Opioid Treatment for Pain and Work and Disability Outcomes: Evidence from Health Care Providers' Prescribing Patterns

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October 15th, 2020

Abstract

Medical conditions that cause pain are a leading reason why workers leave the labor force and seek disability benefits. The fall in the labor supply of individuals with pain has occurred despite the increased availability of medications to treat pain – notably opioids – over the past two decades. The use of opioids to treat pain has risen steadily over time, but the implications for functional status and employment are unclear, and a key empirical challenge in disentangling the effects of opioids on labor supply is that opioid use is correlated with pain and perhaps other unobserved measures of labor force attachment. We therefore use an instrumental variables strategy to examine the relationship between opioid treatment for pain and labor outcomes between 2012 and 2018, which relies on differences in providers' propensity to prescribe opioids to new users adjusted for detailed patient medical characteristics. To calculate provider propensities, we leverage the largest U.S. commercial claims database, through which we observe the prescribing behavior of approximately 76% of active U.S. physicians as well as a large share of non-physician providers who are legally permitted to prescribe opioid analgesics. In addition, we use a novel natural language processing algorithm to analyze medications entered in the free text fields of SSDI applications, allowing us to identify applicants using opioid analgesics and estimate the impact of prescription opioid supply on the number of applicants using opioids specifically. We find that lagged prescription opioid supply has a statistically significant, negative impact on the employment-to-population ratio and the average weekly wage, and a statistically significant, positive impact on SSDI applications overall and applications mentioning opioid use, as well as SSDI initial allowances. Our findings indicate that opioid treatment for pain can have adverse effects on labor productivity and employment, even precipitating more permanent separation from the labor force through SSDI claiming.

Keywords: Disability, Employment, Social Security Disability Insurance, Opioids, Pain

We thank Anne Case, Angus Deaton, Laurie Meneades, Thabo Samakhoana, Alexander Strand, Blue Cross Blue Shield (BCBS) Association, BCBS Alliance for Health Research, and participants at ASHEcon 2018, NBER Workshop on Pain 2019, RAND Drug Policy Research Center Brown Bag Seminar 2019, and meetings of the NBER P01 Improving Health Outcomes for an Aging Population. Lucas Cusimano provided outstanding research assistance. The research reported herein was performed pursuant to grants DRC12000002-05 and RDR18000003 from the US Social Security Administration (SSA), funded as part of the Retirement and Disability Research Consortium, from grant P01AG005842 from the National Institute on Aging, and a gift from Owen and Linda Robinson. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of SSA, any agency of the Federal Government, or NBER. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof.

1. Introduction

Medical conditions that cause pain are an important and growing reason why workers exit the labor force: over half of working-age men who are not in the labor force take pain medication on a daily basis (Krueger, 2017), and musculoskeletal (MSK) disorders – which are commonly associated with chronic pain – are the leading reason for which disabled workers receive Social Security Disability Insurance (SSDI) benefits (Social Security Administration, 2019). The share of SSDI beneficiaries with an MSK disorder has increased from 20.6 percent in 1996 to 33.2 percent in 2018, illustrating the growing impact of pain-related medical conditions on participation in the labor force (Social Security Administration, 2019). The fall in the labor supply of individuals with pain has occurred despite the increased availability of medications to treat pain, such as opioids, over the same time period (Sites, Beach, & Davis, 2014). Opioids are highly potent analgesics, and in principle, more effective pain control could increase labor supply and productivity. On the other hand, the numerous adverse medical consequences of sustained opioid use – including but not limited to dependence and addiction – might offset these gains (Dumas & Pollack, 2008; Kosten & George, 2002; Volkow & McLellan, 2016). Moreover, increased opioid supply in a given area could have negative spillovers to the labor supply of individuals without pain if it increases the risk of recreational drug use and addiction. Understanding the economic trade-offs of opioid treatment for pain at both an individual and broader population level is therefore critical to informing public policy.

This paper investigates the impact of health care providers' opioid prescribing behavior on labor supply, wages and disability claiming. A fundamental empirical challenge in determining whether there is a causal relationship between opioid use and labor outcomes is that opioid use is correlated with the prevalence of pain, and perhaps other unobserved measures of

labor force attachment. We therefore use an instrumental variables strategy exploiting exogenous variation in health care providers' (hereafter "providers") opioid prescribing preferences. This approach draws on a growing literature demonstrating that, under certain conditions, providers' characteristics can predict their propensity to use specific treatments, even after controlling for characteristics of the patients they serve (Barnett, Olenski, & Jena, 2017; Cutler, Skinner, Stern, & Wennberg, 2018; Davies et al., 2013; Epstein & Nicholson, 2009; Perry, 2008; Ringwalt et al., 2014; Sinnenberg et al., 2017; Tamayo-Sarver, Dawson, Cydulka, Wigton, & Baker, 2004). We use medical claims data from large commercial insurers operating across the US to obtain a high-resolution view of providers' opioid prescribing practices across the patients they treat, and develop measures of the propensity to prescribe opioids, and the propensity to prescribe with higher intensity and duration, that are not fully explained by patient characteristics. Our data offer several advantages. First, using claims data allows us to construct a prescribing instrument that is adjusted for patient case-mix to an extent that has not been possible in previous studies. Second, because the vast majority of patients in our sample are covered through the large-group health insurance market, the large majority of them are employed, thereby allowing us to model providers' prescribing behavior holding constant their patients' labor force status. Finally, because our data offer comprehensive geographic coverage, we examine whether providers with higher propensities to prescribe opioids are concentrated within certain geographic areas and relate this to area-level employment, wages and SSDI claiming. Through the development of a novel text-classification algorithm that allows us to analyze free text fields of SSDI applications, we are also able to examine the relationship between providers' opioid prescribing propensities and SSDI claiming among adults using opioid analgesics specifically.

We find that there is a negative, statistically significant relationship between the total supply of prescription opioids in a given year and geographic area (measured as the number of opioid prescriptions filled per 100 adults) and both the employment-to-population ratio and average weekly wage in that area the following year. We also find that there is a positive, statistically significant relationship between the total supply of prescription opioids and SSDI applications overall, applications mentioning opioid use, and initially allowed applications two years later. Specifically, 10 additional opioid prescriptions per 100 adults in a local area leads to: a decrease in the employment-to-population ratio by 1.1 employed persons per 100 people of working age (1.6% decrease relative to the mean); a decrease in the average weekly wage by $48.60 (a 6% decrease relative to the mean); an increase in SSDI applications overall by 0.08 per 100 relevant population (an 8% increase relative to the mean) and an increase in applications mentioning opioid use by 0.03 (a 10% increase relative to the mean); and an increase in the rate of initially allowed applications by 0.02 per 100 relevant population (a 6% increase relative to the mean).

The remainder of the paper is organized as follows. We discuss previous related literature in Section 2, describe our methods and data in Section 3; present results in Section 4, and discuss implications and conclusions in Section 5.

2. Background

Millions of Americans live with chronic pain (Dahlhamer et al., 2018; Verhaak, Kerssens, Dekker, Sorbi, & Bensing, 1998). The prevalence of medical conditions most commonly associated with pain, such as osteoarthritis and low back pain, has grown over time and is projected to increase further in the coming years (Phillips, 2009). Pain is a significant

source of lost labor productivity (Gaskin & Richard, 2012): low back pain, for example, is estimated to result in 149 million lost days of work each year (Guo, Tanaka, Halperin, & Cameron, 1999), and two-thirds of the substantial annual costs associated with this condition are due to decreased labor productivity and wages (Katz, 2006).

Effective treatment of pain can potentially address the functional limitations that compromise work capacity, and therefore increase labor supply. Studies of COX-2 inhibitors support this theory: Butikofer and Skira (2016) find that Vioxx's entry into the Norwegian market decreased absences due to sickness among individuals with joint pain by 7 to 12 percent, and that its subsequent withdrawal increased both lost work days and the probability of receiving disability benefits. In the US context, Garthwaite (2012) finds that the withdrawal of Vioxx in 2004 decreased the labor supply of individuals with joint conditions by 22 percentage points.

As the most potent class of pain medications currently available, opioids are often employed in the management of severe pain that has not responded to other types of treatments (Rosenblum, Marsch, Joseph, & Portenoy, 2008). The medical use of opioid analgesics to treat pain has risen sharply in recent years: between 1999 and 2015, the number of opioid prescriptions per capita in the US tripled (Guy et al., 2017). It is puzzling, then, that individuals with pain have continued to exit the labor force at such high rates despite the increased availability of potent pain medications.

An explanation may lie in the complex nature of opioid therapy for pain. First, the long-term efficacy of opioids in managing chronic pain is controversial: "tolerance" to opioids develops with sustained use, such that over time escalating doses of medication are required to achieve pain relief (Dumas & Pollack, 2008). Individuals receiving long-term opioid treatment for pain can develop physiologic dependence on these medications and even heightened pain

sensitivity, thereby further escalating use (Kosten & George, 2002; Lee, Silverman, Hansen, Patel, & Manchikanti, 2011) – it is therefore unclear whether opioids improve functioning in the long-term (Krebs et al., 2018; Volkow & McLellan, 2016). Second, opioids carry a risk of serious adverse consequences: over time, dependence may lead to opioid misuse, addiction, and even death from overdose (Kosten & George, 2002; Volkow & McLellan, 2016). In contrast to other analgesics such as COX-2 inhibitors, these adverse consequences of opioids can potentially offset gains in functioning and labor productivity associated with improvements in pain control.

The adverse effects of opioids also extend beyond individuals who are prescribed these medications. Prescription opioids are frequently diverted for recreational purposes (Inciardi, Surratt, Lugo, & Cicero, 2007), resulting in negative health spillovers to other individuals in the community. For example, Powell and colleagues (2016) find that in the context of the Medicare Part D roll-out, expanding access to prescription drugs such as opioids for the Medicare population was also associated with increased substance abuse treatment admissions and opioid-related mortality within the under-65 population as well.

The causal impact of opioid treatment for pain on labor outcomes – both for individual patients and the broader community in which they live and work – is therefore unclear. Empirically, there is a clear negative correlation between opioid use and area-level labor outcomes: Krueger (2017), for example, finds that over the past 15 years, labor force participation has fallen faster in counties with larger numbers of opioid prescriptions. Disentangling what causal role – if any – opioids have played in this decline, however, is challenging for several reasons. Consider the following model of labor supply:

$$Y_{ct} = \alpha + \beta Opioid_{ct} + \varphi' X_{ct} + u_{ct}$$

where Y_{ct} is employment in area c in year t. $Opioid_{ct}$ measures opioid use by area and over time, and β is the parameter of interest, measuring the effect of opioid use on employment. X_{ct} is a vector of covariates, and u_{ct} is an error term, which may include unobserved aspects of health and function. One challenge in obtaining an unbiased estimate of β is that opioid use is correlated with the prevalence of pain, which is typically unobserved but also influences area-level labor outcomes. A second challenge in estimating β is the possibility of a reverse causal relationship, whereby weak economic conditions in a geographic area result in higher levels of opioid use and subsequent adverse health outcomes– the "deaths of despair" hypothesis (A. Case & Deaton, 2015; Currie, Jin, & Schnell, 2018; Ruhm, 2018; Venkataramani, Bair, O'Brien, & Tsai, 2020). Obtaining an unbiased estimate of β therefore requires that we leverage exogenous sources of variation in the supply of opioids, that are uncorrelated with both the local prevalence of pain and pre-existing economic conditions.

Instrumental variables estimators offer a potential solution, and one instrument that has been used increasingly for causal inference in the literature is health care providers' preferences and prescribing behavior. There is growing evidence that providers' characteristics, both observed and unobserved, can predict their propensity to use certain treatments even after controlling for the characteristics of the patients they serve (Cutler et al., 2018; Davies et al., 2013; Epstein & Nicholson, 2009; King, Essick, Bearman, & Ross, 2013; Mojtabai, 2002; Tamayo-Sarver et al., 2004) . Provider characteristics including age, gender, race and specialty have been found to significantly influence treatment decisions across both medical and psychiatric conditions (McKinlay, Lin, Freund, & Moskowitz, 2002); less easily observable characteristics such as sensitivity to nonverbal communication have also been noted to be significant predictors of provider's diagnostic skills and hence management decisions (Robbins,

Kirmayer, Cathebras, Yaffe, & Dworkind, 1994). Providers' prescribing decisions, adjusting for case mix, have therefore increasingly been used as instrumental variables in examining the health impacts of such varied classes of medications as antidepressants (Perry, 2008), antipsychotics (Schneeweiss, Setoguchi, Brookhart, Dormuth, & Wang, 2007), chemotherapy (Bosco et al., 2010), non-steroidal anti-inflammatory drugs (Brookhart, Wang, Solomon, & Schneeweiss, 2006), and even opioids (Barnett et al., 2017).

Opioid prescribing is an area where variations in practice patterns are especially pronounced, even when accounting for differences in patients' health conditions (Tamayo-Sarver et al., 2004). Provider characteristics that might influence opioid prescribing rates include specialty (Ringwalt et al., 2014) and their own personal experiences of pain (Sinnenberg et al., 2017). Physicians' opioid prescribing behavior has been used as an instrument in three recent studies examining the link between opioid use and labor outcomes. In an analysis of employment and prescription drug monitoring program (PDMP) data from 10 states between 2013 and 2015, Harris, Kessler, Murray, and Glenn (2019) estimate a statistically significant, negative relationship between per capita opioid prescriptions and employment using the concentration of high-volume opioid prescribers in a county as an instrument for opioid prescriptions. Savych, Neumark, and Lea (2019) examine the relationship between receipt of an opioid prescription and the duration of temporary disability benefits among workers with low back injuries, instrumenting for opioid prescription receipt by a given worker using prescribing patterns for all other injured workers in an area (i.e., a "leave one out" instrument). They find no significant relationship between receipt of any opioid prescription and the duration of disability, but do find a significant positive relationship between receipt of longer term opioid prescriptions and the duration of disability. In contrast, Currie et al. (2018) find no significant impact of county-level

opioid prescribing rates on employment among men, and a small but statistically significant positive impact among women, using opioid prescription rates among adults age 65 and older as an instrument for prescription rates among adults younger than 65. A fourth study by Aliprantis, Fee, and Schweitzer (2019) also examines the relationship between area-level opioid prescribing rates and individual-level employment outcomes using the American Community Survey microdata, not with an instrumental variables strategy but using several alternative modeling approaches including two-way fixed effects regression, controls for local economic conditions, and the construction of comparison groups that shared similar economic conditions prior to the growth in opioid use. They find a statistically significant, negative relationship between opioid prescribing rates and local employment outcomes. Prior research on the impact of prescription opioid use on labor outcomes has therefore yielded mixed findings, but most studies have found a negative relationship.

An important limitation of most of the aforementioned studies, however, is that they lack medical encounter data and are therefore unable to adjust their prescribing instruments for patients' medical characteristics. Savych and colleagues' analysis uses workers' compensation data and therefore contains information about the primary reason for the claim (i.e., low back pain) and treatments received, but does not adjust for the presence of other medical or psychiatric comorbidities that may influence opioid prescribing. An additional limitation of prior studies is the difficulty of adjusting for differences in the labor force attachment of individuals prescribed opioids. Indeed, a key challenge in this literature more broadly has been that comprehensive prescription, medical and employment information are rarely available in the same data source, complicating efforts to adjust for key confounders of the relationship between opioid prescribing and labor outcomes. Finally, prior studies have focused primarily on the impacts of prescription

opioid use on employment, with less attention paid to wages and disability outcomes, specifically SSDI claiming. Yet these outcomes are also important to examine: wages provide information about the labor productivity of workers who remain employed after receiving opioids, while on the other end of the spectrum, SSDI claiming indicates a more severe and potentially permanent disruption in labor supply and has implications for both health care and disability policy.

3. Approach

Empirical Strategy

Our overall empirical approach is to examine the relationship between area-level prescription opioid supply and labor outcomes – specifically, employment, wages and SSDI applications and initial allowances – over the years 2012 to 2018[1] using an instrumental variables strategy. To address the potential endogeneity of opioid prescribing intensity with respect to area-level population characteristics that also influence labor supply– such as health status and the prevalence of pain specifically – we use health care providers' propensity to prescribe opioids for pain as an instrument for area-level opioid supply. This instrument is constructed using a separate commercial claims data source as described in detail below. We therefore use prescribing behavior in a *commercially insured sample,* the majority of whom are – importantly – in employer-sponsored plans and hence currently employed, as an instrument for *overall opioid supply across all adults* in a given geographic area.

[1] As shown in our two stage least squares specification below, opioid prescribing propensity in a given year *t* is used to instrument for the total opioid supply in that same year *t*, and is then used to estimate impacts on employment and wages in the following year *t + 1*, and impacts on disability outcomes two years later in year *t + 2*. Therefore, for our instrument and total opioid supply we use data from 2012-2017; for employment and wage outcomes we use data from 2013-2018; and for disability outcomes we use data from 2014-2018.

We perform an area-level, rather than an individual-level analysis, for two reasons. First, individual-level panel data sources typically do not include detailed information on both prescription medications and labor and disability outcomes, or are not sufficiently large. Second, an advantage of an area-level analysis is that it captures aggregate labor and disability impacts reflecting both individuals prescribed opioids, and spillovers to individuals who are not prescribed opioids but access them via diversion. Our geographic unit of observation is the couma. Coumas are small geographic areas that represent a blend of counties and public use microdata areas (PUMAs). In cases where counties are large, populous and comprised of multiple PUMAs, the county is the couma; in cases where counties are smaller, sparsely populated and multiple such counties are assigned to a PUMA, the PUMA is the couma (Anne Case & Deaton, 2017). This approach is preferred to using counties as the unit of analysis because each couma has a minimum population size of 100,000, thereby reducing measurement error relative to using small, sparsely populated counties. Most of our outcome measures and covariates are reported at the county-level and can therefore be readily crosswalked to the couma-level, since counties are fully nested within coumas. Data reported at the 5-digit zip code level (i.e., SSDI data and the commercial claims data used to calculate our instrument) are crosswalked to coumas using an approach described in **Appendix A1**.

We estimate the following models via two-stage least squares (2SLS):

First Stage: $$OpioidSupply_{c,t-1} = \eta_0 Z_{c,t-1} + \eta_1' X_{ct} + \delta_s + \gamma_t + \epsilon_{ct} \quad (1)$$

Second Stage: $$Y_{ct} = \beta_0 OpioidSupply_{c,t-1} + \beta_1' X_{ct} + \delta_s + \gamma_t + \varepsilon_{ct} \quad (2)$$

In the first stage, we instrument for area-level opioid supply ($OpioidSupply$) in year *t-1* in couma *c* (measured as the number of opioid prescriptions per 100 adults ages 18 and older residing in couma *c* in year *t-1*) using the adjusted propensity *Z* of health care providers in couma

c in year *t-1* to prescribe opioids. In the second stage, we examine the relationship between area-level opioid supply in couma *c* in year *t-1*, and labor outcomes *Y* in couma *c* in the following year *t*. Our labor outcomes of interest include the employment-to-population ratio, the average weekly wage, the overall SSDI application rate (i.e., the number of SSDI applications per 100 adults age 25 to 64), the rate of SSDI applications that mention opioid use, and the rate of initial SSDI allowances. We estimate the lagged effect of opioid prescribing behavior on labor outcomes both to avoid simultaneity bias, and because impacts of opioid treatment on labor supply may take time to emerge. We therefore examine the impact of opioid supply in a given year on the employment-to-population ratio and average weekly wage in the following year; since SSDI claiming represents a more severe decline in labor productivity, we use a two year lag for SSDI-related outcomes.

Our 2SLS model adjusts for state fixed effects (δ_s) to account for time invariant aspects of the state policy and regulatory environment that may affect opioid prescribing and/or the labor market; year fixed effects (γ_t) to adjust for time varying economic and policy changes common to all states (e.g., the CDC's 2016 guidelines on opioid prescribing); and a vector of couma-level covariates *X* that includes the couma's urbanicity,[2] percent of adults ages 25 and older without a high school degree (who are more likely to qualify for SSDI benefits), and share of jobs in the farming, manufacturing or mining industries.[3] Standard errors are clustered at the couma-level.

[2] To estimate couma-level urbanicity, we first obtained each county's 2013 Rural-Urban Continuum Code (RUCC) from the US Department of Agriculture's Economic Research Service (USDA ERS). Each couma was then assigned the population-weighted average of RUCCs across its component counties.

[3] The share of jobs in the farming, manufacturing or mining industries is a time-varying covariate – the data source, the US Department of Commerce's Bureau of Economic Analysis, provides estimates for each year from 2013 to 2018. Urbanicity and education composition, however, are not time varying. The USDA ERS updates RUCCs every decade, so we use the most recent values from 2013 for our entire observation period. The data source for education composition is the American Community Survey, which provides estimates for the full census of US counties only every 5 years. We therefore use the 2013-2017 5-year estimate for our entire observation period.

Data Sources for Opioid Prescriptions, Labor Outcomes and Covariates

Our endogenous regressor, the overall opioid supply in a given area ($OpioidSupply$) as measured by the number of opioid prescriptions per 100 adults, is obtained from the Centers' for Disease Control and Prevention (CDC). The CDC compiles this information from IQVIA Xponent, which collects prescription data from retail pharmacies that together dispense 92% of all retail prescriptions in the US, and estimates the remaining 8% (Centers for Disease Control and Prevention, 2020). We used data for years 2012 to 2017.

Employment counts were obtained from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics data, and were converted to employment-to-population ratios using Census population data for the years 2013 to 2018. The average weekly wage for each year from 2013 to 2018 was obtained from the Quarterly Census of Employment and Wages (QCEW), an administrative dataset which is also publicly available through the BLS. The QCEW data is drawn from mandatory quarterly unemployment insurance contribution reports filed by 95% of US employers and is therefore considered highly accurate.

SSDI application and initial allowance counts were obtained from the Social Security Administration's (SSA) Management Information Services Facility Electronic Disability Database (MEDIB), an administrative data source that records information about SSDI applicants collected on SSA Forms 16 and 3368 at the time of application.[4] These forms gather applicants' zip code of residence and other demographic data, information about applicants' medications, and the initial determination made by the examiner. The MEDIB data are a census of all SSDI applicants whose claims were decided by a state Disability Determination Services office between the years 2014 and 2018. We converted SSDI application and initial allowance

[4] SSA Form 3368 is available here: https://www.ssa.gov/forms/ssa-3368-bk.pdf

counts to application and initial allowance rates per 100 relevant population (i.e., adults age 25-64) using Census population data. We also used SSA's MEDIB data to calculate the rate of applications in which applicants reported taking opioid analgesics. Applicants may enter medication information via a pre-populated drop-down list that includes over 600 different medication names, or through free-text fields, or both (Wu, Mariani, Pu, & Hurwitz, 2020). A key challenge in analyzing medication data is the large share of information entered into free text fields, and the increasing use of free text fields by applicants over time: between 2007 and 2017, 40% of applicants reported their medications using both the drop-down and free text options, while 42% used free text entry only (Wu, Hoffman, & O'Leary, 2019). It is therefore important to account for free text medication data when examining medication use among SSDI applicants, and in particular when assessing temporal trends (Wu et al., 2019). In order to more accurately estimate the number of SSDI applicants taking opioids at the time of application, we therefore developed a novel, deterministic natural language processing (NLP) algorithm to identify opioid analgesics in the free text fields of SSDI application data. This algorithm is described in detail in Maestas, Sherry, and Strand (2020)**.** Briefly, the NLP algorithm identifies both generic and branded opioid drug names in the application free text fields, as well as common misspellings of opioid drug names by leveraging information from additional free text fields in which applicants may indicate *why* they are taking a particular medication. Since our analysis examines opioid treatment for pain, the algorithm identified and excluded from our estimates instances in which opioids were used for an indication other than pain (i.e., opioid-containing cough and cold medications, and buprenorphine or methadone if applicants reported the indication was opioid use disorder [OUD]). The algorithm demonstrated an accuracy rate of 99.92% when hand-checked against 1200 medication entries, and yielded similar yearly estimates of the overall

share of SSDI applicants taking opioids as a different NLP algorithm developed by Wu and colleagues (Wu et al., 2019).

Finally, our covariate data was obtained from several sources. County urbanicity was obtained from the US Department of Agriculture's Economic Research Service, the percent of adults in a county without a high school degree was obtained from the American Community Survey, and county-level job counts by industry were obtained from the US Department of Commerce's Bureau of Economic Analysis.

Constructing an Opioid Prescribing Instrument Using Commercial Claims Data

We use health care providers' propensity to prescribe opioids for pain (Z) as our instrument. Providers' innate propensities to prescribe opioids are not something we can directly observe, so we estimate Z based on observed opioid prescribing behavior in health care claims data. We use Blue Cross Blue Shield (BCBS) Axis® data, an administrative database comprised of claims information submitted by BCBS commercial insurers operating across the country: together, these data comprise the largest collection of commercial insurance claims currently available in the US, covering over 36 million members per month and over 1.5 million health care providers drawn from all 50 states. Claims data are available for the years 2012-2017, and contain selected patient (e.g., age) and provider characteristics (e.g., specialty), as well as detailed geographic information identifying providers' practice location at the 5-digit zip code level. Data on patients' health care utilization is determined using claims for outpatient medical encounters, while patients' health conditions are identified using ICD-9 and ICD-10 codes listed on encounter claims. Prescription data are drawn from a prescription claims file, which contains information on all prescription drugs that were filled by beneficiaries and for which an insurance

claim was submitted.[5] To identify opioid prescriptions, we selected all drug claims with National Drug Code (NDC) codes designated as opioid agonists (including partial agonists and combination agonist/antagonists) by the FDA (as of January 17th, 2017), the National Center for Injury Prevention and Control, the MarketScan 2016 Red Book or Red Book online. We excluded cough syrups, injectable opioids, and opioids administered during inpatient stays. We also excluded methadone, buprenorphine and buprenorphine combination products.[6] The prescription claims can be linked precisely to individual enrollees, but approximately one-quarter of them cannot be definitively linked to the specific provider who wrote the prescription because the provider identifier indicates a provider organization or a pharmacy rather than an individual provider. As a result, these prescriptions also cannot be definitively linked to specific medical encounters. We therefore attribute these opioid prescriptions to an outpatient encounter that occurred on the same day or the day before the prescription was filled.

For *Z* to be a valid instrument, it must be uncorrelated with both our labor outcomes of interest (i.e., employment, wages and disability claiming) and with other patient characteristics that might influence labor outcomes. These include observable characteristics such as health status, but also less easily observable characteristics such as opioid dependence that has not yet been clinically recognized but may influence patients' care-seeking patterns and tendency to request opioid treatment for pain (i.e., "doctor-shopping" behavior). The BCBS Axis® data allow us to readily adjust for observable medical conditions using ICD-9 and ICD-10 diagnosis codes linked to medical encounters. The data also allow us to mitigate bias from unobservable

[5] As is typical of administrative claims data, we can identify prescriptions that were ultimately filled, but cannot identify prescriptions that were written but not filled.
[6] As described later in this section, our instrument was based on patterns of initial opioid analgesic prescriptions to opioid-naïve individuals without evidence of OUD. Buprenorphine and methadone are typically prescribed for either chronic pain or OUD and were therefore excluded.

patient characteristics by restricting our sample to outpatient encounters by patients ages 18-64 who had not filled any opioid prescriptions in the preceding 6 months. Our rationale is two-fold: (1) individuals who are not chronic or frequent opioid users should be less likely to seek out providers primarily on the basis of their perceived laxity in prescribing opioids (i.e., they are less likely to bias observed prescribing rates through "doctor-shopping"), and (2) observing providers' decisions whether or not to *initiate* opioid therapy provides a cleaner measure of their prescribing propensity than assessing their decision whether or not to *continue* existing opioid regimens, some of which they may not have initiated in the first place (for example, if they "inherited" a patient with high levels of opioid use), and considering that chronic opioid therapy is notoriously difficult to wean. There are two other major advantages of the BCBS Axis® data with respect to our research design. First, it contains a large provider sample with broad geographic coverage – nearly all active US physicians and many non-MD providers who are able to prescribe opioids across all 50 states are included in the data, allowing for a comprehensive view of opioid prescribing practices in different parts of the country. Second, the large majority of enrollees are in employer-sponsored plans and are therefore employed at the time we observe them in the data – in effect, this allows us to control for any potential confounding of providers' opioid prescribing behavior by patients' labor force attachment when constructing our instrument, therefore satisfying the requirement that our instrument Z not be correlated with labor force attachment.

We estimate providers' opioid prescribing propensity Z at the couma-year level as follows. From 2012 to 2017, for each couma we identified all outpatient encounters by adults ages 18 to 64 who were continuously enrolled for the prior 6 months, had filled no opioid prescription during that time period, and had no prior OUD diagnosis. We restrict our sample to

outpatient encounters where the rendering provider was a medical professional permitted by law to prescribe opioids in a majority of states: this includes physicians with M.D. and D.O. degrees, nurse practitioners and certain other advanced-practice and specialized nurses, physician assistants and optometrists. We also excluded outpatient encounters with addiction specialists and hospice and palliative care physicians given the unique considerations affecting opioid prescribing in these patient populations.[7] This yielded a sample of 348,119,135 outpatient encounters by 36,558,716 enrollees treated by 970,056 unique providers in all 50 states. Of note, our provider sample was comprised of 727,415 physicians –76% of active US physicians[8] – and 242,641 non-physician providers (Boston et al., 2015; United States Government Accountability Office, 2017; Young et al., 2019).

We pooled encounters within a given couma and year and first calculated two unadjusted measures of opioid prescribing behavior: the percent of encounters resulting in an opioid prescription, and the percent of encounters resulting in a problematic opioid prescription.[9] The latter was defined as an initial prescription with at least one of the following characteristics that are discouraged by current prescribing guidelines (Dowell, Haegerich, & Chou, 2016): days' supply greater than 7; dose greater than 50 morphine milligram equivalents per day; long-acting formulation; or the absence of a documented pain diagnosis at the associated encounter (Rose et al., 2018; Sherry, Sabety, & Maestas, 2018). We then risk-adjusted these prescribing measures to

[7] We determined provider type (i.e., physician versus non-MD provider) and specialty using the primary taxonomy code associated with each rendering provider's National Provider Identifier (NPI) in the National Plan and Provider Enumeration System NPI Registry.

[8] It is estimated that there are 985,026 professionally active physicians practicing in the US today, with approximately 25,010 of these physicians employed by the Veterans' Health Administration and 12,000 employed by the United States Military Health System. These federally-employed physicians are not eligible for our commercial claims sample – our physician sample (N = 727,415) therefore captures at least 76% of active non-federal US physicians.

[9] Recall that, as described earlier, we attribute an opioid prescription to a specific outpatient encounter if it was filled on the same day or the day following the encounter.

purge them of potentially confounding patient characteristics, by modeling each unadjusted prescribing measure in couma *c* and year *t* (p_{ct}) as a function of patient characteristics v_{ct}, state θ and year π fixed effects using log-linear regression:

$$\ln(p_{ct}) = \alpha' v_{ct} + \theta_s + \pi_t + u_{ct} \ , \quad (3)$$

where v_{ct} is the risk-adjustment vector containing the following patient characteristics: the age distribution of patients seen in outpatient encounters in couma *c* and year *t* in our sample,[10] the percent of encounters by female patients, the percent with a diagnosis of mental illness, and the percent with a diagnosis of non-opioid substance use disorder. To comprehensively adjust for the prevalence of numerous pain-related conditions, v_{ct} also includes the average number of specific pain-related diagnoses per encounter in couma *c* and year *t*. Pain-related diagnoses include over 200 specific ICD-9 codes for medical conditions usually accompanied by significant pain, grouped into 18 major classes (e.g., MSK, cancer, gastrointestinal, etc.). In addition, to comprehensively adjust for the underlying medical complexity of patients treated at encounters in our sample, v_{ct} also includes the average number of specific non-pain-related medical diagnoses per encounter. Non-pain-related diagnoses include nearly all other ICD-9 diagnosis codes, grouped into 13 major classes (see **Appendix A2** for full list of diagnoses included in v_{ct}).

We use log-linear models to risk-adjust our prescribing measures, since the unadjusted measures are highly right-skewed. The model residuals, u_{ct}, capture how much *observed* prescribing by providers in couma *c* in year *t* deviates from *expected* prescribing based on patient characteristics, secular trends and time-invariant state characteristics (e.g. major industries,

[10] We adjusted for the age distribution of patients by controlling for the percent of encounters by patients age 45 to 54, and the percent of encounters by patients age 55 to 64.

medical practice environment). The residuals u_{ct} therefore give our adjusted prescribing propensities *Z*: positive values of u_{ct} (and therefore *Z*) indicate that levels of *observed* prescribing in couma *c* in year *t* exceed *expected* prescribing and therefore that providers have a *greater* propensity to prescribe opioids for pain, and vice versa. We estimate separate models for our two prescribing measures (i.e., any prescribing and problematic prescribing), yielding two different versions of our instrument.

5. Results

We first describe our findings on health care providers' opioid prescribing propensities as estimated using BCBS Axis® commercial claims data. We then present the results of our 2SLS models estimating the impact of prescription opioid analgesic supply on local labor outcomes, using provider's prescribing propensities as an instrument for opioid supply.

Risk-Adjusted Prescribing Propensities Estimated in Commercial Claims Data

Table 1 presents summary statistics describing the characteristics of outpatient encounters in the BCBS Axis® data that met our sample inclusion criteria and were therefore used to construct our prescribing propensity instruments. The majority of encounters ultimately included in our sample were by female patients. The distribution of Charlson Comorbidity Scores, with nearly 72% of encounters by patients with a Charlson score of zero, indicates that the majority of encounters were also by relatively healthy patients. Still, a pain-related diagnosis was recorded at 38.9% of encounters and a diagnosis of a mental health disorder was recorded at 32.4% of encounters.

Table 2 presents summary statistics for the two unadjusted opioid prescribing measures calculated at the couma-year level using the BCBS Axis® data: the percent of encounters resulting in any opioid prescription (column 1), and the percent resulting in a problematic initial opioid prescription (column 2). In this commercially insured sample, between 2012 and 2017 on average 3.1 percent of outpatient encounters by opioid-naïve patients resulted in an opioid prescription (column 1), and 1.35 percent of outpatient encounters resulted in a problematic initial prescription (column 2). The values of these unadjusted prescribing measures varied widely, however, across coumas during this time period. The percent of encounters in a given couma and year resulting in an opioid prescription, for example, ranged from 0.6% to 21.4%.

Table 2 also presents summary statistics for the risk-adjusted prescribing propensities that we use as instruments (columns 3 and 4). Propensities are scaled by a factor of 100 such that a propensity of $Z=z$ (where $z > 0$) in a given couma can be interpreted to mean that in that couma, the observed percent of encounters with any opioid prescription exceeds the expected percent of encounters with any opioid prescription by z percentage points. Conversely, a propensity of $-z$ in a given couma indicates that the observed percent of encounters with any opioid prescription is less than the expected percent of encounters with any opioid prescription. Larger values of z therefore indicate a higher propensity, or willingness, of providers to prescribe opioids even after adjusting for patient's medical and demographic characteristics, secular trends and time-invariant characteristics of the state in which the provider practices. Column 3 therefore shows that between 2012 and 2017, in coumas with the lowest risk-adjusted prescribing propensity, there were 3.4 fewer opioid prescriptions per 100 medical encounters than expected based on patient and state characteristics and time trends; in coumas with the highest risk-adjusted prescribing propensity, there were 16.1 additional opioid prescriptions per 100 medical

encounters than expected. Column 4 shows that in coumas with the lowest risk-adjusted prescribing propensity, there were 2.1 fewer problematic initial opioid prescriptions per 100 medical encounters than expected; in coumas with the highest risk-adjusted prescribing propensity, there were 5.8 additional problematic initial opioid prescriptions per 100 medical encounters than expected.

These results indicate that even after risk-adjustment, there remains wide geographic variation in health care providers' opioid prescribing propensities. **Figure 1** illustrates variation in the propensity to prescribe any opioid across coumas, using the year 2015 as an example. Coumas with darker red shading are those with higher provider opioid prescribing propensities. Of note, since our propensity measures are adjusted for time-invariant state characteristics, coumas with higher estimated prescribing propensities are those where providers are outliers in their prescribing behavior even with respect to peers in their own states.

Instrumental Variables Estimates of the Impact of Prescription Opioid Supply on Labor Outcomes

Table 3 presents estimates of the impact of prescription opioid supply on labor outcomes of interest in the same couma. For each specific labor outcome of interest, column 1 shows ordinary least squares (OLS) estimates from a model regressing that outcome on the overall opioid prescribing rate as measured using the CDC prescribing data, and adjusting for the same covariates as our 2SLS specifications (equations 1 and 2). Column 2 presents 2SLS estimates after instrumenting for the overall opioid prescribing rate with health care providers' risk-adjusted propensity to prescribe any opioid as derived from the BCBS Axis® data, and column 3

presents 2SLS estimates after instrumenting with health care providers' risk-adjusted propensity to give a problematic initial opioid prescription.

Table 4 shows the first-stage coefficients: **Panel A** presents first-stage coefficients for models examining the employment-to-population ratio and wages, while **Panel B** presents first-stage coefficients for models examining SSDI outcomes. In **Panel A**, the first stage coefficient on providers' propensity to prescribe any opioid (i.e., 4.04, $p<0.01$) indicates that in coumas where providers prescribe one additional opioid prescription per 100 outpatient encounters than expected based on patient and state characteristics (i.e., the propensity equals 1), this results in an additional 4.04 opioid prescriptions per 100 adults in that couma over the course of a year – this represents approximately a 5% increase in the mean CDC opioid prescribing rate across all coumas, which is 86 prescriptions per 100 adults. Also in **Panel A**, the first stage coefficient on providers' propensity to prescribe a problematic initial opioid (i.e., 8.32, $p<0.01$) indicates that this has approximately double the effect on overall opioid prescriptions in an area. The first-stage estimates in **Panel B** are nearly identical to those in **Panel A** – the minor differences in the coefficients are due to the fact that for SSDI outcomes, we estimate the impacts of opioid supply lagged by two years rather than one year as for employment and wage outcomes, and therefore we use a slightly smaller sample with outcome data from the years 2014 to 2018 only.

Estimates of the impact of prescription opioid supply on the employment-to-population ratio are presented in **Table 3, Panel A**. With both versions of our instrument, we find a negative and statistically significant impact of increased opioid supply on employment. Our estimates in column 2 indicate that one additional opioid prescription per 100 adults in a couma leads to a reduction in the employment-to-population ratio by 0.11 fewer people employed per 100 working-age adults; or scaled differently, 10 additional opioid prescriptions per 100 adults

(which represents an increase in the CDC prescribing rate by only one-third of a standard deviation) leads to a reduction in the employment-to-population ratio of 1.1 fewer people employed per 100 working-age adults, which is a 1.6% decrease relative to the mean of 69.7 people employed per 100 working-age adults. Our estimates in column 3, using propensity to give a problematic initial opioid prescription as an instrument, indicate that 10 additional opioid prescriptions per 100 adults leads to a reduction in the employment-to-population ratio of 1.4 fewer people employed per 100 working-age adults. Interestingly, our IV estimates are larger in magnitude than our OLS estimates (column 1), which indicate that 10 additional opioid prescriptions per 100 adults is associated with a reduction in the employment-to-population ratio by 0.5 fewer people employed per 100 working-age adults. We discuss this further below.

Table 3, Panel B presents estimates of the impacts of opioid supply on the average weekly wage. With both versions of our instrument, we find a negative and statistically significant impact of increased opioid supply on the average weekly wage. Our estimates in column 2 indicate that one additional opioid prescription per 100 adults in a couma leads to a reduction in the average weekly wage by $4.86; or scaled differently, 10 additional opioid prescriptions per 100 adults (which again represents an increase in the CDC prescribing rate by only one-third of a standard deviation) leads to a reduction in the average weekly wage by $48.60, which is a 6% decrease relative to the mean weekly wage of $818.20. Our estimates in column 3, using propensity to give a problematic initial opioid prescription as an instrument, indicate that 10 additional opioid prescriptions per 100 adults leads to a reduction in the average weekly wage of $26.60. This suggests that opioid use has adverse impacts on productivity even among individuals who remain employed. Again, the IV estimates are larger in magnitude than

our OLS estimates (column 1), which indicate that 10 additional opioid prescriptions per 100 adults is associated with a reduction in average weekly wage by $20.90.

Table 3, Panel C presents estimates of the impacts of opioid supply on SSDI application rates. With both versions of our instrument, we find a positive and statistically significant impact of increased opioid supply on SSDI application rates. Our estimates in column 2 indicate that one additional opioid prescription per 100 adults in a couma leads to an increase in the SSDI application rate by 0.008 applications per 100 relevant population (i.e. adults age 25 to 64); or scaled differently, 10 additional opioid prescriptions per 100 adults (which represents an increase in the CDC prescribing rate by only one-third of a standard deviation) leads to an increase in the SSDI application rate by 0.08, which is an 8% increase relative to the mean of 0.98 applications per 100 relevant population. Our estimates in column 3, using propensity to give a problematic initial opioid prescription as an instrument, indicate that 10 additional opioid prescriptions per 100 adults leads to an increase in the SSDI application rate by 0.06 (an increase of 6%). Again, our IV estimates are larger in magnitude than our OLS estimates (column 1), which indicate that 10 additional opioid prescriptions per 100 adults is associated with an increase in the SSDI application rate by 0.06. **Panel D** shows that opioid supply is also estimated to significantly increase the rate of SSDI applications mentioning opioid use. Ten additional opioid prescriptions per 100 adults leads to an increase in the SSDI application rate by 0.03, which is a 10% increase relative to the mean of 0.31 applications per 100 relevant population (column 2); we obtain similar estimates when using propensity to give a problematic initial opioid prescription as an instrument (column 3). This confirms that a primary mechanism by which opioid supply affects SSDI applications is through greater use of prescription opioid medications by SSDI applicants.

Finally, **Table 3, Panel E** presents estimates of the impacts of opioid supply on the rate of initial SSDI allowances. With both versions of our instrument, we find a positive and statistically significant impact of increased opioid supply on SSDI initial allowances. Our estimates in column 2 indicate that one additional opioid prescription per 100 adults in a couma leads to an increase in the rate of initially allowed applications by 0.002 allowed applications per 100 relevant population (i.e. adults age 25 to 64); or scaled differently, 10 additional opioid prescriptions per 100 adults leads to an increase in the rate of initially allowed applications by 0.02, which is an 6% increase relative to the mean of 0.32 initially allowed applications per 100 relevant population. We obtain similar estimates when using propensity to give a problematic initial opioid prescription as an instrument (column 3). Once again, the IV estimates are larger in magnitude than our OLS estimates (column 1), which indicate that 10 additional opioid prescriptions per 100 adults is associated with an increase in the rate of initially allowed applications by 0.01. This implies that the initial allowance rate among opioid-induced applications was 0.25 (i.e., 0.002 [Panel E] / 0.008 [Panel C]), slightly lower than the overall initial allowance rate of 0.32.

6. Discussion and Conclusion

There is a striking negative association between prescription opioid supply and labor outcomes, and understanding to what extent opioid treatment for pain causes adverse employment and disability outcomes is critical to informing both health and economic policy. Our analysis sheds new light on this question. By leveraging the largest available US commercial claims database, we construct a plausibly exogenous measure of health care providers' opioid prescribing propensity that is independent of several important confounders of the relationship

between prescription opioid use and labor outcomes—most notably patients' medical and demographic characteristics and their labor force attachment. Our data enables us to purge our prescribing instrument of these confounders to a greater extent than previous studies, which have lacked detailed information on patients' medical diagnoses, and have also been unable to adjust for either observed or unobserved labor force attachment. By constructing our instrument using a sample of opioid-naïve individuals and examining providers' propensity to give initial opioid prescriptions, we are also able to mitigate potential bias from "doctor-shopping" behaviors to an extent not possible in previous research. We use this prescribing propensity instrument to obtain estimates of the causal impact of prescription opioid supply on the local employment-to-population ratio and average weekly wage. In addition, our analysis is among the first to examine the impacts of prescription opioid use on SSDI claiming and initial allowances, and through our use of a novel NLP text matching algorithm, we provide evidence of impacts on SSDI applications mentioning opioid use specifically. We find a statistically significant, negative impact of prescription opioid supply on the employment-to-population ratio and the average weekly wage, and a statistically significant, positive impact of SSDI applications overall and applications mentioning opioid use, as well as the rate of initially allowed applicants. Specifically, we find that 10 additional opioid prescriptions per 100 adults in a couma leads to: a decrease in the employment-to-population ratio by 1.1 employed persons per 100 people of working age (1.6% decrease relative to the mean); a decrease in the average weekly wage by $48.60 (a 6% decrease relative to the mean); an increase in SSDI applications overall by 0.08 per 100 relevant population (an 8% increase relative to the mean) and an increase in applications mentioning opioid use by 0.03 (a 10% increase relative to the mean); and an increase in the rate

of initially allowed applications by 0.02 per 100 relevant population (a 6% increase relative to the mean).

Across all outcome measures we examined, our IV estimates of the impacts of prescription opioid supply were larger in magnitude than our OLS estimates. This implies that OLS is biased down by an unobserved factor that is negatively correlated with both prescription opioid use and employment across areas. Illicit drug markets are potentially such a factor: greater availability of illicit opioids in a given couma might lead chronic users to substitute away from prescription opioids toward cheaper illicit opioids, and could independently weaken employment by increasing rates of opioid dependence. Our instrumental variable, which is built from opioid prescriptions given to first-time opioid users who are unlikely to already be dependent on opioids, circumvents this confounding pathway.[11] Local economic shocks are another potential factor, which could reduce employment and opioid prescriptions through loss of employer-sponsored health insurance (ESI). Our instrumental variable, which is derived from opioid prescriptions given to employed patients with employer-sponsored health insurance, helps mitigate this confounding as well.

These factors also potentially explain why our estimates of the impact of prescription opioid supply on the employment-to-population ratio are larger in magnitude than those in the literature.[12] Harris et al. (2019) use the number of high-volume prescribers in an area in a given

[11] If OLS were larger than IV, this would have implied OLS was biased by an unobserved confounder positively correlated with prescription opioid use and negatively correlated with employment, such as unobserved pain prevalence, medical complexity, or weak labor force attachment. Our instrumental variable, which is built from prescriptions to employed patients and which incorporates extensive risk-adjustment for pain and medical complexity, was designed to account for this possibility as well. It is nonetheless possible that both types of biases exist in the OLS estimate, but that on net bias from illicit opioid markets (or a factor of this nature) is greater than bias from unobserved area-level pain, medical complexity or labor force attachment.

[12] Harris et al. (2019) estimate that a unit increase in the number of opioid prescriptions per capita leads to a decrease in the employment-to-population ratio by 0.07 (i.e., a 7 percentage point reduction). This implies that an increase in the opioid prescription rate by 10 prescriptions per 100 people should lead to a decrease in the employment-to-population ratio by 0.7 percentage points. In comparison, we estimate that an increase in the opioid

year as an instrument to examine local employment outcomes in the same year – since this instrument is not restricted to the commercially insured, and opioid prescribing and employment outcomes are examined contemporaneously, local economic shocks that reduce both employment and opioid prescriptions in the same year through loss of ESI could therefore bias IV estimates down. Neither Harris et al. (2019) nor Aliprantis et al. (2019) restrict their opioid prescribing instruments to initial users – their estimates may therefore be subject to downward bias if chronic opioid users substitute towards illicit opioids in areas where illicit markets are stronger, as hypothesized above.[13] Finally, sample differences might also account for differences in the magnitude of our IV estimates. Compared to Harris et al., for example, our sample includes additional years of data (2013 through 2018, compared to 2013 through 2015 in Harris et al.), and all 50 states, whereas Harris et al. include only 10 states in their main analysis.[14]

Our study has limitations. First, we have limited years of data, particularly for SSDI outcomes. Second, we are also only able to identify medications filled, not medications prescribed. Third, we must assume that the providers we observe in a given couma are a representative sample of other providers in that couma. Given we observe 76% of active US

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prescription rate by 10 prescriptions per 100 people should lead to a decrease in the employment-to-population ratio by 1.1 percentage points. Aliprantis et al. (2019) estimate log-linear models in which opioid prescribing rates are log-transformed, therefore we are unable to directly compare coefficients between our studies. Instead, we compare the impact of a one standard deviation increase in the log prescribing rate in their study (i.e., 0.39), to a one standard deviation increase in the prescribing rate in our study (i.e., approximately 30 prescriptions per 100 adults). Using their preferred specification (i.e., the specific controls approach), a unit increase in the log prescribing rate leads to a decrease in the employment-to-population ratio among prime-age men by 0.05 and among prime-age women by 0.017. A one standard deviation increase should therefore lead to a decrease in the employment-to-population ratio among prime-age men by 1.95 percentage points and among prime-age women by 0.66 percentage points. In contrast, we estimate that a one standard deviation increase in the opioid prescribing rate should lead to a decrease in the employment-to-population ratio by 3.3 percentage points.

[13] Currie et al. (2018) also do not restrict their instrument to initial opioid users – however, their instrument is based on prescribing patterns to adults age 65 and older only, therefore substitution to illicit markets is a less likely source of bias.

[14] Harris et al.'s (2019) supplemental analysis using national data from the Drug Enforcement Agency's Automated Reports and Consolidated Orders System (ARCOS) does yield slightly larger estimates of the impact of opioid supply on the employment-to-population ratio, relative to their main analysis using prescription drug monitoring program data from 10 states.

physicians, we believe this to be a reasonable assumption. Fourth, our estimates do not capture spillovers that occur from prescribing practices in one couma to labor outcomes in adjacent coumas. However, the fact that coumas are relatively large, representing populations of at least 100,000, helps to mitigate this concern. Finally, while the majority of the patients in our commercial claims data can be assumed to be employed by virtue of the fact that they have large-group coverage, there may be some non-employed individuals who obtain commercial coverage through associations, through a spouse or through the insurance exchanges (though this last category is a small share of the patients we observe). Thus, while we can mitigate bias in prescribing behavior based on patients' labor force status we may not be able to fully eliminate it.

Our findings contribute to the growing literature on the economic consequences of pain and prescription opioid use. Consistent with most other existing literature, we find adverse impacts of opioid use on employment. We also demonstrate that opioid treatment for pain can cause more lasting disruptions in labor market activity through its impacts on disability claiming. Finally, we provide evidence that prescription opioid use decreases wages, suggesting that it has adverse impacts on productivity even among individuals who remain employed. Our findings indicate that where medically possible, decreased reliance on opioid analgesics for pain treatment (and possibly increased use of effective non-opioid pain therapies with fewer adverse effects) can not only improve patients' health, but also work-related functioning and labor outcomes.

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Table 1: Characteristics of BCBS Axis® Encounters Used to Estimate Provider Prescribing Propensities

Mean Age of Patients Seen in Outpatient Medical Encounters	46.3
% Encounters with Patients Age 18-24	8.6
% Encounters with Patients Age 25-44	32.8
% Encounters with Patients Age 45-64	58.6
% Encounters with Male Patients	37.6
% Encounters with Patients with Charlson Score 0	71.7
% Encounters with Patients with Charlson Score 1-4	26.7
% Encounters with Patients with Charlson Score 5+	1.6
% Encounters with Pain Diagnosis	38.9
% Encounters with Mental Illness Diagnosis	32.4
% Encounters with Non-Opioid Substance Use Disorder Diagnosis	4

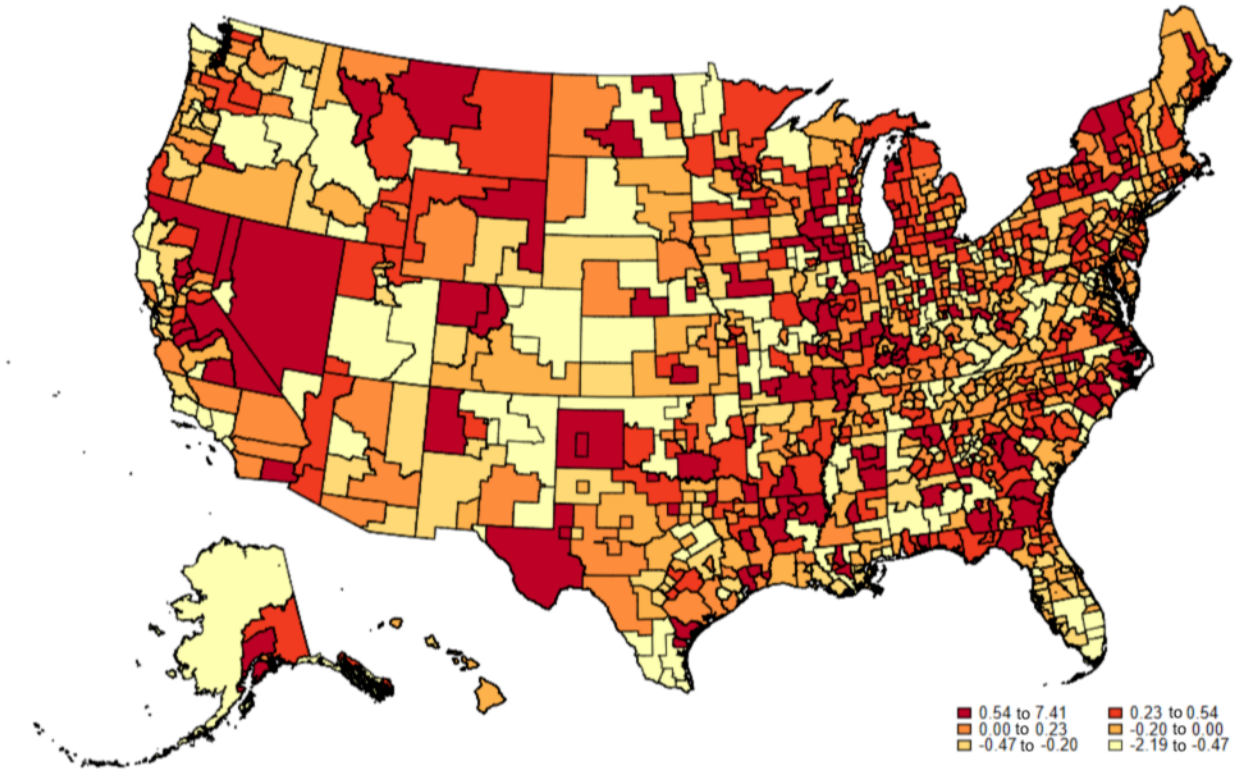
Notes: N=348,119,135 outpatient encounters. Sample restricted to outpatient encounters between January 2012 and December 2017 by opioid-naïve adults (i.e. adults who filled no opioid prescription in the 6 months prior to the encounter) age 18-64 who had been continuously enrolled for at least 6 months prior to the encounter. Encounters with addiction specialists, hospice and palliative care specialists, and non-MD providers who are not licensed to prescribe opioids in a majority of states were excluded.

Table 2: Unadjusted Opioid Prescribing Rates and Risk-Adjusted Provider Opioid Prescribing Propensities from BCBS Axis® Data

	Unadjusted Prescribing Rates (N = 5387)		Adjusted Prescribing Propensities (Instrument) (N = 5387)	
	(1)	(2)	(3)	(4)
	Any Opioid Prescription *(# Prescriptions per 100 Encounters)*	Problematic Opioid Prescription *(# Prescriptions per 100 Encounters)*	Any Opioid Prescription	Problematic Opioid Prescription
Mean	3.1	1.35	0.06	0.04
Standard Deviation	1.1	0.54	0.69	0.38
Range	0.6 – 21.4	0 – 8.2	-3.4 – 16.1	-2.1 – 5.8

Notes: Observations measured at couma-year level. Relative to unadjusted prescribing rates, when calculating adjusted prescribing propensities we control for the age distribution, sex, and both pain and non-pain related medical conditions of patients treated at encounters.

Figure 1: Geographic Variation in the Propensity to Prescribe Any Opioid by Couma, 2015



Notes: Propensities are estimated at the couma-year level. Coumas with positive prescribing propensities (i.e., those with darker orange and red shading) have higher observed opioid prescribing rates than predicted based on patient and state characteristics and secular trends; coumas with negative prescribing propensities (i.e., those with lighter shading) have lower observed opioid prescribing rates than predicted.

Table 3: Impact of Prescription Opioid Supply on Labor Outcomes

	(1) OLS	(2) IV: Propensity to Prescribe Any Opioid	(3) IV: Propensity to Give a Problematic Initial Prescription
		Panel A: Employment-to-Population Ratio *(employed people per 100 working age people)* (Mean = 69.7, SD = 7.5, Range 39.5-97.5)	
Opioid Prescribing Rate	-0.05***	-0.11***	-0.14***
	(0.01)	(0.04)	(0.04)
R-sq	0.66	--	--
N	5387	5387	5387
		Panel B: Average Weekly Wage ($) (Mean = 818.2, SD = 183, Range 511.4-2437)	
Opioid Prescribing Rate	-2.09***	-4.86***	-2.66***
	(0.22)	(1.27)	(0.95)
R-sq	0.55	--	--
N	5387	5387	5387
		Panel C: SSDI Application Rate *(applications per 100 adults age 25 to 64)* (Mean = 0.98, SD = 0.33, Range 0.17-2.83)	
Opioid Prescribing Rate	0.005***	0.008***	0.006***
	(0.000)	(0.001)	(0.001)
R-sq	0.73	--	--
N	4880	4880	4880
		Panel D: Rate of SSDI Applications Mentioning Opioids *(applications per 100 adults age 25 to 64)* (Mean = 0.31, SD = 0.13, Range 0.03-1.13)	
Opioid Prescribing Rate	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
R-sq	0.80	--	--
N	4880	4880	4880
		Panel E: SSDI Initial Allowances *(applications per 100 adults age 25 to 64)* (Mean = 0.32, SD = 0.09, Range 0.08-0.73)	
Opioid Prescribing Rate	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
R-sq	0.70	--	--
N	4880	4880	4880

Notes: ***p<0.01. Observations measured at couma-year level. Standard errors are clustered by couma and shown in parentheses beneath coefficient estimates. Opioid prescribing rates are measured using CDC data, and scaled such that coefficients represent the number of prescriptions per 100 population. Instruments are estimated using BCBS Axis® data. All models adjust for state fixed effects, year fixed effects, the percent of adults in the couma without a high school degree, the percent employed in farming, mining and manufacturing, and couma urbanicity.

Table 4: First-Stage Estimates of the Impact of Opioid Prescribing Propensity on Local Prescription Opioid Supply

Panel A: First-Stage Estimates for Employment and Wage Outcomes

	CDC Opioid Prescribing Rate *(prescriptions per 100 population)* (Mean = 86.5, SD = 30.4, Range 20.4-283.7)	
Propensity to Prescribe Any Opioid	4.04***	
	(0.94)	
Propensity to Give a Problematic Initial Prescription		8.32***
		(1.67)
R-sq	0.53	0.54
First Stage F-statistic	18.62	24.76
N	5387	5387

Panel B: First-Stage Estimates for SSDI Outcomes

	CDC Opioid Prescribing Rate *(prescriptions per 100 population)* (Mean = 88.1, SD = 30.5, Range 23.3-283.7)	
Propensity to Prescribe Any Opioid	4.05***	
	(0.97)	
Propensity to Give a Problematic Initial Prescription		8.23***
		(1.72)
R-sq	0.52	0.53
First Stage F-statistic	17.64	22.96
N	4880	4880

Notes: ***p<0.01. Observations measured at couma-year level. Standard errors are clustered by couma and shown in parentheses beneath coefficient estimates. All models examine the relationship between opioid prescribing propensity (as estimated using BCBS Axis® data) and local opioid prescribing rates (as measured using CDC data, and scaled such that coefficients represent the number of prescriptions per 100 population) adjust for state fixed effects, year fixed effects, the percent of adults in the couma without a high school degree, the percent employed in farming, mining and manufacturing, and couma urbanicity. First-stage estimates from models examining impacts on the employment-to-population and wages (Panel A) use outcome data from 2013 to 2018, and opioid prescribing rates lag outcome measures by 1 year. First-stage estimates from models examining impacts on SSDI outcomes (Panel B) use outcome data from 2014 to 2018, and opioid prescribing rates lag outcome measures by 2 years. This accounts for the discrepancy in sample sizes and slight discrepancy in coefficients. Models examining impacts on the employment-to-population and wages use outcome data from 2013 to 2018, and opioid prescribing rates lag outcome measures by 1 year. Models examining impacts on SSDI outcomes use outcome data from 2014 to 2018, and opioid prescribing rates lag outcome measures by 2 years.

Appendix A1: Approach to Crosswalking Five-Digit Zip Codes to Coumas

All of our data sources report measures at the county-level with two exceptions: SSA's MEDIB data reports applicants' 5-digit zip code (zip5) of residence, and BCBS Axis® data reports health care providers' location at the zip5-level. We must therefore crosswalk zip5s to coumas in order to produce couma-level prescribing propensity measures and couma-level estimates of SSDI outcomes. We use a two step approach in which we first crosswalk zip5s to zip code tabulation areas (ZCTAs), and then crosswalk ZCTAs to coumas.

ZCTAs are geographic areas constructed by the Census Bureau to roughly represent the United States Postal Service (USPS) zip5s.[15] The ZCTA code assigned to an area corresponds to the most frequently occurring zip5 code within that area – therefore, while in most cases the ZCTA and zip5 code for a given address will match, in some cases they may differ, which is why crosswalking zip5s to ZCTAs is a necessary initial step. We do this using the zip5-to-ZCTA crosswalk provided by the Uniform Data System (UDS) Mapper,[16] a joint initiative by the Health Resources and Services Administration (HRSA), John Snow Inc., and the American Academy of Family Physicians that is intended to support analyses evaluating the geographic reach of the Section 330 Health Center Program.[17]

Having crosswalked all zip5s in our SSA and BCBS Axis® data to ZCTAs, we then crosswalk ZCTAs to coumas, starting with the Census Bureau's ZCTA-county relationship file. For a given ZCTA-county pair, this relationship file gives the 2010 Census population for the overlapping geographic area that is common to both the ZCTA and the county, the percentage of the ZCTA's population within the overlapping area, and the percentage of the county's population within the overlapping area. We modify this relationship file by aggregating all counties to their respective coumas, using the county-couma crosswalk developed by Case and Deaton (2017),[18] which yields a ZCTA-couma relationship file. Note that counties are fully nested within coumas, so aggregating counties to coumas is straightforward.

We then use the ZCTA-couma relationship file to assign ZCTAs to coumas. In cases where a ZCTA is fully nested within a couma, all applicants (in the case of SSA data) or providers (in the case of BCBS Axis®) assigned to that ZCTA are assigned to the couma. In cases where a given ZCTA overlaps with multiple coumas (i.e., is not fully nested within a single couma), we assign applicants/providers from that ZCTA to a couma probabilistically, based on the percent population in the ZCTA apportioned to each couma in the ZCTA-couma relationship file. For example, suppose ZCTA A overlaps with both Couma B and Couma C, with 30% of ZCTA A's population in Couma B and 70% in Couma C. Our crosswalk will therefore assign each applicant/provider from ZCTA A to Couma B with a probability of 0.3, and to Couma C with a probability of 0.7.

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[15] Additional details on the construction of ZCTAs are available here: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html

[16] UDS Mapper's zip5 to ZCTA crosswalk is available here: https://www.udsmapper.org/zcta-crosswalk.cfm

[17] Additional information about UDS Mapper is available here: https://www.udsmapper.org/about.cfm

[18] We used the county-couma crosswalk provided as an online data appendix to Case & Deaton (2017), available at https://www.brookings.edu/bpea-articles/mortality-and-morbidity-in-the-21st-century/.

A limitation of the crosswalk is that the most recent Census ZCTA-county relationship file was created in 2010 and therefore the percent of a ZCTA's population assigned to a particular county reflects the 2010 value. Since more recent data apportioning ZCTA populations to counties is not available, we must therefore assume that the distribution of a ZCTA's population among counties (and hence coumas) during our study period (2013-2018) is similar to 2010.

Appendix A2: ICD-9 Codes Used to Adjust for Patients' Medical Complexity in BCBS Axis® Data

To comprehensively adjust our prescribing instruments for patients' medical characteristics, v_{ct} in equation 3 includes the following variables estimated at the couma-year level:

- Average number of pain-related infectious conditions per encounter (i.e. total number of pain-related infectious condition diagnoses recorded across sample encounters in couma *c* and year *t*/total number of encounters in couma *c* and year *t*)
- Average number of other infectious conditions per encounter
- Average number of pain-related endocrine conditions per encounter
- Average number of other endocrine conditions per encounter
- Average number of pain-related nutrition or metabolic disorders per encounter
- Average number of other nutrition or metabolic disorders per encounter
- Average number of pain-related joint disorders per encounter
- Average number of pain-related other musculoskeletal disorders per encounter
- Average number of other musculoskeletal disorders per encounter
- Average number of pain-related cancer or other neoplasm diagnoses per encounter
- Average number of other cancer or other neoplasm diagnoses per encounter
- Average number of pain-related immune and inflammatory disorders per encounter
- Average number of pain-related hematologic disorders per encounter
- Average number of other immune, inflammatory and hematologic disorders per encounter
- Average number of pain-related nervous system disorders per encounter
- Average number of other nervous system disorders per encounter
- Average number of pain-related eye and ear disorders per encounter
- Average number of pain-related circulatory system disorders per encounter
- Average number of other circulatory system disorders per encounter
- Average number of pain-related mouth, jaw and throat disorders per encounter
- Average number of pain-related respiratory disorders per encounter
- Average number of other respiratory disorders per encounter
- Average number of pain-related gastrointestinal (GI) disorders per encounter
- Average number of other GI disorders per encounter
- Average number of pain-related genitourinary (GU) and reproductive disorders per encounter
- Average number of pain-related skin disorders per encounter
- Average number of other skin disorders per encounter
- Average number of pain-related mental disorders per encounter
- Average number of other injury diagnoses per encounter
- Average number of pain-related miscellaneous conditions per encounter
- Average number of other miscellaneous conditions per encounter

Table A2 summarizes the ICD-9 codes corresponding to each type of condition.

Table A2: ICD-9 Diagnosis Codes Assigned to Medical Conditions

Condition	ICD-9 Codes
Pain-related infectious	003.23, 003.24, 015.*, 036.82, 040.0, 040.81, 053.12, 053.13, 053.2*, 053.7*, 053.8, 053.9, 054.1*, 056.71, 060.*, 061, 066.40, 066.49, 072.0, 072.3, 074.1, 074.20, 074.21, 074.23, 088.81, 095.5, 095.7, 099.3, 101, 112.84, 117.5, 122.*, 136.5, 137.3, 321.2, 390, 478.21, 478.22, 478.24, 478.71, 682.*, 683, 686.01, 730.*
Other infectious	Code is between 001-139, or within the categories of V08 or V09, and is NOT already included in the list of pain-related ICD-9 codes
Pain-related endocrine	245.0, 245.1, 249.*, 250.*, 251.5, 268.0, 268.1, 268.2, 277.1
Other endocrine	Code is between 240-259 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related nutrition or metabolic	266.0, 266.2
Other nutrition or metabolic	Code is between 260-278 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related joint disorders	274.0*, 274.9, 275.01, 275.02, 275.03, 275.49, 277.2, 277.30, 277.31, 696.0, 711.*, 712.*, 713.*, 715.*, 716.*, 717.*, 718.0*, 718.1*, 718.2*, 718.3*, 718.8*, 718.9*, 719.1*, 719.2*, 719.3*, 719.4*
Pain-related other musculoskeletal	136.0, 588.0, 721.*, 722.0, 722.1*, 722.2, 722.3*, 722.4, 722.5*, 722.6, 722.7*, 722.8*, 723.0, 723.1, 723.2, 723.3, 723.4, 723.5, 723.6, 724.*, 726.*, 727.0*, 727.2, 727.3, 727.6*, 728.0, 728.1*, 728.81, 728.83, 728.85, 728.86, 728.88, 729.0, 729.1, 729.2, 729.3*, 729.4, 729.5, 729.7*, 729.82, 731.2, 733.1*, 733.4*, 733.6, 733.7, 733.93, 733.94, 733.95, 733.96, 733.97, 733.98, 786.5*, 800-897.*, 920, 921.0, 921.1, 922.*, 923.*, 924.*, 925-949.*, 953.*, 954.8, 954.9, 955-957.*, 958.9*, 959.*, 997.41, 997.62, V13.4, V13.5*, V43.6*
Other musculoskeletal	Code is between 710-739 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related cancer or other neoplasm	140.*, 141.*, 142.*, 143.*, 144.*, 145.*, 146.*, 147.*, 148.*, 149.*, 150.*, 151.*, 152.*, 153.*, 154.*, 155.*, 156.*, 157.*, 158.*, 159.*, 160.*, 161.*, 162.*, 163.*, 164.*, 165.*, 170.*, 171.*, 172.*, 173.*, 174.*, 175.*, 176.3, 176.4, 179, 180.*, 181, 182.*, 183.*, 184.*, 185, 186.*, 187.*, 188.*, 189.*, 191.*, 192.*, 194.*, 195.*, 196.*, 197.*, 198.*, 199.*, 200.*, 201.*, 202.*, 203.*, 204.*, 205.*, 206.*, 207.*, 208.*, 209.*, 218.*, 235.*, 236.*, 237.*, 238.*, 239.*, 357.3, 528.01, 990, V10.*, V58.0, V58.1*
Other cancer or other neoplasm	Code is between 140-239 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related immune or inflammatory	135, 136.1, 279.5*, 446.0, 446.3, 446.4, 446.7, 710.0, 710.1, 710.3, 710.4, 710.5, 714.0, 714.1, 714.2, 714.3*, 714.4, 714.89, 714.9, 720.*, 725
Pain-related hematologic	282.41, 282.42, 282.60, 282.61, 282.62, 282.63, 282.64, 282.68, 282.69, 286.0, 286.1, 289.1

Other immune, inflammatory or hematologic	Code is between 279-289 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related nervous system	321.4, 322.*, 324.*, 325, 332.0, 336.0, 339.*, 340, 341.0, 341.2*, 346.*, 349.0, 350.1, 350.2, 353.*, 354.*, 355.*, 356.0, 356.2, 356.4, 356.8, 356.9, 357.0, 357.1, 357.2, 357.4, 357.5, 357.6, 357.7, 357.81, 357.82, 357.89, 357.9, 359.4, 359.5, 359.6, 359.7*, 359.8*, 359.9, 430, 431, 432.*, 437.4, 437.6, 784.0
Other nervous system	Code is between 320-389 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related eye and ear	360.03, 360.11, 360.12, 376.02, 376.03, 379.91, 380.02, 380.03, 380.14, 383.*, 388.7*
Pain-related circulatory	391.*, 393, 415.1*, 420.*, 422.*, 429.0, 443.1, 443.8*, 443.9, 444.2*, 444.8*, 444.9, 445.*, 447.6, 449, 451.*, 453.0, 453.1, 453.4*, 453.82, 453.83, 453.84, 453.89, 454.0, 454.1, 454.2, 454.8, 457.0, 457.1, 457.2
Other circulatory	Code is between 390-459 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related mouth, jaw and throat	520.6, 522.1, 522.4, 522.5, 522.6, 522.7, 523.3*, 523.4*, 525.11, 526.5, 527.2, 527.3, 528.00, 528.02, 528.09, 528.3, 784.1, 784.92
Pain-related respiratory	478.11, 511.0, 511.1, 517.3, 519.2
Other respiratory	Code is between 460-519 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related GI	455.1, 455.4, 455.7, 475, 530.10, 530.12, 530.13, 530.19, 530.2*, 530.4, 530.7, 531.*, 532.*, 533.*, 534.*, 535.0*, 535.3*, 535.40, 535.41, 535.5*, 535.6*, 535.7*, 536.3, 536.41, 536.8, 537.3, 538, 540.*, 541, 542, 550.0*, 550.1*, 551.*, 552.*, 555.*, 556.0, 556.1, 556.2, 556.3, 556.5, 556.6, 556.8, 556.9, 557.0, 558.1, 558.2, 558.3, 558.41, 558.42, 558.9, 560.1, 560.2, 560.81, 560.89, 560.9, 562.01, 562.03, 562.11, 562.13, 564.1, 566, 567.*, 569.3, 569.41, 569.42, 569.5, 569.61, 569.71, 569.82, 569.83, 572.0, 572.1, 573.4, 574.0*, 574.1*, 574.3*, 574.4*, 574.51, 574.7*, 574.8*, 574.91, 575.0, 575.10, 575.12, 575.2, 575.3, 575.4, 576.1, 576.2, 576.3, 577.0, 577.1, 577.2, 578.*, 789.0*, 789.6*, 789.7
Other GI	Code is between 580-629 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related GU and reproductive	590.00, 590.01, 590.10, 590.11, 590.2, 590.80, 590.81, 590.9, 591, 592.*, 595.1, 596.6, 596.81, 599.0, 599.6*, 601.2, 607.3, 608.2*, 611.0, 611.71, 614.1, 614.2, 614.4, 614.5, 614.7, 614.8, 614.9, 616.5*, 616.81, 616.89, 616.9, 617.*, 620.2, 620.5, 625.9, 629.3*, 633.*, 639.0, 664.0*, 664.1*, 664.2*, 664.3*, 664.4*, 664.6*, 664.8*, 664.9*, 665.0*, 665.1*, 665.3*, 665.4*, 665.5*, 665.8*, 665.9*, 673.*, 674.1*, 674.2*, 674.3*, 788.0, 788.20, 788.29
Pain-related skin	694.4, 695.2, 695.81, 705.83, 707.*
Other skin disorder	Code is between 680-709 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related mental	307.8*

Other injury	Code is between 800-959 or 996-999 and is NOT already included in the list of pain-related ICD-9 codes
Pain-related miscellaneous	338.*, 780.96, V45.89, V50.*, V51.*, V54.*, V57.1, V58.4*, V58.7*, V64.4*, V66.0, V66.1, V66.2, V66.4, V66.7, V67.0*, V67.1, V67.2, V67.4, V68.01
Other miscellaneous	Code is between V45-V52, or V54-V57, or V85.2-V85.4, or within the categories of V42 V42 or V90 and is NOT already included in the list of pain-related ICD-9 codes.

Note: "*" indicates that all subcodes are included.