.155 (0.19)
Percent Rural	0.51 (0.32)	0.524 (0.31)
Percent under 15 Years Old	0.182 (0.03)	0.182 (0.03)
Percent 15 through 19 Years Old	0.065 (0.01)	0.064 (0.01)
Percent 20 through 24 Years Old	0.064 (0.02)	0.064 (0.02)
Percent 25 through 34 Years Old	0.118 (0.02)	0.118 (0.02)
Percent 35 through 44 Years Old	0.119 (0.02)	0.117 (0.02)
Percent 45 through 54 Years Old	0.139 (0.01)	0.135 (0.01)
Percent 55 through 64 Years Old	0.14 (0.02)	0.14 (0.02)
Percent Aged 65+	0.173 (0.05)	0.179 (0.05)
Total Population	189,522 (573,849)	170,258 (525,751)
Number of Primary Care Physicians per Thousand People	0.58 (0.32)	0.34 (0.37)
Number of Cancer Deaths per 100,000 People	234.4 (68.1)	127.6 (129.8)
Top 1 Supply per 100,000 Population		1.43 (2.75)
Top 5 Claim per 100,000 Population		8.36 (8.55)
Number of Liquor Stores		21.92 (65.73)
Number of Bars		24.8 (58.53)
Number of Marijuana-Related Arrests (Sales)		35.10 (117.75)
Number of Marijuana-Related Arrests (Possession)		155.32 (483.22)
Number of Observations	3,191	2,167

Figure 1: Average Per Capita Opioid Prescriptions, 2013-2015



Note: Average opioids per capita data for Arkansas and Texas are for 2014 to 2015.

## 4 Empirical Specification

We estimate the relationship between opioid prescriptions and labor market outcomes using the following equation:

$$Y_{ist} = \beta_0 + \beta_1 O_{ist} + \beta_2 \mathbf{X}_{ist} + \beta_3 R_{is} + \gamma_s^2 + \delta_t^2 + \epsilon_{ist}^2 \quad (1)$$

where  $Y_{ist}$ , is the outcome variable (the unemployment rate, labor force participation rate and employment-to-population ratio) in county  $i$ , MSA/non-metro area  $s$ , in year  $t$ ;  $O_{ist}$  measures the number of Schedule II opioid prescriptions per capita written by practitioners in the same county; and  $\mathbf{X}_{ist}$  is a vector of explanatory variables including measures of the county's demographic composition (i.e. age, gender, race, and ethnicity). We include the number of primary care physicians per thousand residents and the number of cancer deaths per hundred thousand people as proxies for the health status of the county and the overall amount of care being provided.  $R_{is}$  measures the percentage of the county's population that is denoted as rural

in the 2010 Census.<sup>21</sup> Finally,  $\gamma_s^2$  and  $\delta_t^2$  represent metropolitan statistical area (MSA) and year fixed effects respectively.<sup>22,23</sup>

There are multiple reasons to be concerned about an endogenous relationship between prescription opioids and employment outcomes. Opioid prescriptions may be correlated with unobserved factors that also impact labor market outcomes, which could potentially bias the estimates from Equation (1). Counties experiencing declining labor market conditions may also be experiencing worsening population health. If a county population is trending towards both poorer health and economic decline, a spurious relationship between prescription opioid use and labor market outcomes could arise. Second, there is the prospect of reverse causality. If declining economic opportunities in a county lead individuals to engage in increased patterns of substance use, as is shown in Hollingsworth et al. (2017), estimates on  $\beta_1$  will be biased. To address these concerns, we implement an instrumental variables approach using the per capita concentration of high-volume prescribers as exclusion restrictions. The first-stage equation specifies the number of opioid prescriptions per capita as follows:

$$O_{ist} = \alpha_0 + \alpha_1 \mathbf{X}_{ist} + \alpha_2 R_{is} + \alpha_3 \mathbf{Z}_{ist} + \gamma_s^1 + \delta_t^1 + \epsilon_{ist}^1 \quad (2)$$

As described above, we rely on two instrumental variables, both of which measure the number of high-volume opioid prescribing practitioners in a county (or region for the ARCOS analysis): the per capita number of practitioners in a county (region) that are in the nation’s top-five percent of opioid prescriptions written, and the per capita number of practitioners in a county (region) that are in the nation’s top-one percent of opioid doses prescribed.<sup>24</sup> To check for simultaneity bias, we also estimate a 2SLS model with  $O_{i,t-1}$  as the variable of interest and  $\mathbf{Z}_{i,t-1}$  as the instruments. For our instrumental variables approach to work, our instruments must be relevant and orthogonal to the errors in the second stage, (i.e.,  $E[Z'\epsilon] = 0$ ). Any concerns about instrument validity, such as whether the concentration of heavy-prescribing providers is correlated with unobserved health or cultural factors that affect labor market outcomes, will result in violations of the orthogonality conditions. Because our model is overidentified, we can directly test the validity of our orthogonality assumption using tests developed by Sargan (1958) and Hansen (1982). We find no evidence that our instruments are invalid, with p-values ranging

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<sup>21</sup>County-level data on rural population were only available for 2010. We therefore assume a constant share of the rural population from 2010 to 2015. Our results are also robust to assuming a constant rural population.

<sup>22</sup>Because 96 percent of the total variation of prescription opioids per capita is between county means, models with county fixed effects essentially remove all of the variation in the variable of interest. We therefore rely on unique MSA fixed effects to absorb geographic heterogeneity in labor markets.

<sup>23</sup>In the regional analysis, we modify Equation 1 so that  $i$  and  $s$  index regions and states respectively.

<sup>24</sup>We use the national distribution so that our measure of per-capita heavy prescribers is comparable across states.

between 0.4 and 0.8.

We also examine how the treatment effect of opioids varies by the health of the regional economy. To that end, we employ a quantile regression specification to examine the effects of prescription opioids across the distributions of the employment-to-population ratio, labor force participation rate, and unemployment rate (Firpo et al., 2009). We acknowledge that our approach does not account for county-to-county drug flows, due to data limitations. However, over 91 percent of misused opioids are either attained from a provider or a friend/family member, and prior work has shown that, among friends, the majority of face-to-face contacts occur within five miles of an individual’s home (Tilly, 1982; Huckfeldt, 1983; Eagles et al., 2004; Mok et al., 2007, 2010). Furthermore, given the lack of any credible data on county-to-county drug flows, treating each county as an ‘opioid island’ is a reasonable starting point for identifying the effects of opioids on labor markets.

## 5 Results

Table VI reports the estimates from the first-stage equation. These first-stage results indicate that as the number of high-volume opioid-prescribing practitioners in a county increases, per capita opioid prescriptions also increase. The estimated coefficients on the two variables intended to capture the concentration of heavy-prescribing practitioners are both positive and statistically significant at the 5 percent level.<sup>25</sup> A joint significance test of the instruments produces an F-statistic of 17.16, which is above the benchmark value of 10 for instrument strength as outlined in Staiger and Stock (1997). Given that our chosen instruments are similar to one another, we also perform a redundancy test based on Breusch et al. (1999) and Baum et al. (2007) and find that both instruments are contributing to the estimation. Finally, we perform overidentification tests on the validity of our instruments using the Sargan-Hansen test. Results support the validity of our instruments.

We also conduct sensitivity analysis with respect to the definition of ‘high-volume opioid prescribers.’ We repeat our analysis with several alternative definitions of ‘heavy opioid prescribers’ including the number of providers per 100,000 people who wrote opioid prescriptions (or doses) greater than 1.5, 2.0, and 2.5 standard deviations above the national mean. In all cases, we use one instrument for heavy prescriber with respect to opioid prescriptions (i.e. claims)

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<sup>25</sup>We also find that the black and teenage proportions of the population are negatively related to per capita opioid prescriptions in a given county. The rural proportion and number of cancer-related deaths in a county are associated with higher levels of per capita opioid prescriptions. The results for the black population variable are consistent with previous research on racial trends in opioid prescribing (Green et al., 2003; Burgess et al., 2008; Shavers et al., 2010).

and one with respect to opioid doses. Results are available in Appendix Table A2. Column 1 repeats our main specification, with the other columns using alternative definitions for high-volume prescribers. Under all specifications of high-volume opioid prescribers, our instruments are jointly strong (F-statistics greater than 10) and under no specification do our instruments fail the validity test. Additionally, our second stage results are all within one standard error of our preferred specification, reported in Column 1.

Table VII presents the main empirical results on the effects of per capita opioid prescriptions on county labor market outcomes. In each panel, the first column reports the baseline results (without instruments) for the full sample (2010-2015) and the second column presents the baseline results for the analytic sample (the years for which instruments are available, 2013-2015). The third column contains second-stage results from our preferred IV specification. For the specification in the fourth column, we report the results of an IV specification that includes controls for the number of liquor stores, bars, and marijuana-related arrests per county. We include Column 4 as evidence that our findings are attributable to opioid use specifically, rather than an overall pattern of substance use. However, the potentially endogenous relationship between marijuana arrests and opioid use makes Column 3 our preferred specification. In all three panels, we find that the baseline estimates of the full sample are very similar to those of the analytic sample (comparing Columns 1 and 2), mitigating concerns about restricting our analysis to 2013-2015. Panel A reports results with the county-level employment-to-population ratio as the dependent variable. Per capita opioid prescriptions have a strong negative impact on the employment-to-population ratio in the baseline models, and the estimated effects are even larger in the preferred IV specifications. The baseline estimates in Panel A show that a one-unit increase in per capita opioid prescriptions leads to a 6.4 to 6.5 percentage point drop in the employment-to-population ratio, while the IV models estimate a 7.0 to 7.8 percentage point reduction in the employment-to-population ratio. While these estimated effects are quite large, a one-unit increase in opioids per-capita would imply more than doubling the number of opioids in the average county in our sample. For the effects of a more modest increase in prescription opioids, predictions based on the model in Column 3 indicate that a 10 percent increase in per capita prescription opioids leads to a 0.61 percentage point drop in the employment-to-population ratio.

Panels B and C in Table VII explore whether the effect on the employment-to-population ratio operates through the labor force participation rate or the unemployment rates. Our estimates suggest that prescription opioid use affects both. In our preferred IV specification, a

Table VI: First-stage Estimates

	Opioids Per Capita
Providers in Top 5 percent Opioid Prescriptions/100,000 Population.	0.0074** (0.0037)
Providers in Top 1 Percent Opioid Doses/100,000 Population	0.006*** (0.001)
Percent Female	0.692 (0.614)
Percent Black	-0.382*** (0.108)
Percent Hispanic	0.0423 (0.128)
Percent Rural	0.125** (0.057)
Percent under 15 Years Old	-0.147 (0.867)
Percent 15 through 19 Years Old	-3.816*** (1.166)
Percent 20 through 24 Years Old	-0.027 (1.056)
Percent 35 through 44 Years Old	-0.234 (1.693)
Percent 45 through 54 Years Old	-0.088 (1.354)
Percent 55 through 64 Years Old	-0.358 (0.881)
Percent Aged 65+	0.107 (0.832)
Number of Primary Care Physicians/1,000 Population	-0.04 (0.033)
Number of Cancer Deaths/100,000 Population	0.001*** (0.0002)
F-statistic (exclusions)	17.16
Observations	2,167

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

one-unit increase in per capita opioid prescriptions leads to a 6.5 percentage point drop in the labor force participation rate. Alternatively, these estimates imply that a 10 percent increase in per capita opioid prescriptions leads to a 0.56 percentage point reduction in the labor force participation rate. The magnitude of these effects suggests that over 80 percent of the opioid-induced change in the employment-to-population ratio is driven by individuals exiting the labor force. All else the same, a declining labor force participation rate would mean a falling unemployment rate. However, we find that increases in per capita opioid prescriptions increase the unemployment rate as well. In Panel C, our IV results indicate that a one-unit increase in per capita opioid prescriptions leads to a 1.2 percentage point increase in the unemployment rate, though this effect is only marginally significant. Scaling the size of the change in opioids, the model predicts that a 10 percent increase in per capita opioid prescriptions would lead to a 0.1 percentage point increase in the unemployment rate. Our results therefore indicate that high levels of per capita opioid prescriptions have significant adverse labor market effects at the county level, and this is primarily driven through workers exiting the labor force.

We subject the results from our preferred IV specification to a number of robustness checks in Table VIII. Column 1 reports our main specification to facilitate comparison. Column 2 contains a specification using lagged values of opioids per capita (and lagged instruments) to address concerns about simultaneity bias. The estimates in Column 2 are less precise due to the loss of observations, but the results are qualitatively similar to the main specification. We also conduct a series of regressions excluding certain states to verify that our main results are not driven by between-state heterogeneity in data reporting or the aggregation of opioids. The sample for Column 3 excludes the Schedule III Hydrocodone prescriptions from Michigan but this does not substantively change the results. Column 4 examines whether our results are driven by the counties with unusually high opioid prescription rates by excluding all counties from the three states with the highest average per capita opioid prescriptions: Arkansas, Ohio, and Tennessee. Our results actually strengthen when we exclude the high-opioid states. That is, an increase in per capita opioid prescriptions will impact labor markets more adversely in areas with (currently) lower levels of per capita opioid prescriptions. Perhaps suggesting that the proverbial damage has already been done in the high-opioid states. The results in Column 5 are from a sample that excludes Colorado and Ohio, the two states where opioid prescriptions are not limited to those in the Schedule II category. The results do not change substantively, thus this reporting difference is not responsible for our findings. In Column 6, we check that our results are robust to excluding Texas, as opioids per capita in Texas were reportedly very low

Table VII: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes

	Full Sample Fixed Effects	Analytic Sample Fixed Effects	Analytic Sample FE-IV	Analytic Sample FE-IV Incl. Drugs/Alcohol
<b>Panel A: Employment-to-Population Ratio</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita	-0.064*** (0.008)	-0.065*** (0.008)	-0.070** (0.033)	-0.078*** (0.030)
<i>N</i>	3,191	2,167	2,167	2,167
F-statistic (exclusions)			17.16	17.84
Hansen J-Statistic p-value			0.399	0.466
<b>Panel B: Labor Force Participation Rate</b>				
	(1)	(2)	(3)	(4)
Opioids per capita	-0.057*** (0.007)	-0.059*** (0.008)	-0.065** (0.033)	-0.073** (0.030)
<i>N</i>	3,191	2,167	2,167	2,167
F-statistic (exclusions)			17.16	17.84
Hansen J-Statistic p-value			0.374	0.443
<b>Panel C: Unemployment Rate</b>				
	(1)	(2)	(3)	(4)
Opioids per capita	0.019*** (0.003)	0.017*** (0.002)	0.012* (0.007)	0.013* (0.007)
<i>N</i>	3,191	2,167	2,167	2,167
F-statistic (exclusions)			17.16	17.84
Hansen J-Statistic p-value			0.900	0.866

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



in 2014 but nearly doubled the year after; our results are again virtually unchanged. For some instances where we exclude states, our estimates on the effect of opioids on unemployment rates lose precision (and significance), though the point estimates are largely unchanged. This loss of precision does reinforce the conclusion that the primary effect on the employment-to-population ratio is through labor force participation. Finally, in poorer labor markets, more people using prescription opioids may also be receiving disability benefits. Therefore, in Panel B Column 8 we measure the dependent variable as the labor force participation rate conditional on the county's disability rate and find results similar to our main specification. This suggests that higher disability rates are not spuriously generating our main result, but we nevertheless highlight that we cannot separately identify the effects of disability rates and prescription opioids. We discuss this issue in greater detail in the discussion section, but a deeper exploration into the joint relationships between disability, prescription opioids, and labor force participation remains an area for future work.

While our IV specifications using heavy prescribers as exclusion restrictions perform well, it is possible that this variation is driven in part by patient demand for opioids. If this unobservable demand among the patients of these heavy prescribers is correlated with unobservable factors that affect county labor market outcomes, it threatens the validity of our instruments. We therefore repeat our main IV specification with alternative instruments, the results of which are contained in Table IX. Column 1 contains results from a specification where we use the number of prescribers (per capita) in the nation's top 5 percent of claims and top 1 percent of doses of Schedule IV non-opioid narcotics as instruments for per-capita Schedule II opioids. This specification serves primarily as a reference point for the rest of the table. These instruments are relatively weakly correlated with opioid prescriptions, with a first stage joint F-statistic of 7.31. However, they do pass Hansen's J-test, suggesting that they do not violate the orthogonality conditions. Moreover, the estimated opioid effects are similar to our main findings, although the unemployment rate effects are larger in magnitude.

Column 2 contains results where we instrument for per-capita Schedule II opioid prescriptions with the per-capita number of prescriptions for Schedule IV non-opioid narcotics written by the heavy opioid prescribers. When we use these providers' prescribing behavior for other drugs to instrument for Scheduled II opioids, our first stage F-statistics increase to 30.34 and second stage estimates change only slightly. The key feature of this instrument is that we are using the prescribing behavior with regards to other non-opioid drugs of the previously identified high-volume prescription opioid providers. The prescribing behavior of non-opioid drugs should

Table VIII: Robustness Checks: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes

	Main	$O_{t-1}$	No MI	No AR, OH, TN	No CO, OH	No TX	No FL	Non- Disabled Pop Only
<b>Panel A: Employment-to-Population Ratio</b>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Opioids Per Capita	-0.070** (0.033)	-0.062* (0.036)	-0.071** (0.033)	-0.119** (0.058)	-0.071* (0.038)	-0.069** (0.029)	-0.069** (0.033)	
$N$	2,167	1,330	2,167	1,468	1,711	1,665	1,966	
F-statistic (exclusions)	17.16	16.56	19.68	18.13	12.74	22.20	15.52	
Hansen J-Statistic p-value	0.399	0.714	0.500	0.788	0.340	0.510	0.415	
<b>Panel B: Labor Force Participation Rate</b>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioids Per Capita	-0.065** (0.032)	-0.055 (0.035)	-0.066** (0.032)	-0.114** (0.058)	-0.067* (0.038)	-0.062** (0.029)	-0.063* (0.033)	-0.076** (0.033)
$N$	2,167	1,330	2,167	1,468	1,711	1,665	1,966	1,993
F-statistic (exclusions)	17.16	16.56	19.68	18.13	12.74	22.20	15.52	19.17
Hansen J-Statistic p-value	0.374	0.742	0.464	0.872	0.313	0.466	0.408	0.981
<b>Panel C: Unemployment Rate</b>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Opioids Per Capita	0.012* (0.007)	0.013* (0.007)	0.012 (0.008)	0.013 (0.016)	0.011 (0.008)	0.016** (0.008)	0.012 (0.007)	
$N$	2,167	1,330	2,167	1,468	1,711	1,665	1,966	
F-statistic (exclusions)	17.16	16.56	19.68	18.13	12.74	22.20	15.52	
Hansen J-Statistic p-value	0.900	0.863	0.793	0.426	0.885	0.784	0.913	
Excluded Data			Schedule III Hydrocodone prescriptions from MI	AR, OH, TN	CO, OH	TX	FL	

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

not be driven by unobservable demand for opioids. Because we use these providers' prescribing behavior for non-opioids as instruments for per-capita opioid prescriptions, we contend that these instruments are driven by provider behavior and are much less likely to be determined by the general equilibrium process that produces opioid consumption and labor market outcomes. However, it is still possible that the variation that links the Schedule IV prescriptions of the heavy Schedule II prescribers is driven by the presence of the Schedule II prescribers, not the Schedule IV prescriptions. To address those concerns, we include the specifications in Columns 3 and 4, which include the number of heavy opioid prescribers (defined by prescriptions or claims) and the Schedule IV prescriptions of those prescribers. The first stage results are presented in Appendix Table A3 and show that while both instruments in both specifications predict increases in opioids per capita, the strength comes from the Schedule IV prescribing behavior rather than the presence of the heavy Schedule II prescribers. In both Column 3 and Column 4 the F-statistics of the instruments are greater than 10 and we do not reject the null that these exclusion restrictions are valid using the J-test. For all four alternative instrument sets, the second stage results are highly similar to the main findings in Table VII.

Next, we examine how the relationship between per capita opioid prescriptions and county labor market outcomes varies over the support of the dependent variables. While our conditional mean results presented above robustly show that per-capita opioid prescriptions adversely affect county labor markets, there is clear potential for heterogeneous treatment effects. Media reports often associate heavy opioid use with the more rural and economically distressed counties. However, it is ex ante unclear whether the marginal effects of prescription opioids on labor market outcomes are worse in these areas or in areas with tighter labor markets (i.e., higher labor force participation and lower unemployment rates) (Kliff, 2017; Semuels, 2017). To address this issue we estimate quantile regressions to examine the effects of prescription opioids at the 20th, 40th, 60th, and 80th percentiles of each dependent variable. These estimates are presented in Table X. For each outcome of interest, we present both a descriptive model using our baseline specification, as well as our preferred IV specification. We find that the effects of per capita opioid prescriptions on unemployment rates, labor force participation, and employment-to-population ratios are most pronounced in counties with stronger labor markets. While anecdotal reporting on the effects of the opioid epidemic has focused on areas with slack labor markets, these results suggest that perhaps the opioid-related damage has already been done in areas with low labor force participation. These findings are also consistent with the larger marginal effects found in Table VIII Column 4. This interpretation is consistent with the associative findings in

Table IX: Robustness Checks: Effects Opioids Per Capita on County Labor Market Outcomes Using Alternative Instruments

<b>Panel A: Employment-to-Population Ratio</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita	-0.079* (0.045)	-0.077** (0.036)	-0.077** (0.036)	-0.084** (0.034)
<i>N</i>	2,167	2,167	2,167	2,167
F-statistic (exclusions)	7.31	30.34	15.76	16.09
Hansen J-Statistic p-value	0.24	NA	0.86	0.32
<b>Panel B: Labor Force Participation Rate</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita	-0.068 (0.045)	-0.069* (0.036)	-0.075** (0.038)	-0.075** (0.034)
<i>N</i>	2,167	2,167	2,167	2,167
F-statistic (exclusions)	7.31	30.34	15.76	16.09
Hansen J-Statistic p-value	0.16	NA	0.65	0.24
<b>Panel C: Unemployment Rate</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita	0.021*** (0.008)	0.021*** (0.006)	0.020*** (0.006)	0.020*** (0.006)
<i>N</i>	2,167	2,167	2,167	2,167
F-statistic (exclusions)	7.31	30.34	15.76	16.09
Hansen J-Statistic p-value	0.26	NA	0.12	0.60
Instruments	1. Top 1 supply of non-opioid Schedule IV narcotics 2. Top 5 claim of non-opioid Schedule IV narcotics	1. Non-opioid Schedule IV prescriptions per capita among high opioid prescribers	1. Non-opioid Schedule IV prescriptions per capita among high opioid prescribers 2. Top 5 claim opioids	1. Non-opioid Schedule IV prescriptions per capita among high opioid prescribers 2. Top 5 supply opioids

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Hollingsworth et al. (2017). Individuals may be using more opioids in depressed rural counties, but some of these individuals may have already left the labor force. Hence, we find that opioids have the largest marginal effect when labor markets are tighter.

We also examine whether the labor market effects of prescription opioids differ between rural and non-rural counties, as delineated by the BLS metropolitan and nonmetropolitan definitions. These results, reported for the baseline model only, are presented in Table XI. Consistent with our main findings, we find statistically significant negative effects for both rural and non-rural counties. While the estimated effects are slightly larger in magnitude for rural counties, the estimates are not significantly different from one another.

Finally, we utilize the ARCOS data to examine the relationship between prescription opioids and labor market outcomes at the regional level. These results are presented in Table XII. The results again indicate that opioids have a strong adverse effect on the labor market. Column 1 presents results for the baseline model on the full sample of all U.S. states from 2000 to 2016. These results show that a one gram increase in prescription opioids per capita leads to reductions in both the employment-to-population ratio and labor force participation rate as well as an increase in the unemployment rate. However, these effects are smaller than those found in Table VII. In Column 2, we repeat the full sample analysis with the addition of an indicator variable for whether there was a PDMP in place in that area in the year of observation. The results are nearly identical to those found in Column 1.<sup>26</sup> Column 3 presents the baseline results for the analytic sample (2013-2015, the years for which instruments are available) and the results are very similar to results derived using PDMP data (Table VII Column 2). Column 4 reports the IV results for the analytic sample, which indicate an even larger adverse opioid effects on all regional labor market outcomes. Specifically, a one gram increase in prescription opioids per capita leads to a 13.5 percentage point reduction in the labor force participation rate, a 12.7 percentage point drop in the employment-to-population ratio, and a 3.2 percentage point increase in the unemployment rate.

Differences in scale between the ARCOS and PDMP data can be misleading, and it is difficult to convert one to the other. To compare the regional ARCOS analysis with the estimated county PDMP effects from earlier, next we calculate the estimated effects with respect to their analytic sample means. For this exercise, we focus on the IV results from Table VII Column 3 and Table XII Column 4. Using results from the PDMP analysis, doubling opioids per capita at the sample

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<sup>26</sup>The results remain unchanged regardless of whether we use a dummy variable for the implementation of all PDMPs or for the implementation of ‘must access’ PDMPs where physicians are required to check the PDMP database and view the patient’s prescribing history before providing an opioid prescription, as defined in Buchmueller and Carey (2017).

Table X: Quantile Regressions

<b>Panel A: Employment-to-Population Ratio</b>				
	20th pctile	40th pctile	60th pctile	80th pctile
Baseline Model	-0.053*** (0.007)	-0.058*** (0.007)	-0.059*** (0.006)	-0.066*** (0.007)
IV Model	-0.054*** (0.006)	-0.067*** (0.005)	-0.080*** (0.005)	-0.090*** (0.005)
<b>Panel B: Labor Force Participation Rate</b>				
	20th pctile	40th pctile	60th pctile	80th pctile
Baseline Model	-0.047*** (0.006)	-0.049*** (0.006)	-0.049*** (0.005)	-0.059*** (0.006)
IV Model	-0.043*** (0.006)	-0.058*** (0.005)	-0.071*** (0.003)	-0.084*** (0.005)
<b>Panel C: Unemployment Rate</b>				
	20th pctile	40th pctile	60th pctile	80th pctile
Baseline Model	0.019*** (0.001)	0.018*** (0.002)	0.017*** (0.002)	0.016*** (0.003)
IV Model	0.026*** (0.001)	0.029*** (0.001)	0.033*** (0.001)	0.034*** (0.002)
<b>Panel D: Summary Statistics</b>				
	20th pctile	40th pctile	60th pctile	80th pctile
Employment-to-Population Ratio	0.46	0.51	0.55	0.59
Labor Force Participation Rate	0.51	0.55	0.59	0.64
Unemployment Rate	0.051	0.066	0.081	0.103
<i>N</i>	2,167	2,167	2,167	2,167

Includes unique MSA and year fixed effects.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table XI: Robustness Checks: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes. Baseline Model

	Unemp. Non-Rural	Unemp. Rural	LFP Non-Rural	LFP Rural	Emp/Pop Non-Rural	Emp/Pop Rural
Opioids Per Capita	0.016*** (0.004)	0.017*** (0.003)	-0.046*** (0.008)	-0.058*** (0.009)	-0.052*** (0.009)	-0.064*** (0.010)
<i>N</i>	888	1,279	888	1,279	888	1,279

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

mean (a 0.867 unit increase) would lead to a 6.1 percentage point drop in the employment-to-population ratio, a 5.6 percentage point fall in labor force participation, and a 1.0 percentage point increase in the unemployment rate. While in the ARCOS analysis, doubling opioids per capita at the sample mean (a 0.521 gram increase) would lead to a 7.1 percentage point reduction in the employment-to-population ratio, a 6.7 percentage point drop in the labor force participation rate, and a 1.7 percentage point increase in the unemployment rate. Thus, the adverse opioid effects are slightly larger in magnitude for the regional analysis, but they are still very similar to those from the county-level analysis at the unconditional mean.

## 6 Conclusion

This is the first paper to examine the causal effects of per capita opioid prescriptions on highly-visible county and regional labor market outcomes. We exploit plausibly exogenous variation in the concentration of high-volume opioid prescribers as measured by the number of prescriptions written and number of doses prescribed to identify the causal effects. Our findings indicate that prescription opioids have very strong negative effects on employment-to-population ratios and labor force participation rates, and a marginally adverse impact on unemployment rates. We also find that while popular perception associates the opioid epidemic with counties with slack labor markets, the marginal effects of opioids per capita on county labor markets are strongest in counties where the labor markets are tight.

These results are not intended to suggest that all restrictions on the supply of prescription opioids will necessarily improve labor market outcomes or welfare. First, if individuals are

Table XII: Effects Opioids Per Capita (in grams) on Regional Labor Market Outcomes –ARCOS Data

	Full Sample Fixed Effects	Full Sample Fixed Effects	Analytic Sample Fixed Effects	Analytic Sample FE-IV
	PDMP Dummy			
<b>Panel A: Employment-to-Population Ratio</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita (in grams)	-0.032** (0.015)	-0.032** (0.015)	-0.063*** (0.013)	-0.135*** (0.013)
<i>N</i>	15,042	15,042	2,652	2,652
F-statistic (exclusions)				71.09
Hansen J-Statistic p-value				0.950
PDMP Implementation Dummy		Y		
<b>Panel B: Labor Force Participation Rate</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita (in grams)	-0.030** (0.014)	-0.030** (0.037)	-0.058*** (0.013)	-0.127*** (0.012)
<i>N</i>	15,042	15,042	2,652	2,652
F-statistic (exclusions)				71.09
Hansen J-Statistic p-value				0.977
PDMP Implementation Dummy		Y		
<b>Panel C: Unemployment Rate</b>				
	(1)	(2)	(3)	(4)
Opioids Per Capita (in grams)	0.008** (0.003)	0.008** (0.026)	0.016*** (0.003)	0.032*** (0.003)
<i>N</i>	15,042	15,042	2,652	2,652
F-statistic (exclusions)				71.09
Hansen J-Statistic p-value				0.342
PDMP Implementation Dummy		Y		

Includes state and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the state level with 51 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



leaving the labor force because of opioid dependence, restricting the availability of opioids may lead individuals to substitute to heroin or other substances rather than snapping back to work (Compton et al., 2016). Second, if individuals have valid medical conditions for which pain management is necessary, severe restrictions on prescription opioids may make it more difficult for individuals to work, as in Kilby (2015). Determining the extent to which these findings reflect legitimate and/or illegitimate use(s) of opioids is an area for future work with individual-level data. If the results reflect legitimate uses, then society should be informed of the labor market costs associated with the opioid approach to pain management; if the results reflect illegitimate uses, the labor market consequences should be well identified to help motivate public health interventions that can minimize abuse.

One important caveat from these findings involves disability rates. While we show that our results hold when restricting the denominator of the labor force participation rate to non-disabled individuals, the relationship between opioid use, labor market outcomes, and disability rates is more complicated. Previous research has shown that adverse labor market conditions may contribute to higher disability rates (Black et al., 2002; Autor and Duggan, 2003; Erceg and Levin, 2014; Hall, 2015). Similarly, as chronic diagnosed pain is by itself grounds for disability, the direction of causation between opioid use and disability may run in either direction (GAO, 2011; Morden et al., 2014; Meara et al., 2016; Buchmueller and Carey, 2017; Song, 2017).<sup>27</sup> With the data currently available, we do not have the ability to separately identify the effects of disability and opioid use on labor market outcomes. While the statistical tests for validity of our preferred instruments and robustness checks using alternative instruments provide support for our findings, disentangling the importance of disability from prescription opioids remains an area for future work.

Our hope is that these findings contribute towards our fledgling understanding of the comprehensive economic impact of the prescription opioid epidemic. The finding that prescription opioids are subtracting individuals from the labor market means that the opioid epidemic is affecting economic growth, the tax bases of local economies, and the amount of resources available for households to invest in the next generation. Hopefully, these results are useful in garnering resources for further research, as well as for prevention, treatment, and recovery.

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<sup>27</sup>Moreover, people who use prescription opioids may also receive disability benefits at a higher rate and longer duration (Mahmud et al., 2000; Webster et al., 2007; Franklin et al., 2008; Kidner et al., 2009; Ashworth et al., 2013).

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## 7 Appendix

Table A1: Summary Statistics - ARCOS Data

Variable	Full Sample (2000-2016)	Analytic Sample (2013-2015)
Opioids Per Capita (in grams)	0.423 (0.29)	0.521 (0.25)
Employment-to-Population Ratio	0.579 (0.07)	0.559 (0.07)
Unemployment Rate	0.061 (0.02)	0.063 (0.02)
Labor Force Participation Rate	0.616 (0.06)	0.596 (0.06)
Percent Male	0.493 (0.01)	0.495 (0.01)
Percent Female	0.506 (0.01)	0.504 (0.01)
Percent Black	0.099 (0.12)	0.102 (0.12)
Percent Hispanic	0.109 (0.14)	0.122 (0.14)
Percent Rural	0.34 (0.24)	0.327 (0.24)
Percent under 15 Years Old	0.196 (0.02)	0.188 (0.02)
Percent 15 through 19 Years Old	0.071 (0.01)	0.066 (0.007)
Percent 20 through 24 Years Old	0.070 (0.02)	0.071 (0.02)
Percent 25 through 34 Years Old	0.127 (0.02)	0.129 (0.02)
Percent 35 through 44 Years Old	0.135 (0.02)	0.121 (0.01)
Percent 45 through 54 Years Old	0.142 (0.01)	0.135 (0.01)
Percent 55 through 64 Years Old	0.116 (0.02)	0.132 (0.02)
Percent Aged 65+	0.143 (0.03)	0.157 (0.03)
Total Population	342,587 (365,485)	360,167 (525,751)
Number of Primary Care Physicians per Thousand People	0.712 (0.23)	0.720 (0.23)
Number of Cancer Deaths per 100,000 People	207.7 (47.9)	208.8 (49.2)
Top 1 Supply per 100,000 Population		1.43 (2.10)
Top 5 Claim per 100,000 Population		7.79 (6.40)
Number of Observations	15,042	2,652

Standard deviations in parenthesis.

Table A2: Instrument Sensitivity Analysis: Effects of Opioid Prescriptions Per Capita on County Labor Market Outcomes using Different Instruments

Panel A: Employment-to-Population Ratio							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Opioids Per Capita	-0.070** (0.032)	-0.075** (0.035)	-0.060* (0.033)	-0.064* (0.035)	-0.75** (0.35)	-0.063* (0.034)	-0.082** (0.036)
<i>N</i>	2,167	2,167	2,167	2,167	2,167	2,167	2,167
F-statistic (exclusions)	17.16	15.62	18.56	18.53	11.94	11.17	13.30
Hansen J-Statistic p-value	0.40	0.58	0.36	0.56	0.94	0.90	0.32
Panel B: Labor Force Participation Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Opioids Per Capita	-0.065** (0.033)	-0.070* (0.035)	-0.055* (0.032)	-0.060* (0.035)	-0.69** (0.35)	-0.057* (0.034)	-0.077** (0.036)
<i>N</i>	2,167	2,167	2,167	2,167	2,167	2,167	2,167
F-statistic (exclusions)	17.16	15.62	18.56	18.53	11.94	11.17	13.30
Hansen J-Statistic p-value	0.37	0.60	0.51	0.99	0.14	0.91	0.31
Panel C: Unemployment Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Opioids Per Capita	0.012* (0.007)	0.011 (0.008)	0.009 (0.007)	0.009 (0.008)	0.014 (0.008)	0.014* (0.008)	0.013 (0.008)
<i>N</i>	2,167	2,167	2,167	2,167	2,167	2,167	2,167
F-statistic (exclusions)	17.16	15.62	18.56	18.53	11.94	11.17	13.30
Hansen J-Statistic p-value	0.90	0.75	0.61	0.23	0.76	0.44	0.90
Instruments	top 1 supply top 5 claim	plus 2.0SD supply top 5 claim	top1supply plus 1.5SD claim	plus 2.5SD supply plus 1.5SD claim	plus 1.5SD supply plus 2.0SD claim	plus 2.5SD supply plus 2.0SD claim	plus 1.5SD supply plus 2.5SD claim

For a given county, “plus xSD supply” represents the number of practitioners per 100,000 population with opioid doses supplied that are x standard deviations above the national average, and “plus xSD claim” is the number of prescribers with opioid claims that are x standard deviations above the national average.

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A3: First-stage Estimates - Alternative Instruments

	Opioids Per Capita			
<b>Exclusions</b>				
Providers in Top 5 Percent Non-Opioid Schedule IV Prescriptions/100,000 Population	0.010** (0.004)			
Providers in Top 1 Percent Non-Opioid Schedule IV Doses/100,000 Population	0.005** (0.002)			
Non-Opioid Schedule IV Prescriptions Per Capita Among High Opioid Prescribers	1.020*** (0.185)	0.928*** (0.288)	0.779*** (0.264)	
Providers in Top 5 percent Opioid Prescriptions/100,000 Population		0.0009 (0.002)		
Providers in Top 5 Percent Opioid Doses/100,000 Population				0.003 (0.002)
F-statistic (exclusions)	7.31	30.34	15.76	16.09
Observations	2,167	2,167	2,167	2,167

Includes unique MSA and year fixed effects.

Robust standard errors (in parenthesis) are clustered at the MSA/non-MSA regional level with 186 clusters.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .