Employment Shocks and Demand for Pain Medication*†

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Abstract

Declining economic opportunity is often portrayed as one of the drivers of the opioid epidemic. Better employment conditions can, however, affect opioid use through two channels: substance abuse and physical pain from workplace injuries. I measure the effect of employment shocks on demand for pain medication, and to separate these channels, I use a large dataset of opioid and over-the-counter (OTC) painkiller sales. I contrast the effect of labor demand shifts on the use of opioids and OTC painkillers and also modify the shifts to allow for effects to depend on the injury rate of local industries. I find that a 1 percent increase in the employment-to-population ratio decreases the per-capita demand for opioids by 0.20 percent, while it increases the per-capita demand for OTC painkillers by 0.14 percent. To decompose the effect of employment on opioid use in the two channels, I calculate the substitution rate between these pain medications, exploring the introduction of a policy that increased requirements to prescribe opioids. My findings show that during local economic expansions, the decline in opioid abuse is twice as large as the total effect on use while, at the same time, the demand for pain relief medication increases and is related to jobs in high injury industries.

JEL Classification: E32, I12, I18, J20

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1 Introduction

Opioid use is widespread in the United States today, with more than 191 million opioid prescriptions dispensed in 2017 (CDC, 2019). Declining labor market opportunities and worsening employment conditions for less-skilled workers have been explored as one of the reasons for the spike in the use of pain medication (Case and Deaton, 2015; Krueger, 2018). Several studies explore the correlation of economic conditions with opioid use and its health outcomes, finding mostly countercyclical, but some procyclical, effects (Hollingsworth, Ruhm and Simon, 2017; Currie, Jin and Schnell, 2018). One reason for the ambiguous findings is that a higher employment rate can affect opioid use in two opposite ways. It can increase physical pain from workplace injuries, which is correlated with a larger demand for pain medication; at the same time, it can improve mental health, which is correlated with lower demand for pain medication for substance abuse. A simple measure of employment on total opioid use likely confounds labor supply and demand effects and hides important differences between opioid use for physical pain and for substance abuse.

In this paper, I use more than 170 million opioid transactions and more than 1 billion sales of over-the-counter (OTC) painkillers from scanner data in two quasi-experiments to provide new evidence on the mechanisms driving demand for pain medication during local economic fluctuations.[1] Opioids are prescribed for pain but are often used to treat mental health problems, such as insomnia or depression (Rigg and Ibañez, 2010), while OTC painkillers also treats pain but are not used to treat mental health problems (CDC, 2016). This key difference allows me to separate employment effects that operate through a physical pain channel from effects that operate through a substance abuse channel.[2] Because health—including the demand for pain medication—is correlated with a variety of local labor supply shocks, the ordinary least squares (OLS) estimates of the impact of employment on use of pain medication are likely biased. To identify the causal effect of employment, I build a shift-share instrument, also known as a Bartik instrument, for local demand shocks and contrast, within the same county, effects on demand for opioids and OTC painkillers. The instrument is a weighted sum of national industry employment growth (excluding own county employment), where the weight is the county-industry mix in the base year.

My results show that an increase in the employment-to-population ratio of 1 percent decreases the per-capita demand for opioids by 0.20 percent and, importantly, increases

[1] My data measure shipments of opioids to a point of sale or distribution to consumers and sales of OTC painkillers directly to consumers. I interpret both as measures of use or demand, which I use interchangeably.

[2] I refer to the physical pain channel as a channel where opioids are used to treat physical pain, as prescribed by a doctor, and are imperfect substitutes to OTC painkillers. I refer to the substance abuse channel as the use of opioids for any other reason than what they are prescribed for. I define these channels more carefully in the conceptual framework in Section 2.

the per-capita demand for OTC painkillers by 0.14 percent. The results are very similar when considering morphine milligram equivalents (otherwise known as MME, a morphine index that standardizes opioids into an equianalgesic dose). I interpret the increase in the demand for OTC painkillers as evidence that the need for pain relief increases in response to a positive employment shock. The negative effect on opioids shows that employment affects other channels—unrelated to physical pain—that drive down opioid use. To understand these opposite effects, I set up a simple framework of how changes in employment affect individuals' use of pain medication. In the framework, higher employment increases the need for pain relief due to workplace injuries (Asfaw, Pana-Cryan and Rosa, 2011) and at the same time increases the opportunity cost of using opioids due to missed work opportunities and time spent under its effects (Arkes, 2007).

To test for the physical pain channel, I construct a second shift-share instrument and allow it to vary by industry non-fatal injury incidence rates and by usage of workers' compensation (WC) systems. If physical pain, aggravated by workplace injuries, is the main channel driving the demand for pain medication, positive employment shocks from industries where a worker is more likely to get injured will increase the demand for pain medication even more. Using different measures of occupation's types, I complement the injury shift-share analysis with a heterogeneous analysis by the baseline share of manual jobs in a county.

The results show that in high injury industries, the per-capita demand for opioids is slightly positive and significant, while in low injury industries, the point estimate is still negative. This finding is evidence that by focusing on industries with a high incidence rate, the procyclical component of the demand for opioids is larger and even becomes predominant. The change in demand for OTC painkillers is also larger when employment increases in industries that have the highest injury incidence rate. These two results suggest that the increase in demand for pain medication is related to workplace injuries. This pattern is robust to how I define the injury rate. A similar result is found in the heterogeneous analysis: the effect on opioid use is negative and is of larger magnitude in counties that have fewer manual jobs in the baseline, and it is closer to zero in counties with more manual jobs. In contrast, the positive effect on OTC painkillers is larger in counties with more manual jobs.

Given the evidence of the physical pain and substance abuse channels affecting opioid use in opposite directions, I set up a strategy to decompose the net effect of employment on opioid use in these two channels. With this goal, I estimate the substitution between opioids and OTC painkillers. I explore a state-run policy that increased requirements to prescribe opioids: the introduction of "must-access" Prescription Drug Monitoring Programs (PDMPs). PDMPs are state-run databases that contain information about opioid prescriptions to patients. The program informs physicians and pharmacists of a patient's prescription history, with the goal of stopping the prescription or dispense if the use pattern seems suspicious. The must-access version requires that doctors consult the database before writing an opioid prescription, and it has been found to decrease opioid abuse and its related health outcomes (Buchmueller and Carey, 2018). I use a difference-in-differences framework to measure the short-term effect of the introduction of this policy on the use of opioids and OTC painkillers. The effect is measured in the three states that implement it during my period of analysis. I find that the introduction of PDMPs decreases the per-capita demand for opioids by 6.4 percent and increases the per-capita demand for OTC painkillers by 7.6 percent. These estimates imply that a decrease in 1 opioid pill is associated with an increase of 1.76 OTC painkiller pills.

I use these estimates to decompose the effect of labor demand shocks on opioid use for physical pain and for substance abuse. To address physical pain, opioids and OTC painkillers are imperfect substitutes; for substance abuse, they are not substitutes (e.g., individuals do not use OTC painkillers to get high, to go to sleep, or to relieve anxiety or stress). I combine the substitution ratio and the employment elasticity of OTC painkillers to calculate the employment elasticity of opioids due to physical pain. The difference between this value and the total employment elasticity of the demand for opioids, obtained in the first part of the analysis, is the share of opioid use due to substance abuse.

I find that the employment elasticity of opioids due to physical pain equals 0.08, an evidence that opioid use to treat physical pain is in fact procyclical. On the other hand, employment elasticity of opioids due to substance abuse is countercyclical and is equal to -0.27. A back-of-the-envelope calculation suggests that the reduction in substance abuse would result in 0.91 fewer new opioid abusers and 1,795 fewer dollars lost on productivity per county-quarter; the increase in opioid use to treat physical pain suggests that if no pain treatment were available, 5,936 dollars would be lost in productivity due to the increase in pain.

My results provide novel evidence that better employment conditions have dual effects on the demand for pain medication. This evidence is relevant for two reasons. First, improving economic conditions to fight opioid abuse has larger effects than what is obtained estimating the total effect on use. Second, a local economic expansion causes an increase in demand for pain relief, which is concentrated among those in more manual jobs and industries with a higher injury rate. Access to pain treatment, in the form of painkillers or others, may allow these workers to join, or remain in, the labor force. Because physical pain is currently a growing and important health problem in the United States (Case and Deaton, 2015; Krueger, 2018), my results support the notion that policies that constrain the access to opioids need to be compensated with policies that address physical pain (Kilby, 2015).

My paper speaks to three strands of the literature. First, my paper is related to the literature measuring the effect of workplace injuries on health. The effect of workplace activities on health was previously discussed in Rosen (1986), and most of the evidence in this area is correlational (Harkness et al., 2004; Virtanen et al., 2012). One exception is Hummels, Munch and Xiang (2016), who show that trade shocks increase total hours worked and decrease health outcomes in Denmark. In this paper, I also provide a causal estimate by constructing an injury shift-share instrument for labor demand. The effect on demand for pain medication of an exogenous increase in jobs where a worker is more likely to get injured highlights the channel of workplace injuries.

Second, the fact that I use pain medication to infer demand for pain relief also connects my paper to the literature that looks at the effect of medical technologies (such as medications) in allowing individuals to join, or remain in, the labor force (Bütikofer and Skira, 2018; Garthwaite, 2012; Daysal and Orsini, 2012). My findings suggest that workers, especially those in more manual occupations, need a medical technology to manage the increase in pain as a consequence of higher employment.

Third, my paper speaks to the literature estimating how economic conditions affect physical and mental health (Ruhm, 2000; Charles and DeCicca, 2008; Bradford and Lastrapes, 2014) and more specifically speaks to the literature on opioid use and opioid-related health outcomes. I add new evidence by measuring the effect on use, while most papers focus on the effect on opioid overdoses and other extreme outcomes. Previous studies have shown that an increase in a county's unemployment rate increases the opioid death rate (Hollingsworth, Ruhm and Simon, 2017; Pierce and Schott, 2018). The studies that measure the effect of economic fluctuations on opioid use have mixed results. Carpenter, McClellan and Rees (2017) finds no effect on use and some countercyclical effects on substance abuse.

The paper most similar to mine is from Currie, Jin and Schnell (2018), who measure the effect by demographic groups and find results that are procyclical for older women and countercyclical for men. However, to the best of my knowledge, previous studies focus on the net effect of employment. My paper is the first to contrast opioids to an imperfect substitute—OTC painkillers—which allows me to show the different channels that connect employment shocks to opioid use. My results suggest that the effect of changes in employment on opioid use due to substance abuse is significantly attenuated if the physical pain channel is not considered.

This paper is organized as follows: Section 2 presents a simple conceptual framework of demand for pain relief, which introduces the two different mechanisms of how labor demand shocks can affect use of opioids. Section 3 describes the opioid and OTC-painkiller data. Section 4 presents the shift-share empirical approach to estimate the effect of labor market conditions on the use of pain medication. Section 5 presents the main results, results using the injury shift-share, and robustness checks. Section 6 calculates the substitution rate using the second identification strategy and decomposes the employment elasticity of demand for opioids in the physical pain and substance abuse channels. Section 7 concludes.

2 Conceptual Framework

In this section, I introduce a simple conceptual framework to predict how changes in employment affect the demand for OTC painkillers and opioids. I first discuss changes in individual behavior that help understand the patterns in the data.[3] Individuals maximize a utility function where physical pain decreases overall utility. Physical pain can be attenuated with pain relief medications. Any combination of opioids and OTC painkillers can be used to obtain pain relief.[4] However, the use of opioids has an opportunity cost because of the time spent under its effects and side effects. Individuals face a cost minimization problem, where they choose how much to purchase of each medication given their pain tolerance level.

First, in an expanding economy, the need for pain relief is expected to increase due to an increase in physical pain. First, the composition of workers is expected to change, with new and less experienced hires and workers with existing health conditions joining the labor force (Autor and Duggan, 2003; Currie and Madrian, 1999). Second, the pace of work can also become more intensive, and third, physical capital can depreciate faster, increasing the likelihood of workplace injuries (Asfaw, Pana-Cryan and Rosa, 2011). Correlational evidence shows that physical demands of work increase reports of pain and aggravation of symptoms (Waddell and Burton, 2001), and pain in the workplace is a common symptom, with more than half of the workforce suffering from it (Stewart et al., 2003). In one the few causal estimates in this literature, Hummels, Munch and Xiang (2016) show that a positive trade shock increases the intensity of both on-the-job activities and the rate of injuries and sickness among workers.

Second, while demand for pain relief increases with an expanding economy, the opportunity cost of using opioids for substance abuse motives increases. This increase is due to

[3] A recent literature shows that the countercyclical effect of economic conditions on mortality is mostly the result of general equilibrium effects and not the result of a change in employment status per se (Miller et al., 2009; Stevens et al., 2015; Crost and Friedson, 2017). However, there is still agreement that the effects of economic conditions on health outcomes, especially mortality, are mostly procyclical due to mental health reasons and are countercyclical due to physical health reasons (Ruhm, 2000, 2003; Charles and DeCicca, 2008; Bradford and Lastrapes, 2014). In the last year, Ruhm (2015) also shows that mortality from accidental poisoning—which includes deaths from opioid abuse and is related to mental health issues—spiked.

[4] Opioids and OTC painkillers operate in different ways to attenuate pain. This difference is key to the idea that they are imperfect substitutes to treat physical pain but not for other reasons opioids may be used. Appendix Section B provides a more detailed explanation of how these medications work.

missed work opportunities and to the reduced need to cope with stressful events, such as not having a job (Browning and Heinesen, 2012; Eliason and Storrie, 2009). The literature shows some evidence of the effect of economic conditions on drug use, but it has focused mainly on smoking and drinking, finding mostly countercyclical responses (Ruhm and Black, 2002; Xu, 2013). Few studies have looked at the effect on other drugs, mostly due to lack of data, and findings vary with type of drug. Specific drug characteristics, such as if it is legal and how long the effect lasts, change how its use is affected by economic conditions (Arkes, 2007; Martin Bassols and Vall Castelló, 2016; Carpenter, McClellan and Rees, 2017). Descriptive studies show that among those who misuse opioids, more than 60 percent mention reasons such as to get high, to sleep, or to relieve anxiety or stress (Rigg and Ibañez, 2010; Evans and Cahill, 2016). In addition, the opportunity cost of opioid is related to the time spent under its effects and side effects that cannot be spent in productive activities. Even if using as prescribed, the patient may feel drowsy and impaired to do certain activities.[5]

As a result, in an expanding economy, the effect of the first channel—physical pain—will increase the demand for opioids, while the effect of the second channel —substance abuse—will decrease the demand for opioids. Which effect predominates when there is an employment shock is an empirical question, which I explore in this paper. In Section 6, I calculate the substitution rate between opioids and OTC painkillers and show evidence of the expected effect on opioid use if I were to isolate each of these channels.

3 Data and Sample

In this section I present the sources of data I use in the main analysis, how variables are constructed, and descriptive statistics.

3.1 Data

I use two main sources of data to capture prescription opioids and OTC painkillers sales: retail stores' weekly sales from the Nielsen Retail Dataset and shipments of opioids from the Drug Enforcement Administration's Automated Reports and Consolidated Orders System (ARCOS). Employment is measured using the Quarterly Workforce Indicators (QWI). Both datasets are available at the retailer-weekly level or more frequently, while the employment data are available only at the county-quarter level. To standardize the analysis, I aggregate pain medication sales to the county-quarter level, creating a variable of total sales.

[5]For example, the leaflet of Vicodin, one of the most popular opioid medication brand in my data, warns that the medication may impair mental and physical abilities and compromise the ability to perform potentially hazardous activities, such as driving and operating machinery (Abbvie, 2017).

Opioid transactions data To obtain the quantity of opioid prescription pills in each county, I use the ARCOS dataset (Washington Post, 2019). It contains every transaction of pain pills containing scheduled substances in the United States. The *Washington Post* made public a subset of these data, containing nearly 180 million transactions of oxycodone and hydrocodone pills, from 2006 to 2012, where the destination is a point of sale or distribution to consumers (e.g., hospitals, retail pharmacies, practitioners). Oxycodone and hydrocodone are the most commonly prescribed and abused opioids; oxycodone is the active ingredient in medications such as Percocet and OxyContin, and hydrocodone is in medications such as Vicodin and Lortab. In my period of analysis, oxycodone and hydrocodone correspond to approximately 70 percent of the total grams of opioids distributed in the country (ARCOS, 2012).[6] Tablets are also the most common prescribed form of opioids, representing approximately 73 percent of the total transactions of opioids.

On average, a county sells 915,113 opioid pills per quarter, distributed by approximately 559 distinct providers. There are 2,994 counties that receive at least one shipment of opioid in the sample period; of these, 97.6 percent receive a shipment every quarter of the sample, composing a balanced panel of 28 quarters. The remaining 70 counties have less frequent opioid sales but are kept in the analysis.

Over-the-counter painkiller sales data The Nielsen Retail Dataset consists of stores' weekly sales from 2006–2016. The initial sample is composed of stores that sell at least one unit of OTC painkillers in the period of analysis. To avoid contaminating the analysis with the effect of stores opening and closing, which itself can be a consequence of economic changes, I use a balanced panel of 23,743 stores, spread over 2,211 counties. This panel corresponds to 55.63 percent of the initial sample of stores.[7]

The retail data are available by product and contain more than one billion weekly registered sales of 14,852 unique OTC painkillers.[8] The sample consists of 23,083 unique stores, nearly equally split among drugstores, mass merchandisers, and food merchandisers. A very small share (2 percent) consists of convenience stores—of these, most are located in gas stations.

[6] Other less commonly abused opioids include oxymorphone, hydromorphone, tramadol, tapentadol, morphine, and methadone. The literature has shown that these opioids are less responsive to policy changes (Kilby, 2015; Mallatt, 2017).

[7] The results, however, are very similar when using the unbalanced sample.

[8] Nielsen categorizes unique products by unique Unique Product Codes (UPCs). A UPC corresponds to a unique product in terms of brand, quantity, and packaging. The products in the data are not grouped by the active substance but by their recommended use. I identify OTC painkillers by considering products in the following modules: pain remedies, headache; pain remedies, alkalizing effervescents; pain remedies, arthritis; and pain remedies, back and leg.

Employment data from the Census Bureau The employment data come from the QWI, available through the Census Bureau. The source of the data is the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata, which covers over 95 percent of U.S. private sector jobs. It reports the number of jobs at the beginning of the reference quarter by their two-digit North American Industry Classification System (NAICS) industry.

3.2 Variable Construction

I use per-capita measures for the main outcomes and predictors. The per-capita demand for opioids and OTC painkillers are constructed by adding the total number of pills of each medication sold in a county-quarter and dividing by the total population living in a county. The population counts come from the National Cancer Institute's Surveillance Epidemiology and End Results (Cancer-SEER) program. The per-capita demand for MME is constructed in a similar way, after converting opioid pills into MME and then adding the total MME sold in a county-quarter. The MME of each opioid drug is obtained using the Food and Drug Administration National Drug Code Directory, which contains information about each drug. The main predictor — employment-to-population ratio — is constructed by dividing the total employment in a county, given by QWI, by the total population in that county in a year.

In the analysis using the injury shift-share instrument for employment, I split industries by their injury rates using two different measures of this rate. First, I consider the incidence rate of total non-fatal workplace injuries and illnesses, extracted from the Survey of Occupational Injuries and Illnesses (SOII) by the Bureau of Labor Statistics (BLS, 2005). It contains the number of non-fatal injuries and illnesses per 100 full-time workers in 2004.[9] Second, I use WC claims rate by industry. WC provides partial medical care and income to workers who suffer work-related injuries and illnesses. While the SOII is a survey, WC claims come from administrative data. Although the estimates using either measure are expected to be similar, some studies have found that the number of collected WC claims is higher than the estimated number of injuries in the SOII (Boden and Ozonoff, 2008). There is no central source of WC claims in the United States, and details of WC systems vary by state. I take statistics from Ohio to calculate industries with highest rate of WC claims because they were made publicly available by the National Institute for Occupational Safety and Health (NIOSH, 2019). Although, ideally, the data would be from before the period of analysis, the data at the NAICS two-digit industry level is available only as an average from

[9] I use these data for all 20 NAICS sectors except for mining. SOII warns that mining does not follow the recordkeeping requirements followed by other sectors and therefore is not comparable.

2001 to 2015 (Wurzelbacher et al., 2016). I use these two measures to rank industries and split them in high injury industries — those above the median of the injury rate — and low injury industries — those below the median. Appendix Table A.1 shows the injury rate by industry using each measure.

For the heterogeneous analysis, I split counties in high and low share of manual occupations using the 2000 Census. The share of manual jobs is constructed using the manual task component of occupations, defined in Autor and Dorn (2013).[10] I split the counties in above, or below, the median of the share of manual occupations.

3.3 Descriptive Statistics

The use of opioids varies widely across the country, with some counties having more than 100 pills distributed per person in a year. Figure 1 shows two maps with the average number of pills per capita sold in a year for opioids and OTC painkillers. The figure shows some known facts—such as that the Appalachian region presents a large per-capita consumption of opioid pills (CDC, 2017)—but also shows that there is significant geographic heterogeneity in the use of both medications.[11] There is no clear relationship between the two medications, as shown in Appendix Figure A.1; the correlation of the per-capita demand for these medications is -0.06.

Table 1 shows that, on average, 9.80 opioid pills are demanded per capita per county-quarter. Most of the pills are weak—with no more than ten MME per pill. Another outcome of interest is the MME per capita, which shows the amount of active substances consumed instead of pills consumed. On average, 91.50 MME are consumed per capita; more than two-thirds are contained in weak opioid pills. Panel B shows that, on average, 10.10 OTC painkillers are consumed per capita, an average not much different from the opioid per capita. However, as shown in Figure 1, the sample of OTC painkillers does not cover as many low-populated places as the sample of opioids does; considering only counties present in both samples, the average of opioid pills consumed per capita is even higher and is equal to 10.15.

Panel C of Table 1 shows county characteristics related to employment. The employment-

[10] To build the share of each measure by county, I follow three steps. First, from the 2000 Census, I obtain the share of jobs in a county by 15 occupation groups. Second, for each group, I calculate the average manual score of the occupations. Third, I calculate the median score among the occupation groups and split them in, above, or below the median score. Finally, each county receives a manual employment share, which is the share of jobs above the median of the manual index.

[11] The figure also shows that the opioid data cover a larger region than the OTC painkiller data. I show in Section 5.3 that the results are valid when restricting the analysis to a common sample for both medications. However, when calculating the substitution rate between these two medications, the estimates speak to counties where data for both are available.

to-population ratio equals 0.33, on average. Restricting jobs to those in industries with a low injury incidence rate, the average employment-to-population ratio equal 0.12; in industries with a high injury incidence rate, it equals 0.18. The numbers are similar when separating industries by the WC claim rate. The last rows show that occupations in a county are, on average, 38 percent manual.

4 Empirical Approach

In this section, I present the empirical approach used to identify the effect of changes in local labor employment on the demand for pain medication. Specifically, I want to measure how sales of opioids and OTC painkillers respond to a local labor demand shift. The reduced-form relationship of interest is

$$Y_{ct} = \beta Employment_{ct} + [county\, FE] + [year\text{-}quarter\, FE] + \epsilon_{ct}, \tag{1}$$

where Y_{ct} is the log of per-capita sales of opioids or OTC painkillers in county c and time t, defined as a year-quarter and $Employment_{ct}$ is the log of the employment-to-population ratio in county c and time t. The employment-to-population ratio, instead of the unemployment ratio, informs about the availability of jobs in the county where the household resides. This ratio is not as sensitive to individuals leaving the labor force in times of economic crisis, which is especially important in my context since labor force participation is correlated with the opioid epidemic (Krueger, 2018).[12]

I include year-quarter indicators to control for determinants of demand for pain medication that vary uniformly across counties over time, such as regulations and launching of new medications at the national level. County fixed effects controls for sale patterns that vary across counties but are fixed over time, such as taxes and regulations of how medications can be sold or prescribed or lifestyle disparities among counties that influence the use of pain medications. The effect of employment is then identified from within-county variations in the demand for pain medication, relative to changes in other counties, after controlling for time effects.

[12] Population can change as a result of migration in response to labor demand shocks (Arthi, Beach and Hanlon, 2019), so I could potentially be introducing an endogenous variable in the denominator. For easier interpretation, I keep the employment-to-population ratio in the main analysis, but I show in a robustness check that my estimation is robust to using total employment instead of the ratio.

4.1 Shift-Share Instrument for Labor Demand

The challenge to estimate Equation 1 is that local labor supply characteristics affect local employment and the use of pain medication. Especially in the case of opioids, reverse causality is an important concern; several papers examine the effect of opioids on labor supply (Aliprantis, Fee and Schweitzer, 2019), the opposite of what I am interest at. In addition, the supply of opioids is an important determinant of use (Ruhm, 2019; Borgschulte, Corredor-Waldron and Marshall, 2018), so the OLS estimates can simply reflect that counties with higher employment also have higher supply of opioids.

To measure the effect of changes in labor demand, I need a shock that only shifts the demand, with no effects on supply. I introduce a shift-share shock in a strategy similar to Currie, Jin and Schnell (2018), which is one of the many variations to study local economic shocks introduced by Bartik (1991). I construct the instrument by interacting the national employment growth rate by industry with the county's initial-year industry composition:

$$LaborDemand_{ct} = \sum_{j \in sectors} \left(\frac{employment_{cj2004}}{employment_{c2004}} \cdot \frac{\sum_{k \in counties \neq c} employment_{jkt}}{\sum_{k \in counties \neq c} employment_{jk2004}} \right), \qquad (2)$$

where $employment_{jkt}$ equals the total number of jobs in sector j, county k, and year-quarter t. The first term is the share of employment in each industry in the base period, which equals one when summed over all industries in a county. I use 20 NAICS sectors, listed in Appendix Table A.1. The base period is the average industry composition in 2004.[13] The second term is the national employment growth rate by industry in relation to the base year. I use leave-one-out means to construct the growth rate, leaving the county out of the average growth rate when calculating the value of the instrument for that county. This avoids idiosyncratic industry-location components of employment to mechanically affect the first stage, improving its predictive power, which could make the instrument endogenous (Goldsmith-Pinkham, Sorkin and Swift, 2018; Autor and Duggan, 2003).

Looking at the effect at the industry level matters because industries suffer fluctuations at different intensities and times and therefore adjust their labor demand differently. A county with a heavy presence of manufacturing in the base year will be more affected by future manufacturing shocks, while a county with a higher share of agricultural jobs in the base year will be more affected by variations in this sector. Figure 2 shows the national

[13]I use 2004 to maximize the number of states included in the analysis (47) while still setting it before the period of analysis since the availability of data on pill medications starts in 2006. This choice allows for the inclusion of all states in the continental United States, except Massachusetts and the District of Columbia, which have QWI data only after 2010 and 2005, respectively. The results are robust to variations in the base period.

growth rate of the industries considered in the analysis.

The identifying assumption of my instrumental variable (IV) approach is that after controlling for county and time fixed effects, changes in the shift-share instrument for labor demand in a county are unrelated to changes in pain medication sales in this county, except through their effect on employment.

The fact that the instrument is composed of two parts—the share and the shift—makes it harder to pin down where the exogenous variation comes from. In the last few years, there has been new research trying to decompose the underlying identification assumption. Since I am interested in the impact of shifters, my approach is closer to the identification assumption developed in Borusyak, Hull and Jaravel (2018): the relationship is causal if the shifter is as-good-as-random conditional on shares and my controls.[14]

The period of analysis covers 2006–2016 for OTC painkillers and 2006–2012 for opioids, which provides enough variation in employment to be captured by the instrument. Having 20 sectors also ensures that the variation in my instrument does not come from one specific sector in a county or region, which is important for the validity of the instrument.

For inference, I use the standard-error correction proposed by Adão, Kolesár and Morales (2019), who show that in a shift-share design, commonly used standard errors tend to over-reject the null hypothesis. This happens because regression residuals are correlated across regions with similar shares; intuitively, two counties with similar shares not only have similar exposure to the shifters (as expected) but will also have similar values of the residuals.

Using the instrument for employment in Equation 2, *LaborDemand*, I obtain the following first stage:

$$Employment_{ct} = \gamma LaborDemand_{ct} + [county\, FE] + [year\text{-}quarter\, FE] + \eta_{ct}. \quad (3)$$

The second stage is simply Equation 1 replacing $Employment_{ct}$ with the predicted employment using the exogenous labor demand shock in the first stage, $\widehat{Employment}_{ct}$.

4.2 Injury Shift-Share Instrument for Labor Demand

To emphasize the role of workplace injuries as a channel affecting demand for pain medication, I modify the construction of the instrument and the first-stage regression. First, I rank industries by one of the two measures of injury rates discussed in Section 3, the incidence rate of non-fatal injuries and illnesses or the WC claims rate. Second, I split industries in

[14] Goldsmith-Pinkham, Sorkin and Swift (2018) develop an alternative approach, where the full vector of shares works as an instrument for the endogenous variable. The identification comes from having such shares as random conditional on the shifters. In my case, this assumption may not hold (e.g., the percentage of local jobs allocated in an industry (share) may be correlated with labor supply factors).

high and low injury rates, defined as above and below the median of the injury rate. Third, I define the first stage to consider only employment from a group of these industries. For example, for industries in the high injury group, the first stage is given by

$$EmploymentHI_{ct} = \lambda LaborDemandHI_{ct} + [county\,FE] + [year\text{-}quarter\,FE] + \varepsilon_{ct}, \quad (4)$$

where $EmploymentHI_{ct}$ is the employment-to-population ratio considering only jobs from high injury industries in the numerator and $LaborDemandHI_{ct}$ is the labor demand shift-share instrument for labor demand considering also only the national growth rate of high injury industries. The instrument is defined, in this example, as

$$LaborDemandHI_{ct} = \sum_{\substack{j \in sectors \\ j \in highinjury}} \left(\frac{employment_{cj2004}}{employment_{c2004}} \cdot \frac{\sum_{k \in counties \neq c} employment_{jkt}}{\sum_{k \in counties \neq c} employment_{jk2004}}\right). \quad (5)$$

The second stage is unaffected and follows the main specification. For the low injury industries, the first stage and construction of the shift-share instrument follow the same logic.

5 Effect of Employment on Demand for Pain Medication

In this section, I estimate the effect of labor demand shocks on the demand for pain medication. I start with the naive estimator—OLS—and show that the results are similar to what is found in the raw data. This estimator shows the use of pain medication for a certain employment change that combines the effect of labor supply and demand. Next, I show the results using the shift-share estimator of labor demand, which provides a causal estimate of the effect of the shift on demand for pain medication. After, I adjust the shifts to account for the injury incidence rate in each industry. Last, I check the robustness of my results.

5.1 Instrumental Variable Results

My IV strategy identifies local employment changes that are due to changes in the national employment growth rate. Figure 3 shows the predictive power of the shift-share instrument for labor demand. An increase of 1 percent in labor demand corresponds to an increase of approximately 0.86 percent in the employment-to-population ratio. The F-statistic is large in both samples, above 600. Both first stages are strong and ensure that I have a valid instrument. Appendix Table A.2 reports the first-stage results.

Table 2 shows the main results of the paper, using the two-stage least squares (2SLS) strategy to obtain the effect of a change in employment on demand for pain medication. Columns 1 and 3 show OLS estimations, following Equation 1. In this naive estimation, an increase of 1 percent in employment increases the total quantity of opioids sold by 0.11 percent and increases the quantity of OTC painkillers sold by 0.32 percent. The OLS reports the demand for pain medication in equilibrium, considering the supply from doctors and the demand from patients. The concern is that by regressing demand for pain medication on local employment growth, the estimates will be biased due to several local labor supply shocks. Even after controlling for my set of fixed effects, omitted variables and reverse causality can still bias the results. The bias moves the point estimate in the same direction as found in Currie, Jin and Schnell (2018).

The IV results are reported in columns 2 and 4 of Table 2. An increase of 1 percent in the employment-to-population ratio decreases the per-capita demand for opioids by 0.20 percent. From an average sale of 9.80 pills per capita, per county and quarter, this decrease means that 0.02 fewer pills per capita are sold with an increase in employment.The effect on OTC painkillers, however, is positive; a 1 percent increase in employment increases the demand for OTC painkiller pills by 0.14 percent. From an average sale of 10.10 pills per capita, this increase in demand reflects an increase of 0.01 pills per capita, per county, and quarter.

Table 3 extends the analysis to different outcomes. Although the number of pills have been shown to matter in decisions of how much to prescribe (Chiu et al., 2018), it does not say much about the quantity of active substance consumed. In Table 3, I show the effect of employment on type of opioid consumed in two different ways. First, I split the total number of pills per capita in two categories, weak and strong (those with more than ten MME per tablet).[15] Second, I measure the effect on MME, overall and in strong and weak pills. The effect on MME is very similar to the effect on opioid pills shown in Table 2. Because I focus on oxycodone and hydrocone pills, there is not much variation in the MME of pills in the data—more than two-thirds have between 7.5 and 10 MME. The small variation in MME in opioid pills in my data explains why the results on pills and on MME are similar. The point estimate of the effect of employment on the demand for stronger medications is more negative both in terms of pills and MME. However, the average consumption of stronger opioids is much lower, so the effect of employment shocks on opioid use is still concentrated

[15] I do not perform the weak-strong analysis using OTC painkillers because they are identified by UPCs in the data. Contrary to opioids, which are identified by NDC, no simple crosswalk exists between UPCs and NDCs. It is therefore harder to obtain details of each medication, such as active substances and concentration levels. Even after matching UPCs to a third-party dataset, I could obtain detailed information for less than a third of products, resulting in noisy estimates.

in weaker opioids.

5.2 The Role of Workplace Injuries

In this section, I introduce two estimation strategies to help understand the mechanisms driving the demand for pain medication. The main results show that although opioids and OTC painkillers are both pain medications, they respond differently to changes in employment. As discussed in the conceptual framework in Section 2, one potential reason is that while use of OTC painkillers is motivated only by physical pain, the use of opioids is also motivated by substance abuse. To test for this, first I estimate the effects using the injury shift-share instrument defined in Equation 5. This provides causal estimates of how changes in employment from industries with different injury rates affects the demand for pain medication. Second, I implement a heterogeneous analysis using the main instrument and splitting counties by the share of manual occupations in the baseline.

Table 4 shows the results of the injury shift-share instrument. First, across both panels, the main results presented in Table 2 remain consistent: a higher employment-to-population ratio causes a decrease in demand for opioids and an increase in demand for OTC painkillers. The decline in opioid use remains negative for low injury industries, as shown in column 1; however, for high injury industries, the effect becomes closer to zero and even positive, while still significant, as shown in column 2. These estimates show that when the increase in employment comes from industries with a higher likelihood of a worker getting injured, the demand for opioids due to the physical pain channel becomes larger, driving the point estimate up.

Columns 3 and 4 reinforce this perspective for OTC painkillers. A 1 percent increase in the employment-to-population ratio in industries with a high injury rate increases the demand for OTC painkillers by 0.21 percent, a point estimate larger than what is found for overall employment in Table 2. When the increase in employment comes from an industry with a low injury incidence rate, the point estimate is close to zero and insignificant. The results in panel B, where industries are classified by the usage of WC systems, follow the same pattern.

To supplement this evidence, I return to the main instrument, which considers labor demand shifts from any industry, and run a heterogeneous analysis of characteristics of occupations in a county. Table 5 shows the results. Overall, the demand for opioids remains countercyclical in all subsamples, and the demand for OTC painkillers remains procyclical. However, two main differences appear: the effect of a 1 percent increase in the employment-to-population ratio on the demand for OTC painkillers in counties with a large share of manual jobs is a 0.23 percent increase, even larger than the estimates for the whole sample, while the estimates for counties with a low share of manual jobs is closer to zero. On the other hand, the effect of a 1 percent increase in the employment-to-population ratio on the demand for opioids in counties with a small share of manual jobs is even more negative than the whole sample estimates and is equal to a 0.48 percent decrease. The fact that the coefficient becomes closer to zero in counties with more manual jobs is again evidence that the physical pain motive to use opioids is larger in these cases.

5.3 Robustness Checks

In this section, I show that my results are robust to changes in my main specification. First, I show that results hold when I use a balanced sample, keeping the same estimation strategy or using a two-period analysis. Second, I show that results are robust to using total employment and total use of pain medication instead of the ratio divided by the population. Third, I control for the share of individuals insured in a county to understand the effect of access to health insurance in regard to the demand for pain medication. These results are consistent with those presented in Section 5.

The first test is to change the sample and reproduce the analysis with the subset of counties whose opioid and OTC painkiller sales are observed in every quarter. Doing this reduces the sample size of opioids from 82,692 to 60,586, mainly because some counties used in the main sample do not have OTC information. It also reduces the sample size of OTC from 95,462 to 60,586 because in the main sample, OTC data are available until 2016, but opioid data are available only until 2012. Panel A of Appendix Table A.3 shows the results for this subsample. Although the coefficients change slightly, they still point in the same direction as the main results in Table 2. In panel B of Appendix Table A.3, I keep the balanced sample but restrict the period of analysis to 2006 and 2012 only, at the annual level, in a framework similar to the original shift-share setting in Bartik (1991). The point estimates point in the same direction as the main specification, but the reduced sample size results in slightly larger standard errors.

The second test is to use total employment and total use of pain medication instead of the ratio divided by the population. This test addresses concerns that migration is itself a response to employment shocks (Arthi, Beach and Hanlon, 2019), which could introduce an endogenous denominator in my variable of interest. Appendix Table A.4 shows that the point estimates are very similar in this specification, so my results do not seem to be affected by changes a county's population size.

The third test is to include the percentage of individuals insured by county as a control.

Because health insurance is the most common way to obtain prescription medication, and because approximately half of the population in the United States obtains insurance through an employer (KFF, 2019), a mechanical relationship between the increase in employment and the increase in individuals insured could explain a higher opioid use. Although my point estimate is negative—an expanding economy decreases opioid use—my estimate could be a lower bound if access to health insurance increases with an economic expansion and it also increases opioid use. I test for this following Currie, Jin and Schnell (2018) and the strategy in Heutel and Ruhm (2016), adding the percentage of individuals insured in a county as a control. The data are obtained from the estimated share of the county population with insurance, provided by the Census Bureau's Small Area Health Insurance Estimates (SAHIE). Appendix Table A.5 shows that the point estimate of employment is very similar to the main estimation in Table 2. The similarity in the point estimate is evidence that health insurance is not a relevant channel to explain my results.[16]

6 Decomposing the Employment Elasticity of Opioids

To provide a measure of substitution between opioids and OTC painkillers, in this section, I explore a quasi-experiment that increases the cost of obtaining prescription opioids and compare its effects on the demand for opioids and OTC painkillers. Using the rate of substitution between the two medications, I calculate the share of the employment elasticity of opioids estimated in Table 2 that would be expected if opioids were only used for physical pain.

6.1 Empirical Approach

To calculate the quantity of opioids that are substituted with OTC painkillers, I explore the introduction of a policy that decreased access to opioids while keeping physical pain constant. The policy is the implementation of PDMPs, which varies at the state level. One important variation among PDMPs is the requirement that prescribers consult the program before prescribing controlled substances, which the literature calls must-access PDMPs. Buchmueller and Carey (2018) show that this variation of the policy is most likely to reduce the misuse of opioids. My identification strategy explores the variation at the timing of adoption of

[16]One limitation of this analysis is that the ratio of the insured population can be an endogenous variable, so this test could introduce a "bad control" bias in the estimation (Angrist and Pischke, 2008). This introduces a selection bias if, after controlling for county and year-quarter fixed effects, an exogenous change in employment changes the composition of the pool of insured individuals. Since the point estimate is very similar to the estimation without controlling for ratio of insured, this problem is likely insubstantial.

must-access PDMPs in a difference-in-difference framework.[17]

The estimated equation is as follows:

$$Y_{st} = \delta PDMP_{st} + [state\, FE] + [year\text{-}quarter\, FE] + \xi_{st}, \tag{6}$$

where Y_{ct} is the log of per capita sales of opioids or OTC painkillers in state s and time t, defined as a year-quarter, and $PDMP_{st}$ is a binary variable equal to one if state s enacted PDMP on or after quarter t, and zero otherwise. Data on the date of implementation of must-access PDMPs come from the Prescription Drug Abuse Policy System (PDAPS, 2019). The first must-access PDMPs were implemented in 2012. Since the ARCOS data are only available until the end of 2012, my estimation has two important limitations: the effect is based on the implementation of the policy in three states only, which were the first to implement and therefore the effect may differ from future implementations, and the effect is measured right after the implementation, corresponding to the immediate short-term effect.[18] After 2012, other states are treated; since the impact on those states could differ, and in this section I am interested in the ratio of the effect on opioids and OTC painkillers, I estimate the effect on both medications only until the end of 2012.

6.2 Effect of PDMP on Demand for Pain Medication

Table 6 shows the results of the estimation of Equation 6. After the PDMP, the per-capita demand for opioid pills decreases by 6.4 percent, while the per-capita demand for OTC painkillers increases by 7.6 percent. My finding for opioids is of the same magnitude of what has been found in the literature (Buchmueller and Carey, 2018, 2019; Kilby, 2015); the effect on OTC painkillers is a novel estimate. Since the introduction of PDMPs decrease the demand for opioids while increasing the demand for OTC painkillers, I interpret this as an indication that the two pain medications are imperfect substitutes.

To obtain the substitution rate, I interpret the PDMP as an increase in the cost of obtaining opioids, which does not affect physical pain. My estimation shows that the introduction of PDMPs reduces the use of opioids by 0.62 pills per capita, while it increases the use of OTC painkillers by 1.09 pills per capita. This suggests that to keep the level of pain relief constant, a reduction in one opioid pill needs to be compensated with an increase of 1.76 OTC painkiller pills.

[17] The data are aggregated to the state level for this analysis because that is the level of variation. Because I have only three states treated, I show in Appendix Table A.6 that the estimates are not driven by any one of these states.

[18] The states are Kentucky (July 2012), New Mexico (September 2012), and West Virginia (June 2012).

6.3 Recovering the Components of the Effect of Employment on Opioid Use

Using the rate of substitution between opioids and OTC painkillers, and the employment elasticities of demand estimated in Section 5, I provide evidence of the share of the elasticity of opioids attributable to the physical pain channel, and the residual is attributed to substance abuse.

First, considering only the effect of a labor demand shift on pain relief, the demand for opioids is expected to respond similarly to the demand for OTC pills after adjusting for the substitution rate. The main results, presented in Table 2, show that a 1 percent increase in the employment-to-population ratio increases the per-capita demand of OTC painkillers by 0.014 pills. Since opioids and OTC painkillers are substituted at a ratio of 1.76, the expected effect on opioid use is an increase of 0.008 pills per capita, or an increase of 0.08 percent.

Second, I suppose that a positive labor demand shock only increases the opportunity cost of opioid use, with no effect on the demand for pain relief. This effect is obtained from the difference between the employment elasticity of opioids, estimated in in Table 2, and what cannot be explained by the simulation in the previous paragraph. A 1 percent increase in the employment-to-population ratio decreases opioid use by 0.20 percent, which corresponds to a decrease in 0.019 pills per capita. The effect due to increased demand for pain relief only was calculated as an increase of 0.008 pills per capita; the difference—0.027 pills per capita—is attributed to the decrease in use only due to substance abuse. This decrease in opioid use for substance abuse corresponds to 0.27 percent.

This calculation is a strategy to recover each channel of the effect of labor demand shocks on the demand for opioids. If the ratio of substitution calculated in the previous step changes, these values also change slightly, but the evidence of the two channels —physical pain and substance abuse— that pull opioid use up or down during local economic fluctuations remain. These estimates suggest that the per-capita demand for opioids for pain relief in fact increases by 0.08 percent with a 1 percent increase in the employment-to-population ratio, while the per-capita demand for opioids for substance abuse decreases by 0.27 percent.

6.4 Implications for Health Outcomes

In this section, I discuss the policy relevance of the effect of changes in employment on the demand for pain medication using a back-of-the-envelope calculation. I first calculate what the estimated effect on painkillers means in terms of opioid prescriptions. Second, I extrapolate the effect on use to effects on health outcomes, separating the analysis of a decrease in substance abuse from an increase in use for physical pain.

The employment elasticity of the demand for opioids is equal to −0.20, as shown in Table 2, or 0.02 fewer pills per capita per county-quarter. After scaling this up by the average population in a county in the balanced sample, the increase in employment results in 1,969.66 fewer pills per county-quarter. The number of prescribed opioid pills depends on several factors, such as the characteristics of the patient and the medical reason for the prescription. I consider the estimate that, on average, 30 pills of hydrocodone/acetaminophen (5 mg/325 mg) are prescribed after surgery procedures (Howard et al., 2019)—this is the substance concentration found in the most popular brand of opioid in my data. The effect can then be translated into 65.65 fewer opioid prescriptions per county-quarter. Considering the decomposition presented in the previous subsection, the same calculation means that an increase of 1 percent in the employment-to-population ratio decreases the number of opioid prescriptions for substance abuse by 88.63 and increases the number of opioid prescriptions for physical pain by 26.26.

How the share of prescriptions for substance abuse affect the risk of misuse and abuse depends on several factors, such as the duration of the prescription, medical comorbidities, and the individual's history of drug abuse. I assume that the 88.63 opioid prescriptions are given to different opioid-naive individuals, of whom approximately 1.03 percent are expected to become dependent on, abuse, or overdose (Brat et al., 2018). This mean that 0.91 fewer individuals will abuse opioids by county-quarter. To obtain a dollar value of this reduction, I consider the cost of substance abuse treatments and of loss in productivity. The reduction of 0.91 individuals abusing opioids represents a decrease in expenditures of 10,875 2010 dollars (Florence et al., 2016) in annual treatment and 16.83 fewer days missed at work per year (Goplerud, Hodge and Benham, 2017). Considering the average weekly wage in 2010, this means a decrease in lost productivity in the amount of $1,795 (Bureau of Labor Statistics, 2019).

The consequences on health outcomes of an increase in opioid use for pain relief depend on how well pain is managed with this medication. The more interesting exercise in this case is what are the expected consequences if opioid prescriptions were not available and individuals remained in pain. This is an upper bound because opioids and OTC painkillers are imperfect substitutes and opioids may have other substitutes, such as medical marijuana (Powell, Pacula and Jacobson, 2018). However, this calculation is still of interest because, with the increase in restrictions to prescribe opioids in the last years (Frieden and Houry, 2016), doctors and patients have manifested concerns about being left without alternatives to address pain (Kertesz et al., 2019). I assume the demand for the extra 26.26 prescriptions for physical pain are given to different individuals with moderate pain. If opioids were removed from the market and these individuals were left in pain, then health costs would increase by

118,590 2010 dollars, and lost productivity would sum up to 5,936 2010 dollars (Gaskin and Richard, 2012).

7 Discussion and Conclusion

In this paper, I explore the more immediate effect that economic conditions have on the use of pain medication and compare two opposite channels that can affect the use of pain medication. At the same time that a higher employment rate is correlated with improved mental health and lower opioid abuse, it is correlated with increased workplace injuries and physical pain, which is expected to increase the demand for pain medication.

My results show that the demand for opioids is countercyclical—the employment elasticity of the demand for opioids is equal to -0.20. At the same time, the demand for OTC painkillers is procyclical—the employment elasticity of the demand for opioids is equal to 0.14. The effect on opioids is large and negative with employment shocks from industries with a low injury rate, but the effect is close to zero and is even positive for shocks from high injury industries; the positive effect of OTC painkillers is driven mostly by high injury industries. A similar pattern is found in the heterogeneous analysis, where counties are split by the share of manual jobs. These findings shows that employment shocks increase the demand for pain relief, which suggests a higher prevalence of physical pain in the population.

The fact that opioids are countercyclical despite the procyclical effect found for OTC painkillers is evidence that opioid substance abuse decreases during local economic expansions. I provide evidence that the effect of a 1 percent increase in the employment-to-population ratio leads to a decrease of 0.27 percent in opioid use for substance abuse and to an increase of 0.08 percent in use for physical pain.

My results have important policy implications. First, improving employment conditions to fight opioid abuse has larger effects than what is obtained considering only the total net effect on use. The opposite is true when a county is hit by a negative employment shock; therefore policies that address mental health problems need to be in place to avoid an increase in opioid abuse. Second, an expanding economy will cause an increase in demand for pain relief, concentrated among those in more manual jobs and in industries with a higher injury rate, and therefore policies that constrain access to opioids need to be compensated with policies that address physical pain. Finally, although I do not incorporate dynamic effects in my analysis, some of the individuals who start to use opioids due to workplace injuries may become dependent; thus, workplace policies informing workers about medication and risks of opioid abuse are important during local economic expansions.

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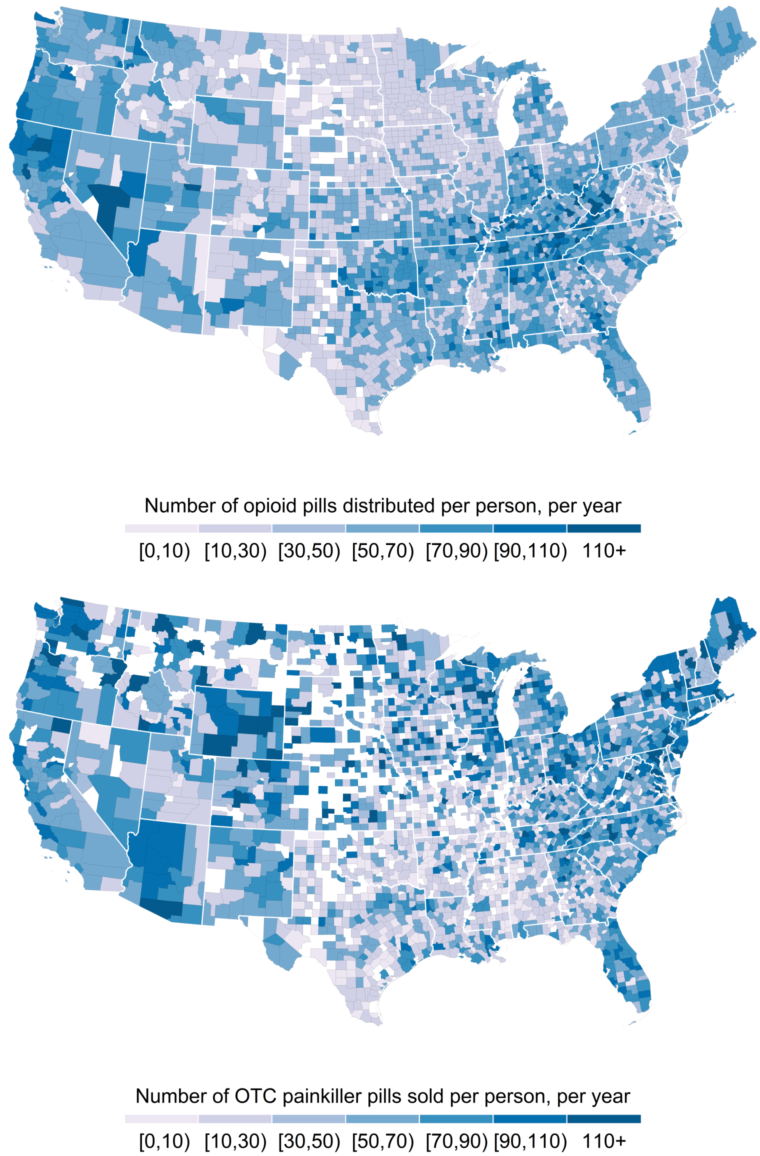
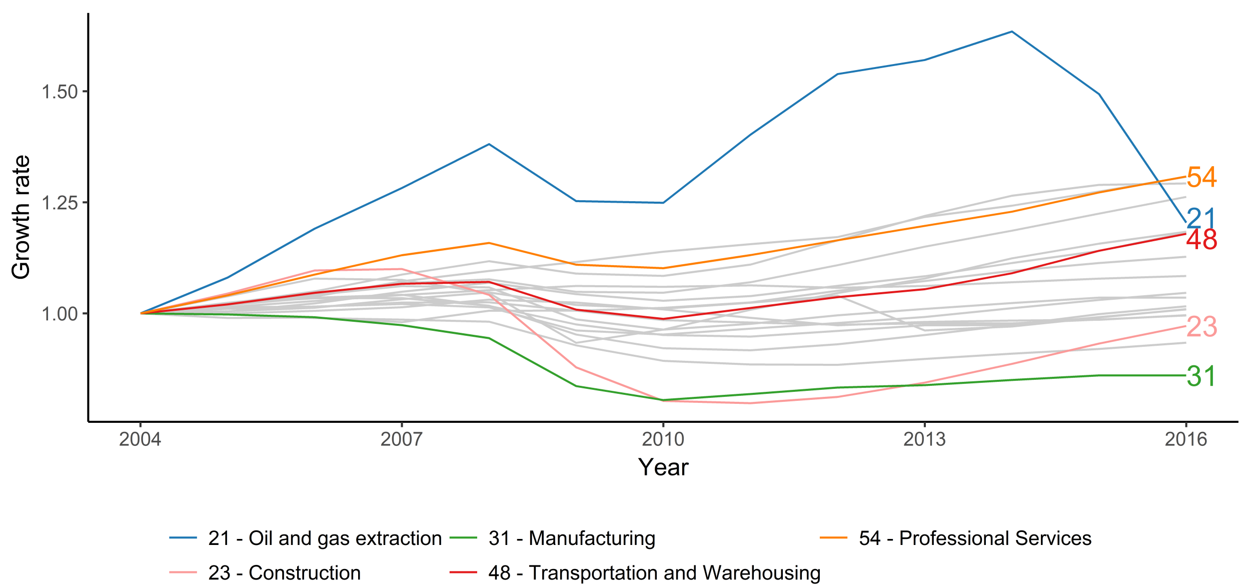
Figure 1: Map of Number of Pills per Person in a Year



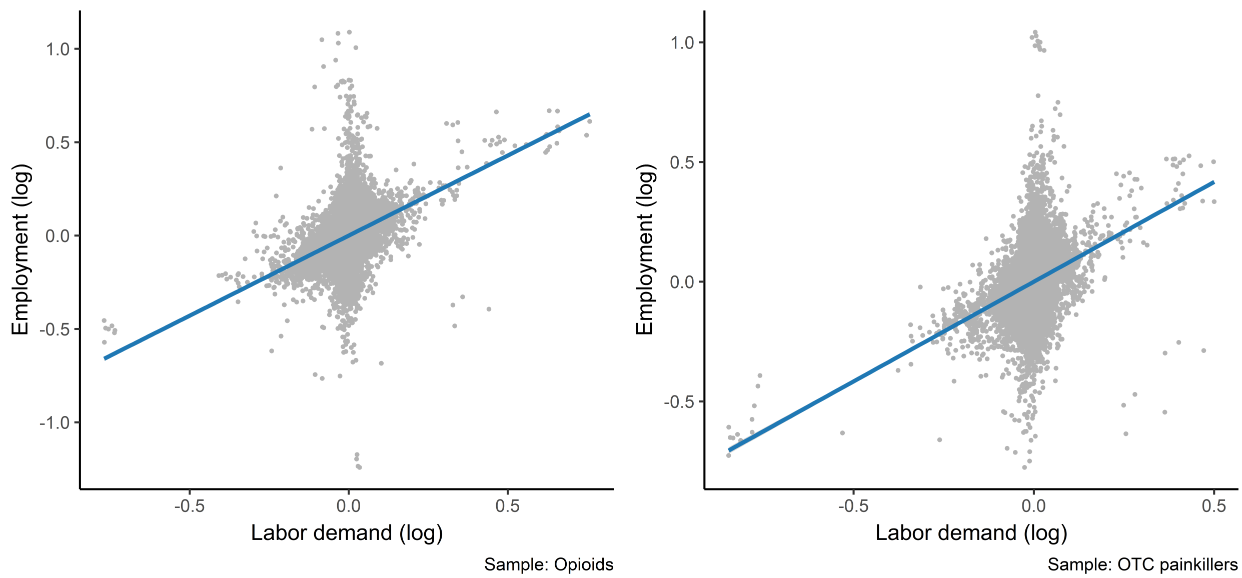
Notes: This figure shows two maps with the average number of pills per capita sold in a county. The map on top shows the average number of opioid pills distributed in a county in a year divided by the county's population; the map at the bottom shows the average number of OTC painkiller pills sold in a county in a year divided by the county's population. Blank counties are counties for which no data are available.

Figure 2: Growth Rates of Sectors over Time



Notes: This figure plots the growth rate since 2004 of the 20 NAICS sectors used to build the instrument over the time of analysis. All 20 sectors are used in the analysis; five sectors are highlighted only for illustrative purpose. These growth rates are the shift used in the construction of my instrument for labor demand.

Figure 3: First-Stage Results



Notes: This figure plots the partial first-stage regressions of the main specification, which measures the effect of labor demand shocks on local employment, controlling for county and year-quarter fixed effects. The x-axis is the residualized shift-share instrument of labor demand shocks, obtained from the residuals of a regression of the log of the instrument on county and year-quarter fixed effects. The y-axis is the residualized employment-to-population ratio, obtained from a regression of the log of employment-to-population ratio on the same fixed effects. The figure on the left shows the first stage in the sample of opioids, while the figure on the right shows the first stage in the sample of OTC painkillers.

Table 1: Summary Statistics

	Mean	SD
Panel A: Opioids painkillers		
Pills per capita	9.80	7.49
Weak pills	9.07	6.85
Strong pills	0.73	1.07
Morphine-miligram-equivalents per capita	91.50	75.60
In weak pills	68.60	54.00
In strong pills	22.90	31.80
Panel B: OTC painkillers		
Pills per capita	10.05	7.65
Panel C: County characteristics		
Employment-to-population ratio (EPR)	0.33	0.13
EPR by industry characteristics:		
Low injury-incidence rate	0.12	0.08
High injury-incidence rate	0.18	0.07
Low WC claims rate	0.13	0.07
High WC claims rate	0.17	0.08
Share of manual occupations	0.38	0.05

Notes: This table shows the summary statistics of the main datasets used in the analyses. The number of observations in each panel is the following: 82,682 in panel A, 95,462 in panel B, and 82,682 in panel C. The unit of observation is a county-quarter. The county characteristics in panel C is based on the opioid sample, which spans over a shorter period (2006–2012) but includes more counties, as shown in Figure 1. The corresponding statistics in the OTC-painkiller sample are very similar. Panel A shows statistics of the opioid outcome in pills per capita and MME per capita. Each variable is split into weak and strong, which corresponds to medications with ten or less MME per table and more than ten MME per tablet. Panel B shows statistics of the only OTC-painkiller outcome, pills per capita. Panel C shows county characteristics that are predictors or are used in the heterogeneous analysis. The first five rows correspond to the employment-to-population ratio, overall, split by jobs in industries with low and high injury incidence rates and split by jobs in industries with low and high WC claims rate. Splitting the sample by industry does not add to the total employment-to-population ratio because not all industries are included in the calculation of these rates, as described in Section 3. The last row corresponds to the share of jobs considered manual in a county using the 2000 Census.

Table 2: Effect of Local Employment on Demand for Pain Medication

	Opioid pills (log)		OTC pills (log)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Employment (log)	0.114***	-0.196***	0.321***	0.143***
	(0.023)	(0.005)	(0.036)	(0.014)
F-stat (1st stage)		1189.799		609.002
Mean	9.805	9.805	10.057	10.057
Observations	82,692	82,692	95,462	95,462

Notes: This table shows the result of four separate regressions. Columns 1 and 3 are OLS estimations, and columns 2 and 4 are IV estimations. The dependent variable in columns 1–2 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in columns 3–4 is the log of the quantity of OTC painkiller pills per capita sold by county-quarter. The independent variable is the log of the employment-to-population ratio (predicted using the shift-share instrument for labor demand shocks in the IV regressions in columns 2 and 4). All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table 3: Effect of Local Employment on Demand for Pain Medication, by Strength in Pills and Morphine Milligram Equivalents

	Opioid pills (log)		MME (log)	
	Weak	Strong	Weak	Strong
	(1)	(2)	(3)	(4)
Employment (log)	-0.279***	-0.384***	-0.287***	-0.293***
	(0.008)	(0.011)	(0.012)	(0.008)
Mean	9.205	0.746	69.662	23.433
Observations	80,868	80,868	80,868	80,868

Notes: This table shows the result of four separate regressions. Columns 1 and 2 show the outcomes in terms of the log of opioid pills per capita. Column 1 shows the result for the log of the quantity of weak pills sold per capita, which are pills whose MME per pill is not greater than ten. Column 2 shows the result for the log of quantity of strong pills sold per capita, which are pills whose MME per pill is greater than ten. Columns 3 and 4 show parallel results, but the outcome is in terms of MME instead of pills. Column 3 shows the result for the log of MME sold per capita considering only the subset of weak pills. Column 4 shows the result for the log of MME sold per capita considering only the subset of strong pills. The independent variable in all regressions is the log of the employment-to-population ratio (predicted using the shift-share instrument for labor demand shocks). All regressions include county fixed effects and year-quarter fixed effects. The sample size is slightly smaller than in the main table because counties with zero sales of one of the types of pills are dropped from the analysis because of the logarithmic form. To standardize, I keep only observations with a sale of at least one pill per category in a quarter. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table 4: Effect of Local Employment in Industries with Different Injury Rates on Demand for Pain Medication

Panel A: By Injury-Incidence Rate				
	Opioid pills (log)		OTC pills (log)	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Employment (log)	-0.051***	0.049***	-0.007	0.209***
	(0.002)	(0.003)	(0.007)	(0.009)
Mean	9.806	9.806	10.057	10.057
Observations	82,666	82,666	95,462	95,462
Panel B: By Worker's Compensation (WC) Claim Rate				
	Opioid pills (log)		OTC pills (log)	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Employment (log)	-0.099***	-0.007***	0.014	0.248***
	(0.004)	(0.002)	(0.010)	(0.006)
Mean	9.805	9.805	10.057	10.057
Observations	82,691	82,691	95,462	95,462

Notes: This table shows the result of eight separate IV regressions. The dependent variable in columns 1–2 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in columns 3–4 is the log of the quantity of OTC painkiller pills per capita sold by county-quarter. In Panel A, the predictor is the log of the predicted employment-to-population per capita considering only jobs in industries below (columns 1 and 3) or above (columns 2 and 4) the median injury incidence rate in the SOII data. In Panel B, the predictor is the log of the employment-to-population per capita considering only jobs in industries below (columns 1 and 3) or above (columns 2 and 4) the median of worker's compensation claims rate in the Ohio data. Both estimations are second-stage results of the first stage specified in Equation 4. All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The sample size varies in some estimations because a few counties do not have any jobs in the type of industry used to construct the variable of employment. The mean of the dependent variables are listed in levels.

Table 5: Effect of County-Level Employment on Pain Medication, by Share of Manual Occupations in a County

	Opioid pills (log)		OTC pills (log)	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Employment (log)	-0.477***	-0.046***	0.001	0.226***
	(0.015)	(0.011)	(0.034)	(0.024)
Mean	9.736	9.878	12.138	7.334
Observations	42,685	40,007	54,112	41,350

Notes: This table shows the result of four separate regressions. It shows heterogeneous effects of the main results, reported in Table 2, splitting the sample by county's characteristics. In all regressions, the predictor variable is the log of the employment-to-population ratio. The dependent variable in columns 1–2 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in columns 3–4 is the log of the quantity of OTC painkiller pills per capita sold by county-quarter. The table splits the sample by low and high shares of manual jobs, based on the measure built in Autor and Dorn (2013). All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

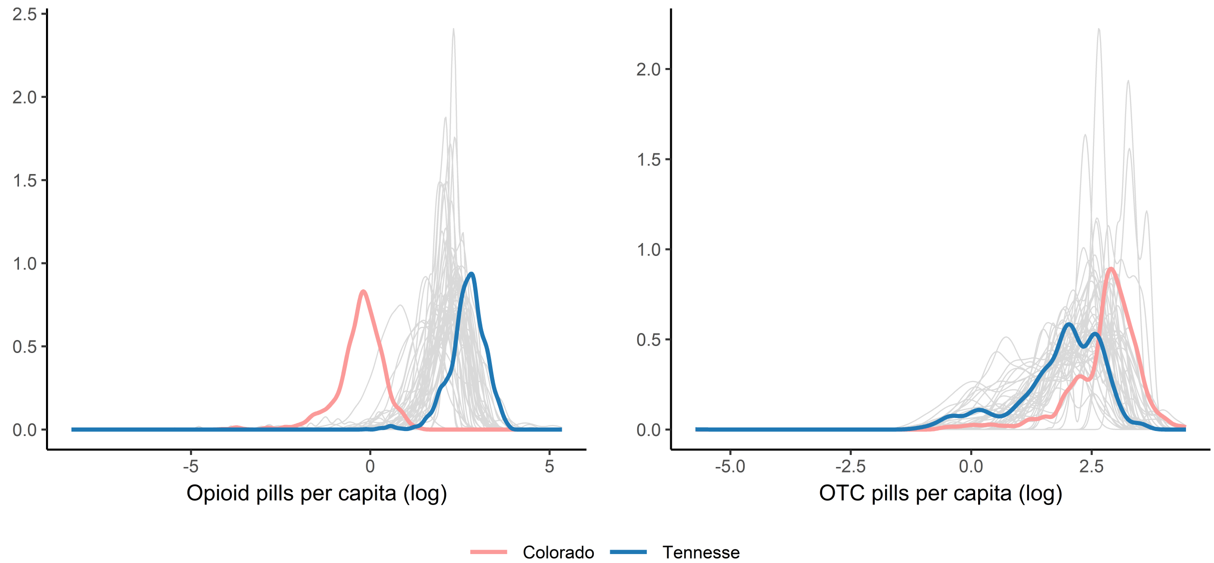
Table 6: Short-Term Effect of Restrictions on Opioid Prescriptions on Demand for Pain Medication

	Opioid pills (log)	OTC pills (log)
	(1)	(2)
PDMP	−0.064***	0.076***
	(0.017)	(0.029)
Mean	9.64	14.30
Observations	1,316	1,316

Notes: This table shows the result of two separate regressions. The dependent variable in columns 1 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in column 2 is the log of the quantity of OTC painkiller pills sold by county-quarter. The independent variable is an indicator variable if a state has an enacted must-access PDMP law. The only states with must-access laws enacted in the period of my sample are Kentucky (July 2012), New Mexico (September 2012), and West Virginia (June 2012). I use a balanced panel covering the same counties and periods in both datasets. All regressions include state fixed effects and year-quarter fixed effects. Standard errors are clustered at the state level. The mean of the dependent variables are listed in levels.

Appendix A: Additional Figures and Tables

Figure A.1: Density of the Distribution of Pain Medication, by State



Notes: This figure plots the distribution of the logarithm of the per-capita demand for each pain medication by state. The left panel shows the distribution for opiod pills, and the right panel shows the distribution of OTC painkiller pills. For illustrative purposes, the figure highlights two states, with low and high per-capita use of opioids in the left panel. The same states are highlighted in the right panel, showing that in the raw data, there is no clear geographic relationship between the use of opioids and OTC painkillers.

Table A.1: NAICS Sectors and Incidence of Injuries and Worker's Compensation Claims

NAICS	Description	Injury ratio	WC claims ratio
11	Agriculture, Forestry, Fishing and Hunting	**5.69**	4.02
21	Mining		**4.68**
22	Utilities	**5.16**	**4.67**
23	Construction	**5.8**	**5.69**
31-33	Manufacturing	**6.61**	**6.78**
42	Wholesale Trade	**4.28**	**4.7**
44-45	Retail Trade	**4.16**	3.72
48-49	Transportation and Warehousing	**7.13**	4.18
51	Information	1.86	1.98
52	Finance and Insurance	0.84	0.61
53	Real Estate and Rental and Leasing	3.09	**4.63**
54	Professional, Scientific, and Technical Services	1.17	1.63
55	Management of Companies and Enterprises	2.47	2.5
56	Administrative and Support*	2.03	**5.12**
61	Educational Services	1.76	1.68
62	Health Care and Social Assistance	**4.88**	**5.43**
71	Arts, Entertainment, and Recreation	3.68	4.16
72	Accommodation and Food Services	3.03	**4.31**
81	Other Services, Except Public Administration	2.5	3.22
92	Public Administration		

Notes: This table shows the 20 NAICS sectors used in the construction of the shift-share instrument and the industry injury ratios. Column 3 shows the injury incidence ratio per 100 full-time workers based on data from the 2004 SOII; the injury ratio for the mining sector is not reported because it cannot be compared to other sectors. Column 4 shows the WC claims rate per 100 full-time workers using data from 2000–2015 from Ohio. The injuries and WC claims ratio for the public administration sector (92) were not reported in the period of analysis. Values in bold are industries above the median of each ratio, which are called high injury industries in the estimations. *The complete description of sector 56 is "Administrative and Support and Waste Management and Remediation Services."

Table A.2: First-Stage Estimation of the Effect of County-Level Labor Demand Shocks on Employment

	Employment (log)	
	(1)	(2)
Labor Demand (log)	0.857***	0.833***
	(0.025)	(0.034)
F-stat (1st stage)	1189.799	609.002
Mean	0.328	0.341
Observations	82,692	95,462

Notes: This table shows the first-stage regression of the main specification, shown in Equation 3. The dependent variable in columns 1 and 2 is the log of the employment-to-population ratio by county-quarter. The independent variable is the log of the shift-share instrument for labor demand shocks. All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table A.3: Effect of County-Level Employment on Demand for Pain Medication: Balanced Sample

Panel A: Balanced sample		
	Opioid pills (log)	OTC pills (log)
	(1)	(2)
Employment (log)	-0.154***	0.253***
	(0.005)	(0.015)
Mean	10.411	9.963
Observations	60,586	60,586

Panel B: Balanced annual sample, two periods		
	Opioid pills (log)	OTC pills (log)
	(1)	(2)
Employment (log)	-0.279***	0.570***
	(0.014)	(0.022)
Mean	10.142	10.526
Observations	4,327	4,327

Notes: This table shows the result of four separate regressions. The dependent variable in column 1 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in column 2 is the log of the quantity of OTC painkiller pills per capita sold by county-quarter. The independent variable in both panels is the log of the employment-to-population ratio (predicted using the shift-share instrument for labor demand shocks). Panel A reproduces the main result of Table 2 but for a balanced sample of counties where data for both opioids and OTC painkillers exist in all periods. The regressions in panel A include county fixed effects and year-quarter fixed effects. Panel B reproduces the analysis using the balanced sample but for data at the annual level and for only the first and last period of analysis where data exist for opioids and OTC painkillers (2006 and 2012). The regressions in panel B include county fixed effects and year fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table A.4: Effect of County-Level Employment on Demand for Pain Medication

	Opioid pills (log)	OTC pills (log)
	(1)	(2)
Employment (log)	-0.182***	0.229***
	(0.005)	(0.013)
Mean	915,113.378	1,717,557.717
Observations	82,692	95,462

Notes: This table shows the result of two separate regressions; the difference to the main table is that the variable for employment and the outcome variables are not divided by the population. The dependent variable in column 1 is the log of the quantity of opioid pills sold by county-quarter. The dependent variable in column 2 is the log of the quantity of OTC painkiller pills sold by county-quarter. The independent variable in all regressions is the log of employment (predicted using the shift-share instrument for labor demand shocks). All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table A.5: Effect of County-Level Employment on Demand for Pain Medication, Controlling for the Ratio of Insured Population

	Opioid pills (log)	OTC pills (log)
	(1)	(2)
Employment (log)	-0.196***	0.137***
	(0.005)	(0.014)
Mean	9.805	10.057
Observations	82,692	95,462

Notes: This table shows the result of two separate regressions. The dependent variable in column 1 is the log of the quantity of opioid pills per capita sold by county-quarter. The dependent variable in column 2 is the log of the quantity of OTC painkiller pills per capita sold by county-quarter. The independent variable in all regressions is the log of the employment-to-population ratio (predicted using the shift-share instrument for labor demand shocks). All regressions control for the ratio of individuals insured by county, extracted from the SAHIE data. The coefficient of this ratio is equal to -0.008 in column 1 and 0.129 in column 2. All regressions include county fixed effects and year-quarter fixed effects. Standard errors for all regressions use the AKM adjustment for shift-share designs. The mean of the dependent variables are listed in levels.

Table A.6: Short-Term Effect of Restrictions on Opioid Prescription on Demand for Pain Medication, Different Treated States

	Opioid pills (log)			OTC pills (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	-0.059^{***}	-0.070^{***}	-0.063^{***}	0.046	0.104^{***}	0.072^{*}
	(0.017)	(0.016)	(0.017)	(0.030)	(0.015)	(0.041)
States with PDMP	KY, NM	KY, WV	NM, WV	KY, NM	KY, WV	NM, WV
Mean	9.641	9.641	9.641	14.30	14.30	14.30
Observations	1,288	1,288	1,288	1,288	1,288	1,288

Notes: This table shows three different strategies to measure the the effect of the introduction of PDMPs on the demand for opioids and OTC painkillers, varying the group of treated states. Columns 1 and 4 drop West Virginia (WV) from the analysis, columns 2 and 5, New Mexico (NM), and columns 3 and 6, Kentucky (KY). All regressions control for state and year-quarter fixed effects. Standard errors are clustered at the state level. The mean of the dependent variables are listed in levels.

Appendix B: Background on Pain Medication

Pain medication—also know as analgesics—exist in three main forms in the Unites States: opioids, non-steroidal anti-inflammatory drugs (NSAIDS), and acetaminophen. Opioids are regulated substances and are sold only with prescription; NSAIDS and acetaminophen are sold over the counter. These drugs reduce the feeling of pain exploring different mechanisms in the body. As a result, they also present different risks from frequent use.

Opioids include opiates—drugs derived from the poppy plant—and synthetic drugs. The first group includes prescription painkillers such as Vicodin, Percocet, and OxyContin, and the second group includes methadone and fentanyl (the latter a synthetic opioid 50 times more potent than heroin). Pain, as touch or taste, is a sensory signal; feeling pain is a signal of harm captured by a nerve receptor and processed in the brain. Our body naturally produces a chemical similar to opioids—endorphins—which block pain by connecting to neuron receptors (called mu opioids that are found in the brain and in other parts of the body) and also block the response to this signal in the brain. Opioids connect to the same receptor, but they are more powerful and capable of blocking more pain.

Opioids can become addictive because mu opioids are also found in an area of the brain responsible for releasing dopamine—a "feel-good" chemical. The connection between endorphin and dopamine is usually connected to physical exercises, such as a "runner's high" from running. Individuals also develop a tolerance for opioids over time, needing a higher dose to achieve the same sensation.

While opioids cause both analgesia and euphoria by affecting the reward system in the human body, NSAIDS and acetaminophen work only in reducing the production of chemicals related to pain. Popular brands of NSAIDS include Advil (ibuprofen), Bayer Extra Strength (aspirin), and Aleve (naproxen sodium). Acetaminophen is the active substance in brands such as Tylenol and Excedrin. NSAIDS work by reducing the production of a chemical that intensifies the feeling of pain (prostaglandins). There is a debate in the medical literature about how acetaminophen works, with some evidence that it works by also blocking the cyclooxygenase (COX) enzyme; although no agreement has been reached, its mechanism of action is closer to NSAIDS than to opioids (Toussaint et al., 2010).

Although opioids became known for its effectiveness in treating chronic pain, there is no agreement in the literature that it is more effective than other methods, especially when weighting the risks of addiction and overdose (Frieden and Houry, 2016). Although heavy use of NSAIDS can damage the stomach, and with acetaminophen, the liver, neither carries the mortality risk of opioids (Solomon et al., 2010).