The US Opidemic: Prescription Opioids, Labour Market Conditions and Crime

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Abstract

In response to the recent opioid crisis, US states have implemented several policies to reduce the dispensing of opioids and contain drug mortality. We analyse the effectiveness of these laws and their unintended fallouts on labour participation and crime at the local level. Using multiple data sources and a difference-in-difference set-up, we show that the laws targeting the supply for opioids yield larger reductions in prescribed drugs compared to the demand-side policies, particularly in the absence of cross-bordering effects. We observe an improvement in labour market participation and higher crime rates following the enforcement of some of the policies considered.

Keywords: Prescription Opioids, Drugs, Labour Market, Crime.
JEL codes: I18, E24, K14.

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1 Introduction

In 2016, according to the Centres for Disease Control and Prevention (CDC) more than 52,000 Americans died of drug overdoses and three out of five deaths involved a form of prescription opioid abuse. This figure corresponds to an average of four deaths every hour, i.e. more than those caused by car crashes and shootings combined. Around 2 millions Americans currently suffer from a prescription painkiller abuse disorder and although the absolute incidence is greatest in big cities like Chicago and Baltimore, the devastation also affects rural areas such as Appalachia, New England and the Midwest. In fact, many of the victims hail from white middle-class suburbs and rural towns.

Indeed, the misuse of and the addiction to opioids, which include prescription pain relievers, heroin, and synthetic opioids such as fentanyl, constitute a serious national crisis affecting public health as well as social and economic welfare. In October 2017, US President Donald Trump defined the country's opioid crisis as a "public health emergency" and one month later the US Council of Economic Advisers reported the true cost of the opioid drug epidemic for the year 2015 to be around US$ 504 billion, corresponding to approximately 2.8% of the US GDP.[1] As a response to this dramatic crisis, many US states have progressively enacted a number of laws to restrict the prescribing and the dispensing of controlled substances and to contain the mortality rates linked to the abuse of opioids.

In this paper we assess the impact of five sets of opioid state laws on labour market conditions and illegal activities at the local level. In doing so, we draw on a number of opioid-related policies adopted in the US since the early 2000s, namely Prescription Drug Monitoring Programs (PDMPs), Pain Management Clinics Laws (PMCLs), Doctor Shopping Laws (DSLs), Good Samaritan Laws (GSLs) and Naloxone Access Laws (NALs). Some of these regulations are targeted at reducing the amount of Prescription Opioids (POs) sold either on the demand (DSLs) or the supply (PMCLs and PDMPs) side. Vice versa, NALs and GSLs have been designed to decrease the number of fatal overdoses by providing incentives to abusers to seek for medical assistance in case of an overdose emergency. Using a difference-in-difference set-up and linking various sources of county-level panel data, we exploit the staggered timing in the implementation of these laws across US states to identify their causal effect on local economic and crime outcomes over the period 2000-2014.

First, we provide new empirical evidence on the effects of these opioid state laws on the amount of drugs dispensed per capita. We focus on a variety of opium-based substances that are classified as Schedule II or Schedule III drugs, which are associated to high and moderate risks of abuse, as defined by the US Controlled Substances Act of 1970. We consider hydromorphone, methadone, meperidine, oxycodone, hydrocodone, fentanyl and morphine. Moreover, following Brady et al. (2014), we account for the relative potency of these opiates, so that each drug is converted into Morphine Equivalent units (MEs), which summarise the total amount of

[1] This figure encompasses the costs of health care, lost productivity, criminal justice, plus the value of statistical life, i.e. the estimated cost for each opioid-related overdose death. See the report by the Council of Economic Advisers (2017) for details.

(potentially substitute) active components sold. In this respect, we address the following questions: *(i)* does the implementation of these state laws actually reduce the amount of opioids prescribed, and *(ii)* are the laws targeting the supply or those restraining the demand the most effective in diminishing the quantity of prescription analgesics per capita?

On the one hand, we find that the implementation of supply-side opioid state laws and of those contrasting opioid-related mortality reduce the grams of POs per capita sold. On the other hand, we observe a weak positive effect of DSLs on POs, which casts some doubts on the efficacy of laws aiming at the demand for opioids. In terms of magnitude, the negative effect of the laws affecting the supply (particularly PMCLs) accounts to a 30% reduction in POs dispensed. Notably, we estimate even larger effects in areas that are not adjacent to other states, which indicates that the restrictions to POs are more effective when commuting to a different state (and obtain the desired drugs there) is more costly. In terms of policy implication, this result suggests that extending stricter regulations at the federal level might perhaps lead to better efficacy.

Furthermore, we implement a battery of robustness checks and placeboes on our main results. These additional tests support our findings. Our results are stable and not systematically affected by potential confounding factors, including the introduction of Medicare Part D in 2006 and the reformulation of OxyContin in 2010. On top of that, we estimate the link among the amount of legally-dispensed POs, opioid state laws and mortality rates. We find statistically significant correlations with drug-related deaths while, as expected, we do not detect any relationship with mortality related to other causes.

At a subsequent stage, we assess whether the set of laws impact other relevant dimensions of local economies: *(iii)* do opioid state laws have an indirect impact on labour market participation and on illegal activities? In terms of theoretical prediction, the answer to this question is ambiguous. According to one scenario, lowering the amount of dispensed POs may drive people out of drug-abuse. Here, we would also expect an improvement in labour market conditions at the local level. We observe that the reduction in the amount of POs following the implementation of some opioid state laws leads to an increase in employment and a decrease in both unemployment and inactivity rates. Interestingly, such effects are more pronounced for females, whites and adults in the age range 25-64. A second hypothesis is that (heavy) users might turn to the black market in response to the lower availability of legal POs, hence increasing their propensity to commit drug-related crimes, while being in precarious employment or even staying out of the labour force. Our findings also show a consistent increase in crime rates, especially those related to the sale and possession of opium and synthetic drugs, coming with the implementation of some laws. We corroborate this evidence exploiting a novel dataset on incarceration rates at the local level. We notice that the supply-side regulations for pain management clinics (PMCLs) have a positive unforeseen impact on the total prison population, which poses further socio-economic and welfare challenges to the US system.

Our overall estimates capture the prevalent effects of the laws at the local level. Yet, when we differentiate the analysis by the initial level of consumption of POs, we find that the improvements in the labour force participation dominate in the areas that are less exposed to the consumption of opioids at the beginning of the period, while the increases in crime rates prevail in the areas that suffer the highest initial exposure to POs.

Given its severity, it is not surprising that the impact of state policies on this dramatic epidemic is being increasingly investigated. However, most of the works focus on health-related issues or belong to the medical literature. Early contributions to the literature do not find consistent evidence on the impact of opioid-related regulations on mortality rate and hospital admissions, possibly due to the short time series of data employed. Brady et al. (2014) show that PDMPs are not fully effective in reducing the amount of per capita opioids dispensed, while Meara et al. (2016) do not observe any clear evidence of the impact of state laws on opioid abuse behaviour. On the contrary, Popovici et al. (2017), who focus exclusively on the implementation of PMCLs and DSLs, find weak negative effects of both types of laws on overdose mortality and hospital admissions in a difference-in-difference framework. Additionally, Rees et al. (2017) find a negative effect of NALs and GSLs on mortality, while Buchmueller and Carey (2018) detect an effect in reducing the opioid misuse only when looking at the mandatory ("must-access") version of the PDMP. Finally, Alpert et al. (2018) show that the reformulation of OxyContin in 2010, from being crushable to its abuse-deterrent version, increases the incidence of heroin-related deaths.[2]

With our analysis we address the limited economic-oriented literature on the topic. In doing so, we use a comprehensive setting: we look at the sets of regulations implemented at the state level over a 15-year period and their implications for the supply and the demand for POs. Moreover, to the best of our knowledge, this is the first work that considers the effects of state opioid regulations on the local labour market participation and among the very few that look at illegal activities.[3] While existing studies are typically unconcerned about the labour market impacts of opioid-abuse regulations, those related to the economics of crime are rather scant as well. Using a sub-sample of counties in the US, Mallatt (2017) estimates that the implementation of PDMPs yields an overall drop in the amount of oxycodone dispensed while causing an increase in heroin crimes in the most opioid-dense counties. In another paper, which exploits timing and geographic location of a crackdown on legal pharmaceutical suppliers in Florida, Meinhofer (2017) studies the supply-side effect of PDMPs on drug abuse and crimes. She finds mild effects of spillovers from substitution to illegal drugs. With respect to the existing studies, we are able to provide results that stem from the complete coverage of the US population for a period of fifteen years and that refer to a broad list of criminal activities.[4]

This paper is also the first contribution analysing how the legal and illegal markets of

[2] A growing body of the literature is also looking at the patients' characteristics that predict opioid abuse, such as mental health problems and histories of substance abuse (Ives et al., 2006; Pergolizzi et al., 2012), while other papers examine the role played by physicians (Barnett et al., 2017; Currie and Schnell, 2018; Schnell, 2017).

[3] A recent paper by Carpenter et al. (2017) estimates the relationship between economic conditions and the use of illicit drugs (POs, cocaine, and heroin). They find that substance use disorders involving alcohol, marijuana, analgesics, and hallucinogens are strongly countercyclical.

[4] To our knowledge, there exists a third analysis on the relationship between opioids and crime by Deza et al. (2017), which focus on violent and property crimes in a 5-year time interval (2007-2012). However, this is not publicly available at the time of writing.

opioids react to shocks to the supply and to the demand for POs. Under state and federal law, selling controlled substances (including POs) without authorisation is considered as a felony. The same applies to possessing controlled substances without a prescription. Despite these legal deterrents, the illegal market remains a relevant source of POs for many users. This is especially true for the heavier users, who might struggle to get out from addiction as policy markers are restraining access to medical POs. This pattern is confirmed by the National Survey on Drug Use and Health (NSDUH), according to which around 30% of interviewed misusers turn to the illegal market to obtain their habitual supply of POs. Our results suggest that reducing POs in the legal market may have unintended consequences on illegal activities. We find, in fact, that PMCLs bring about a consistent two-fold increase in the arrest rates for property, violent, drug related crimes and a significant rise in the incarceration rates. Per contra, GSLs yield a decrease by 8 arrests every 1,000 inhabitants in reported total criminal activity and by 6.4 arrests every 1,000 inhabitants for drug-related crimes, which are likely to be due to the immunity and mitigation in court granted to the person that seeks medical assistance under these regulations.

The remainder of the paper is organised as follows: section 2 describes the opioid crisis and the related policies implemented in the past decades. The data and the empirical strategy are presented in section 3 and the main results in section 4. We discuss our findings in section 5.

2 Overview on Prescription Opioids

In this section we describe the opioid crisis that has struck the US in the recent decades. We then illustrate the different policies that have been implemented over time across the US states and we outline the theoretical predictions of the effects of these laws on the amount of POs dispensed by practitioners, on labour market indicators and on crime.

2.1 The US Opioid Crisis

Opioids belong to a class of drugs derived from opium, a naturally occurring compound in poppies that produces euphoria, pain relief, and sedation. These drugs have been used for centuries for recreational and medicinal purposes because of their powerful analgesic effect. They can be ingested, snorted or injected and are often co-abused with depressants such as benzodiazepines to enhance the high. In some cases, particularly with fentanyl, they are laced with heroin to strengthen its effect. Others, such as methadone and buprenorphine, are used medically in replacement therapies for addicted users (Paulozzi, 2012). However, with prolonged use the body starts relying on them and the user becomes physically dependent. The addiction to these drugs produces a physical and psychological dependence that is hard to overcome and results in devastating and painful consequences to the user.

Since the late 1990s, the rapid escalation in the use of prescription and non-prescription opioid drugs has originated the so-called "opioid epidemic" or "opioid crisis" in the US. Over the past thirty years opioids have been increasingly prescribed for the treatment of chronic non-cancer pain, such as back pain or osteoarthritis, and even though medical professionals now recognise their side effects and their potential for abuse, they remain a staple of modern pain management. As a result, this phenomenon has now reached alarming levels in the US, with over 50,000 drug overdose deaths only in 2015, of which 63 per cent reportedly involving opioids (Council of Economic Advisers, 2017).

Several key factors have contributed to the crisis. First, pharmaceutical companies have marketed their drugs as safe and effective for treating pain despite evidence showing that in most, but not all, cases the risks might outweigh the benefits. Many doctors and patients have been initially persuaded by these advertising campaigns.[5] Then, doctors have had to balance the pressure received by advocacy groups (some of which were pharma-backed), medical associations and increasing pressure to treat patients quickly and efficiently. Opioids provided a quick answer to these problems. Also, some risk factors make certain sub-populations particularly vulnerable to POs abuse, including people with mental illness or a history of other substance abuse and those who live in rural areas and on a low income (Ives et al., 2006; Pergolizzi et al., 2012). Finally, inappropriate and unnecessary prescriptions have brought to a scenario where there are so many pills circulating – those prescribed in 2015 being enough "to medicate every American around the clock for three weeks", according to the CDC – that they are often diverted to family members or friends of patients or to the black market.[6]

2.2 Opioid State Laws and Their Potential Effects

The reaction of the policy makers to the opioid crisis has come primarily at the state level, with the implementation of different laws in different states at different times. The target of these policies varies in terms of the individuals involved (patients, prescribers, pharmacists) and of the types of limitation. Specifically, these regulations can be grouped into five categories, which are described in Table 1, while the timing of their implementation across US states is summarised in Figure A.1. In accordance with this classification, our identification of the effects of each policy relies on the indicators provided by Mallatt (2017) and by Popovici et al. (2017).[7] We look at the response in terms of the amount of drugs sold in each area and of different socio-economic outcomes such as the participation rate on the labour market and crime. Table 2 summarises the expected effects of each set of regulations on the outcomes considered.

Two sets of regulations are meant to target the supply for POs. PDMP is the most commonly and well-studied policy. It consists of state-level databases that monitor the prescription and

[5] Purdue Pharma, the maker of OxyContin, and some of its higher-ups paid more than US$ 600 million in fines in 2007 for their misleading marketing claims, and POs makers and distributors are now facing several lawsuits on similar grounds.

[6] Opioid users typically find their habitual dose of drug: from dealers/strangers (4.3%); from the internet (0.1%); by other means (4.4%); from doctors (23.8%); buying/taking it from friends or relatives (14.6%); and free from friends or relatives (53%). Those in the latter category report that their friends or relatives obtained the drugs from doctors themselves 87% of the times (Meinhofer, 2017).

[7] The variable PDMP comes from Mallatt (2017), the other indicators are taken from Popovici et al. (2017). We also employ similar variables as computed by Meara et al. (2016), Rees et al. (2017) and Buchmueller and Carey (2018) for robustness. Despite referring to different (or smaller) samples, when we use the indicators from these other sources we obtain comparable results (omitted for brevity but available upon request).

Table 1: Laws on Prescription Opioids

Law	**Name**	**Description**
PDMP	Prescription Drug Monitoring Program	Implementation of a system that collects information on prescriptions of controlled substances and that allows physicians and pharmacists to view a patient's prescribing history.
PCML	Pain Management Clinics Law	Set of regulations concerning the minimum requirements for a pain management clinic to be allowed to dispense prescription drugs.
DSL	Doctor Shopping Law	Obligation for patients to reveal to a health care practitioner about previous prescriptions received from other doctors and prohibition to obtain drugs through fraud, deceit, misrepresentation, etc.
GSL	Good Samaritan Law	Laws that grant immunity from prosecution (or mitigation in sentence) for people who call 911 in the case of an overdose emergency.
NAL	Naloxone Access Law	Laws that provide immunity to health care professionals who prescribe or administer naloxone to reverse an opioid overdose in case of emergency.

the dispensing of controlled substances. The information contained in the system is available to all authorised health-care providers including physicians and pharmacists with the purpose of preventing improper drug prescription or dispensing and drug diversion. In some states, under certain circumstances, prescribers and dispensers are required to access the PDMP by law (hence, called "must-access"), while in others the use of this system is voluntary. Since the early 2000s, PDMPs have been increasingly implemented across US states. Full national coverage has been reached in 2017 with Missouri, which was the last state to adopt this type of regulation.

PMCLs embody all regulations that aim at preventing inappropriate prescribing and dispensing of controlled substances within clinics specialised in pain management. These clinics have been such a great source of prescription drugs that they are sometimes called "Pill Mills". They have become such an increasing issue in the opioid epidemic that PMCLs have been implemented in one every five states since the mid-2000s. Although there is substantial heterogeneity across states, regulations associated with PMCLs typically provide for requirements concerning the ownership, the licensing procedures, the operational standards and the personnel qualification of pain management clinics, facilities or practice locations. These interventions have resulted in a massive shutdown of pain management clinics that did not meet the new standards (Meinhofer, 2017).

Both PDMPs and PMCLs induce a shock on the supply side of the market for POs, i.e. they provide for restrictions to the agents supplying drugs (doctors and pharmacists). As a consequence, we expect the two policies to have an unambiguously negative effect on the amount of POs dispensed. On the one hand, (heavy) users might turn to the black market in substitution for the legally dispensed POs, hence committing more drug-related crimes. Also, these circumstances might be correlated with a lower propensity to work. Coherently, we might find an increase in the risk of opioid-mortality possibly due to the lower quality of the drugs exchanged in the illegal markets. On the other hand, these laws potentially slow down the diversion from the legal to the illegal market for drugs. Thus, it may be that the amount of POs in the illegal market drops, indirectly forcing people out of drug-abuse. Then, we would expect an improvement in the labour market measures. These latter hypotheses are in line with our findings.

DSLs are also directed at reducing the amount of opioids sold but they involve the demand side as they impose restrictions on the patients rather than on the suppliers. They refer to any regulation that prohibits doctor shopping, i.e. the practice of obtaining controlled substances from multiple healthcare practitioners without the prescribers knowledge of the other prescriptions. The number of states that have adopted these laws has doubled since the year 2000, and is currently around a third of the total. DSLs limit a patient's ability to seek medications from multiple providers and prohibit withholding of any information that may be relevant to the physician or the pharmacist. Curtailing access to POs for non-medical use in this manner is potentially effective as health care providers are the most commonly cited source for POs used non-medically (Substance Abuse and Mental Health Services Administration, 2014).

This set of regulations is expected to negatively affect the amount of opioids available on the market from the demand side, especially when prescriptions are unnecessary or excessive. Then, this would lower mortality, while the predicted impact on labour market participation and crime would be equivalent to the one induced by PDMPs and PMCLs, as described above. Nevertheless, there is some evidence of doctors over-prescribing in response to this policy. In some circumstances, physicians may decide to prescribe higher doses of opioids to their patients in order to avoid them accessing the black market. Schnell (2017) argues that although altruistic physicians prescribe less opioids in the presence of a secondary (illegal) market, they also tend to prescribe more on average (i.e. they are altruistic) the more they are concerned with their patients' health. In the same way, we conjecture that physicians might respond to doctor shopping laws with an increase in the amount of opioids prescribed, to avoid that their patients turn to the illegal and more dangerous market to take up drugs of lower quality and without professional supervision.

Finally, as a consequence of the unprecedented increase in the number of overdose deaths due to POs abuse, several states have implemented GSLs and NALs. These laws have been designed and implemented with the intention to reduce the fatality rate linked to the abuse

Table 2: Theoretical Prediction of Opioid-Related Policies

Laws	Predictions			
	ME Units Dispensed	Mortality Risk	L Mkt Participation	Crime
PDMPs	-	-/+	-/+	-/+
PMCLs	-	-/+	-/+	-/+
DSLs	-/+	-/+	-/+	-/+
GSLs	-/+	-/+	-/+	-
NALs	-/+	-/+	-/+	-

of opioids. They aim at containing the number of fatal overdoses by providing incentives and support to those seeking medical assistance in the case of an overdose emergency. NALs allow to administer naloxone, a lifesaving medication that blocks or reverses the effects of an opioid overdose, to individuals experiencing an overdose due to opioids without incurring in any civil, criminal or disciplinary prosecution. GSLs grant some form of immunity or mitigation in prosecution or at sentencing for people who call emergency medical assistance in the case of an overdose. These laws have been enforced fairly recently (since 2010) in most of the states that currently have such regulations. Their predicted effects are potentially ambiguous. On the one hand, increased access to medical assistance and counselling, both in the case of NAL and of GSL, might improve health and psychological conditions of drug abusers and persuade them to quit drugs. In this case, we would expect an improvement in labour market outcomes and a reduction in drug-related crimes. In particular, GSLs are expected to determine a reduction in drug-related crimes because of the immunity and mitigation in court granted to the person that seeks medical assistance. On the other hand, these laws reduce the opportunity costs associated to drug abuse. Hence, we might observe an increase in the quantity of POs and a worsening of labour market outcomes.

3 Data and Empirical Strategy

In this section we describe how we combine various sources to build our main dataset. Then, we illustrate the empirical strategy and provide some descriptive statistics.

3.1 Construction of the Dataset

The data on POs comes from the Automation of Reports and Consolidated Orders System (ARCOS), which is run by the Office of Diversion Control of the US Drug Enforcement Administration. Since the Controlled Substance Act of 1970, in fact, manufacturers of controlled substances are required to provide information on the amount of drugs produced and sold in the US. Hence, the yearly ARCOS reports provide a record of the quantities (in grams) of each controlled active ingredient sold in the US. This information is disaggregated at the 3-digit zipcode level across all states of the US.

We focus our analysis on hydromorphone, methadone, meperidine, oxycodone, hydrocodone, fentanyl and morphine. These are the most commonly used opioid analgesics and are classified as Schedule II or Schedule III drugs.[8] Additionally, we build an overall indicator that accounts for the relative potency of these drugs, so that each drug is converted into Morphine Equivalent (MEs) units.[9] Since it considers the overall amount of opioids, this will be our main indicator

[8] The order of the Schedule decreases with the abuse potential of the drug. For instance, heroin is classified as a Schedule I substance, while Schedule V drugs include cough preparations with less than 200 mg of codeine per 100 ml. Schedule II and Schedule III substances are considered to have a high to moderate potential for abuse, respectively, and to lead to psychological or physical dependence.

[9] In choosing the multipliers to convert into ME units we follow Brady et al. (2014). Hence, we rescale substances according to the following: hydromorphone by 4, methadone by 7.5, meperidine by 0.1, oxycodone by 1, hydrocodone by 1, fentanyl by 75, morphine by 1.

to quantify the consumption of POs.[10]

In order to build our dataset, we match the information on prescription drugs from ARCOS to the official population intercensal estimates and the Bureau of Labour Statistic (BLS) labour force data at the county level using the 2000 and the 2010 zip-to-county crosswalks produced by the MABLE/Geocorr Application of the Missouri Census Data Center. The intercensal estimates include counts of the overall population and by sex, age band and race/ethnicity group, while the BLS data contains counts of the total number of employed and unemployed people. In order to run the analysis on the labour market indicators by gender, race and age sub-groups, we also aggregate individual information from the American Community Survey (ACS) at the county level to our dataset. Then, we link them to the Uniform Crime Reporting (UCR) Program Data provided by the Federal Bureau of Investigation, which contains the number of arrests disaggregated by county, by main demographic characteristics and by type of crime. County-level arrest data consider both less serious and more frequent property criminal activities, on the one hand, and more serious and less frequent violent crimes, on the other. Using the UCR standard definitions, we divide the total crime category into two main components: *(i)* violent, which includes murders, rapes, robberies and aggravated assaults, and *(ii)* property, which covers burglaries, larcenies and motor-vehicle thefts. Additionally, we take into account drug-related crimes that involve the possession and selling of different substances such as opium, cocaine, marijuana and other synthetic drugs. Along with the UCR data on arrests, we also exploit a novel dataset on incarceration rates at the county level provided by the Vera Institute of Justice to corroborate our results on crimes.[11] Data on mortality rates comes from the Global Health Data Exchange (GHDx), which is run by the Institute for Health Metrics and Evaluation at the University of Washington.

Finally, we follow Autor et al. (2013) and convert all data to commuting zone (CZ) level. This is to ensure a better estimation of the effects on the labour market and crime and alleviate any concern related with migration flows.[12] Our final sample comprises 741 commuting zones across the US that we follow for 15 years (2000-2014). To our knowledge, this is the first paper evaluating the effects of prescription drugs laws that exploits such an extensive dataset, both in terms of time period and of geographical coverage.

3.2 Empirical Model

We employ a typical regression difference-in-difference setting such that:

$$Y_{cst} = \alpha + \beta Law_{st} + X'_{cst}\theta + \delta_t + \gamma_c + \epsilon_{cst}, \tag{1}$$

where Y_{cst} is the outcome of interest measured in CZ c, in state s and in year t. The set Law_{st} includes dummy variables for each regulation as from Table 1, which take value

[10] The two definitions, POs and MEs, will be used interchangeably in the remainder of the paper.

[11] As explained in their website (`http://trends.vera.org/incarceration-rates`), data on county jail population come from the Bureau of Justice Statistics (BJS), the Annual Survey of Jails (ASJ) and the Census of Jails (COJ). See Kang (2015) for details.

[12] Nevertheless, we also check the consistency of our results using county-based boundaries (see section 4).

1 when the regulation is in force in a given state and 0 otherwise. Hence, the coefficient β corresponds to the treatment effect of interest, as it should capture the effect of a regulation – while controlling for the others – on different outcomes. We analyse such effect on the quantity of drugs distributed, on labour market indicators and on crime.[13] We also control for a set X'_{cst} that contains information on the classic characteristics of the population in the CZ (total population and shares by gender, age band and race), the CZ-specific share of the manufacturing sector, the state GDP and two dummies for whether the state has passed a law on medical or recreational use of marijuana, respectively. The economic variables are included to account for differences in the industrial composition and economic conditions that might be correlated with the average usage of POs in the area as suggested by Carpenter et al. (2017), while the indicators for marijuana laws control for the potential substitution of opioids with medical marijuana.[14] We also account for regional fluctuations by adding division-year fixed effects.[15] Finally, we include CZ and year fixed effects, while errors are clustered at the state level.[16]

A critical assumption for our identification strategy is that states enacting the policies and those that do not adopt them must behave in a similar way in the pre-implementation period. This is known as the parallel trends assumption, which posits that the average change in the comparison group represents the counterfactual change in the treatment group if there were no treatment. The event-study analysis represents the standard way to test for the existence of trends in the pre-adoption period. Hence, we also estimate the following equation:

$$Y_{cst} = \alpha + \sum_{\pi=-4}^{-1} \beta_{l,\pi} Law_{l,st+\pi} + \sum_{\tau=1}^{4} \beta_{l,\tau} Law_{l,st+\tau} + \beta_{-l} Law_{-l,st} + X'_{cst}\theta + \delta_t + \gamma_c + \epsilon_{cst}, \quad (2)$$

which allows for 4 pre- and 4 post-treatment effects for each law l, while still controlling for the enforcement of all the other laws $(-l)$.[17] For states that do not pass law l, we assign an implementation year at random and center π and τ accordingly. The remaining control variables and fixed effects are defined as in Equation 1. According to this specification, leads and lags are identified by the coefficients $\beta_{l,\pi}$ and $\beta_{l,\tau}$, respectively. If the leads $\beta_{l,\pi}$ are not statistically different from zero, this implies we can assume that the parallel trends assumption holds. The $\beta_{l,\tau}$ coefficients, instead, allow us to examine whether the treatment effect of law l fades, increases or stays constant over time.

[13] Outcome variables for drugs are expressed in grams per capita, while for labour market and mortality indicators we compute the share over the relevant population. Following the recent literature of crime, our econometric specification exploits logarithms. As in Dix-Carneiro et al. (2017), we add one to the count of criminal activities in order to circumvent sample selection issues that would emerge from deleting observations with no reported crimes. We rescale the crime rate by 1,000 to facilitate the interpretation.

[14] To rule out the possibility that economic factors might affect our estimated coefficients of interest, we also run the model with a lagged set of control variables and find identical results.

[15] Subscripts are omitted in favour of an easier notation.

[16] The clustering of the errors at this geographical level derives from the fact that the treatment (i.e. the introduction of the policies) is implemented at the state level. Yet, any other level of clustering provides better results in terms of statistical power of our estimates.

[17] In the case of NALs we can only identify 2 post-treatment effects, as these laws have been implemented in very recent times.

Additionally, we use equation 2 to implement a battery of placebo tests, where, following Bertrand et al. (2004), we assign the treatment and the implementation year at random.[18]

3.3 Descriptive Analysis

Table A.1 reports the descriptive statistics of the main outcome and control variables used in the analysis. Drug quantities are expressed in Morphine Equivalent grams per capita (MEs). Overall, more than half a gram of ME units of opioids per capita was dispensed in the period considered. This corresponds to around 230 kilograms of ME substances dispensed on average in each CZ every year.This figure is computed by multiplying the average ME units (0.564) to the average population in each CZ. The most commonly sold substances are oxycodone and hydrocodone, with around 0.1 grams per capita.

Figure A.2 shows the average quantity of ME units of drugs sold year by year since the introduction of each policy. The portion of the graphs to the left of the dashed vertical line corresponds to the years prior to the onset of each law. The graph shows a clear increase in the average amount of drugs dispensed per capita, which is only slowed down after the introduction of the policies (to the right of the dashed line). The only exception seems to be DSLs, for which only a temporary deceleration can be observed. In the case of PMCLs, conversely, the adoption of the law yields a sharp decrease in the ME quantity sold.

Over the entire period considered (2000-2014) the average employment and unemployment rates are around 58% and 4%, respectively (Table A.1). Moreover, on average, 5 criminal events per 1,000 inhabitants are recorded in each CZ, most of which are property-related (around 4.5 crimes). A similar figure is reported for drug-related crimes, which are largely due to arrests for drug possession.

Table 3 lists the ten CZs at the top and at the bottom ends of the distribution of MEs sold on average during the period 2000 - 2014. Prescribing rates for opioids vary widely across

Table 3: Top and Bottom CZs by MEs Consumption

Top ME Consumption						**Bottom ME Consumption**					
CZ	State	MEs	ERate	URate	IRate	CZ	State	MEs	ERate	URate	IRate
Daytona Beach	FL	2.968	0.517	0.037	0.446	Van Horn	TX	0.085	0.675	0.033	0.292
Cincinnati	IN	1.769	0.612	0.041	0.348	McAllen	TX	0.104	0.493	0.051	0.456
Birmingham	AL	1.689	0.472	0.040	0.488	Eagle Pass	TX	0.117	0.476	0.075	0.448
Medford	OR	1.542	0.524	0.048	0.428	Crystal City	TX	0.119	0.486	0.053	0.461
Bangor	ME	1.526	0.583	0.037	0.381	Del Rio	TX	0.120	0.507	0.038	0.455
Asheville	NC	1.450	0.557	0.032	0.410	Alpine	TX	0.125	0.575	0.048	0.377
Redding	CA	1.439	0.495	0.052	0.453	Dupree	SD	0.137	0.532	0.058	0.410
Pikeville	KY	1.426	0.393	0.038	0.569	Sioux Center	IA	0.158	0.704	0.022	0.274
Chico	CA	1.405	0.509	0.059	0.432	Worthington	MN	0.167	0.663	0.030	0.307
Eureka	CA	1.366	0.509	0.042	0.449	Columbus	NE	0.174	0.685	0.024	0.291
Average		*1.658*	*0.517*	*0.043*	*0.440*	*Average*		*0.131*	*0.580*	*0.043*	*0.377*

Note: for each CZ, we display the name of the most populous city.

[18] We apply the following simulation procedure for each set of laws: first, we randomly select 25 states out of 50 and classify them as treated states, i.e. as if they were affected by the law; then, we draw a year at random from a distribution between 2000 and 2014 and re-center leads and lags accordingly (Bertrand et al., 2004).

states, with the highest (lowest) amounts sold in Delaware and Rhode Island (South Dakota and Nebraska). This ranking provides descriptive evidence for substantial variations in MEs across US CZs and within regions. For instance, Texas contains many CZs in the bottom distribution of MEs but also CZs (such as Seymour, TX) which belong to the top ten percentile. As far as the labour market conditions, measured by the employment (ERate), unemployment (URate) and inactivity (IRate) rates, we can observe a positive association between worse labour market outcomes and high consumption of ME units. As the bottom row of Table 3 suggests, the average performance of the CZs in the high end of the ME consumption distribution is different from the one of the CZ belonging to the bottom end of the same distribution. For instance, the difference in the employment rates (0.517 and 0.580, respectively) amounts to 6.3 percentage points.

Additionally, Figure A.3 in Appendix describes the geographical distribution of the average MEs in the years 2000 and 2014 (top and bottom panels, respectively). We observe an unambiguous variation across CZs and years, with the colder (darker blue) areas, distributed predominantly in the central regions, indicating lower levels of POs per capita. Vice versa, the warmer (darker red) the area, the higher the consumption of MEs. This is the case of the Atlantic and the Pacific coastal regions. At the same time, the two maps demonstrate an extraordinary increase in opioid usages across the country during the last fifteen years. Indeed, had we considered the 2000 quartile distribution for the year 2014 as well, we would have obtained an almost entirely dark red map. As a matter of fact, the top percentile of the average MEs distribution in 2000 roughly matches the threshold of the first quartile for the year 2014.

4 Results

In this section we present the results of our analysis. We first analyse which set of policies is more effective in reducing the amount of total ME units sold in each CZ. Then, we check whether the regulations affect the mortality rate associated to different causes. Finally, we investigate their indirect impact on the labour market participation and on criminal activity.

4.1 Prescription Opioids

Table 4 shows the main results on the amount of ME prescription drugs sold in each CZ. In columns 1 to 5 we consider one set of state laws at a time, while in columns 6 to 9 we include all five law indicators in the same regression. Our preferred specification is the one shown in column 8, as it includes not only CZ and year dummies but also division-year fixed effects, which should account for regional fluctuations over time. Moreover, it controls for all types of opioid-related laws at the same time, so that the effect of each one of them is correctly accounted for. Nevertheless, the coefficients in this specification are consistent with the ones displayed in columns 1-5.

Our empirical evidence generally suggests a reduction in POs following the enforcement of

Table 4: Effect on Drug Quantities

Dependent variable	(1) MEs	(2) MEs	(3) MEs	(4) MEs	(5) MEs	(6) MEs	(7) MEs	(8) MEs	(9) MEs
PDMP	-0.029					0.036*	-0.013	-0.012	-0.040
	(0.040)					(0.021)	(0.034)	(0.029)	(0.029)
PMCL		-0.172***				-0.085***	-0.153***	-0.169***	-0.275***
		(0.034)				(0.021)	(0.023)	(0.026)	(0.066)
DSL			0.013			0.033	0.061	0.074*	0.154***
			(0.047)			(0.041)	(0.049)	(0.039)	(0.052)
NAL				-0.011		0.039	0.038	-0.014	0.072
				(0.059)		(0.041)	(0.026)	(0.035)	(0.053)
GSL					-0.130*	-0.065	-0.076*	-0.121**	-0.181*
					(0.071)	(0.039)	(0.040)	(0.048)	(0.091)
Observations	11,115	11,115	11,115	11,115	11,115	11,115	11,115	11,115	11,115
R-squared	0.813	0.815	0.812	0.812	0.814	0.795	0.799	0.817	0.967
Weights	✓	✓	✓	✓	✓		✓	✓	✓
Year-Division FE	✓	✓	✓	✓	✓			✓	✓
State Linear Trends									✓

Note: Population-weighted OLS estimates, where the weight is computed as the share of the population in the CZ relative to the national population. All regressions include year and CZ fixed effects. Other controls include indicators for: population, share of females, share of people in working age, share of over65, share of whites, share of manufacturing, state GDP, state laws on marijuana. Errors are clustered at the state level.
* p<.10 ** p<.05 *** p<.01.

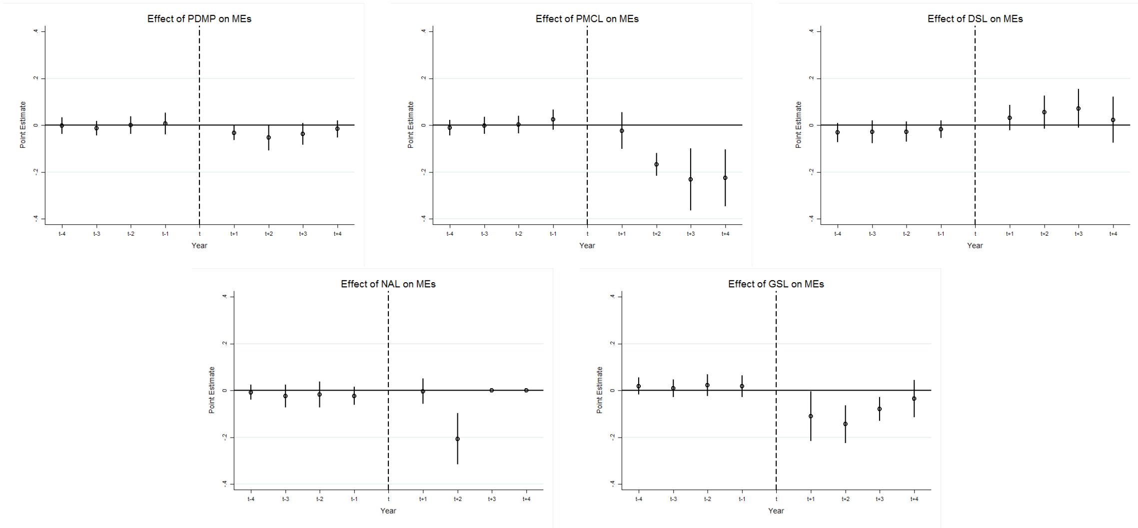
most state laws.[19] The effects that we find in the specification described above are confirmed by the event-study analysis based on Equation 2 that is shown in Figure 1. In all cases the reported plots suggest that the parallel trend assumption holds, as the coefficients in the pre-treatment period are never statistically different from zero. This indicates that there is no plausible systematic pattern in ME units sold prior to the introduction of any opioid state law. In other words, it provides empirical support to the statement that in the absence of treatment the drugs sold per capita in the treatment and the control units do not differ from each other significantly.

We observe an overall negative effect of the laws targeting the supply side on the amount of MEs dispensed, particularly in the case of PMCL. The two policies have a negative impact on the dependent variable: while the effect of PDMP is negative but somewhat weak, being it in the range between -0.03 and -0.05 p.p. in the first two years, PMCL appears to yield a sharp and large decrease by around -0.15 to -0.23 p.p. in the quantity of POs sold right after the second year since the enactment of this law. Likewise, the magnitude of the coefficient from Table 4 suggests that the introduction of PMCL leads to an average reduction in the amount of ME units by 0.17 grams, i.e. by 30%. A similar pattern occurs for the two laws aiming at reducing the number of fatal overdoses, namely NALs and GSLs. The former triggers the reduction in POs after the first year, while the latter has a more sudden impact, although it appears to fade after a while.[20] Yet, the average effect predicted by the coefficient associated to GSL, implies a significant reduction in ME units by 21%. In both cases, the decrease in POs is likely to be due to an improved access to medical assistance that these laws promote.

[19] We test whether the effects are driven by outliers so we run the model excluding one state at the time and find consistent results (omitted for brevity).

[20] There are only two lags for NALs because of their very recent implementation.

Figure 1: Event-Study Analysis: Effect on Drug Quantities



Note: Coefficients are estimated as in Equation 2. 95% confidence intervals are shown and standard errors are clustered at the state level.

The only exception to this overall negative impact is due to the regulations tackling doctor shopping behaviour (DSL). The enforcement of DSLs yields an overall rise in POs dispensed by 13%, however the evidence is not particularly robust, as the event-study analysis displays positive but not statistically significant coefficients in the post-treatment period. We suspect that this (however weak) increase might be due to the physicians over-prescribing opioid painkillers even after the enactment of these laws, in order to avoid that patients would turn to the illegal drug market, where they might find uncontrolled substances and use them without any supervision. If the patients are aware of such mechanism, then the policy becomes ineffective.

In order to further corroborate the validity of our analysis, we run a battery of placebo tests based on equation 2 where the date of implementation for each policy is drawn at random (Figure A.4), as explained in section 3. In the presence of strong heterogeneity in trends, the placebo treatments would show an effect comparable with our baseline coefficients. Here, the lack of statistical significance for the estimated coefficients in both the pre- and the post-periods supports our strategy.

In addition to the placebo tests, we run some robustness checks, which are displayed in Table A.2. Column 1 reports the same specification as column 8 from Table 4, with the exception that estimates are now weighted by the population in the CZ. Estimated coefficients are in line with the previous results. In column 2 we account for the introduction of Medicare Part D in 2006, a federal program that subsidizes the costs of prescription drugs and of prescription drug insurance premiums for Medicare beneficiaries. The exposure to this new social security program is proxied by the share of people aged 65 or over, interacted with a dummy variable that takes value 1 in the years after 2006 and 0 otherwise. As expected, the amount of POs sold increases with a higher exposure to the Medicare Part D program, but the estimated coefficients associated to the five laws do not differ from the baseline. In column 3 we consider the reformulation of OxyContin that took place in 2010 and that made it more difficult to abuse this drug (Evans et al., 2017). Hence, we include an interaction between the amount of oxycodone sold in each CZ in 2000 and a dummy that takes value 1 in the years after 2010.[21] In this case, the coefficient associated to the interaction term is statistically significant and suggests that the reformulation of OxyContin has brought about an increase in the amount of opioid prescribed by 0.7 grams of ME units. Previous works show that the reformulation of OxyContin has been followed by a significant drop in the number of prescriptions of this drug across the US (Alpert et al., 2018; Schnell, 2017). At the same time, however, there is also evidence of substitution towards other opium-based substances, especially fentanyl (Alpert et al., 2018), which is likely to be the driver of such positive effect. Yet, this does not change the main results, suggesting that the introduction of the abuse-deterrent formulation of OxyContin does not influence the impact of the laws on the amount of POs.

Furthermore, we test whether the specification based on CZs yields different results than the one based on county administrative boundaries (Table A.3). We do this because of two reasons. First, the definition of CZ does not perfectly align with state borders.[22] Given that our treatment varies at the state level, we want to ensure that the effects of the laws are not confounded by discrepancies in border definition. Column 1 displays the estimated coefficients for such county-based specification, which are consistent with the main results from Table 4: the onset of PMCLs and GSLs yield a reduction in ME units by 30 and 26%, respectively, while DSLs determine an increase by 17%; the effect of the other laws is statistically null. Second, we want to be able to distinguish between areas that are adjacent to another state (i.e. outer counties) and those that are not (i.e. inner counties). It may be that the opioid state laws do not have an identical effect on the consumption of POs across counties that belong to the same state because some users, especially those residing close to another state, might cross the border in their search for drugs. A crude hint is given by the differences in ME units per capita sold. These amount to 0.53 grams in the inner counties, and to 0.58 in the outer counties. These figures indicate that the quantity of POs sold in the counties that are far away from the state border tends to be lower than in the case where people face a shorter distance to travel to get to a different state and obtain their drugs there. However, the quantity of MEs sold in counties that share their border with a state where opioid laws are not enforced is even lower (0.47 grams per capita), suggesting the existence of some kind of opioid-related border-crossing behaviour.

Column 2 shows the effects for all counties that do not share their border with another state, while columns 3 and 4 pertain to outer counties where the adjacent state has at least one opioid law and does not have any of such laws enforced, respectively. As expected, most laws are more powerful in the inner counties, where coefficients imply stronger effects in terms of magnitude and of statistical significance. For the counties that share the border with another state the heterogeneous response to the implementation of the laws supports the existence of the

[21] This methodology is equivalent to the one used by Alpert et al. (2018), Evans et al. (2017) and Mallatt (2017).

[22] We aggregate our data at the CZs level because they are generally recognised as the ideal geographical unit when evaluating labour market outcomes, to alleviate any migration flow concerns across CZs.

cross-bordering effect hypothesised above. In particular, the consumption of POs in the outer counties that are adjacent to a regulated state does not seem to react much to the enforcement of opioid state laws: PCMLs yield a drop in POs by only 14% and DSLs have a statistically weak positive impact by 14%. Conversely, when the state across the border does not have any opioid state law in place, the quantity of POs per capita is drastically reduced by the enactment of PMCLs (by 47%), NALs (by 31%) and GSLs (by 14%). In the former case, opioid users from outside are more likely to commute to the county to obtain the desired drug, hence the demand remains high even when a law is enacted.[23] In the latter case, the users residing in the county might choose to commute to the contiguous unregulated state, hence reinforcing the negative impact of the laws on the amount of ME units per capita. This result is particularly important in terms of policy implication because it suggests that in the absence of confounding cross-bordering effects the impact of the opioid-related policies would be much higher than the one we estimate overall.

In Table A.4 we break up the effect of the state laws distinguishing between CZs with low (Panel A), medium (Panel B) and high (Panel C) exposure to POs. In doing so, we fix the distribution of MEs units at the first available year, that is 2000, and we define the exposure to POs as low, medium and high based on the overall distribution of MEs in 2000. Column 1 shows the differentiated effects of the laws on the amount of POs dispensed. Here, the estimated coefficients imply the existence of stronger effects the higher the initial consumption of legal POs in the CZ.[24]

Finally, we look at the effect of the state laws on the different substances deriving from opiates that we consider in the main indicator (ME), namely hydromorphone, methadone, meperidine, oxycodone, hydrocodone, fentanyl and morphine (Table A.5). Coefficients show that the negative impact of the introduction of PMCLs is clearly driven by the decreases induced on methadone (by 0.08 grams per capita), oxycodone and hydrocodone (both by around 0.03 grams per capita) and fentanyl (by 0.003 grams per capita). Recent works by Mallatt (2017) and Meinhofer (2017) find that PMCLs induce a reduction in the quantity of oxycodone per capita by 18% and 59%, respectively. Our estimates for oxycodone (and its close substitute hydrocodone) lay within this range, with an average drop by 30%. As far as NALs and GSLs are concerned, we find that the former yield very slight reductions in some substances and no changes in others, while in the latter case the overall decrease we find on the ME indicator is due to a drop in the quantity of oxycodone by 47% (column 4).

4.2 Mortality Rates

Since the late 1990s, a reversal in the downward mortality trends, as well as in morbidity rates, has been observed in the United States. Many studies correlate the increased availability of POs for pain treatment with the rise in the mortality rate (e.g. Case and Deaton, 2015). Hence, we assess the relation between the amount of ME units and the mortality rate in Table A.6, Panel

[23] The average quantity of MEs in these counties is 0.71 grams per capita.

[24] Similar results are found when we exclude from the sample all states that had at least one of the laws implemented by 2000. This applies to both Tables A.4 and A.10 (see discussion in the next subsections).

A. First, we observe a strong correlation between POs and mortality rate associated to mental and substance use disorders, which include several forms of drug addiction. This evidence is coherent with the recent medical literature such as Han et al. (2015). Moreover, we find that POs are positively and statistically related to mortality rate for pain-generating conditions that are typically treated with opioids, namely injuries. For cancer we obtain a large coefficient but this is not significant. Conversely, no link is found with other non-communicable diseases (skin, eye, oral diseases and congenital defects) and deaths caused by force of nature (including conflicts and terrorism). We implement this latter battery of robustness checks as placebo, as there is no predicted relation between these causes of mortality and the use of opioids.

In Panel B we examine the effect of the state policies on mortality rate. We do not expect to observe the enforcement of the laws analysed to be linked to mortality for reasons that are not directly related to opioid use (namely, mental and substance use disorders). Patients diagnosed with conditions such as cancer are typically prescribed opioids to treat the pain provoked by the disease, not to cure the disease itself. As a matter of fact, we do not find systematic statistically significant associations between the enactment of the state policies and the mortality rate for reasons other than drug use, with the exception of death by injury and GSLs, where the negative coefficient might be due to the increased access to medical assistance fostered by the law.

4.3 Labour Market Conditions

We then turn to look at whether the state policies to contrast the opioid crisis have an unintended impact on labour participation. This is a novel result, as, to our knowledge, there is no existing empirical evidence in the literature on this matter.

Table 5: Effect on Labour Participation

	(1)	(2)	(3)
Dependent variable	ERate	URate	IRate
Panel A:POs			
MEs	-0.002	0.001**	0.001
	(0.002)	(0.000)	(0.002)
Panel B: Laws			
PDMP	-0.001	0.000	0.001
	(0.002)	(0.001)	(0.002)
PMCL	0.006**	-0.003***	-0.003
	(0.003)	(0.001)	(0.003)
DSL	0.006**	0.001	-0.008***
	(0.003)	(0.001)	(0.002)
NAL	0.002	-0.000	-0.001
	(0.003)	(0.002)	(0.003)
GSL	-0.001	0.000	0.001
	(0.003)	(0.001)	(0.002)
Observations	11,115	11,115	11,115

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level.
* p<.10 ** p<.05 *** p<.01.

First, we evaluate the effect of average opioid consumption on the overall employment, unemployment and inactivity rates (Table 5). In Panel A we find some (however weak) evidence that the amount of POs sold is negatively related to employment. In particular, the quantity of ME units sold is positively and statistically linked to the unemployment rate. Conversely, we observe a slight improvement in the labour market indicators due to the enactment of opioid state laws (Panel B), especially in the case of the ones that aim at reducing the amount of POs (PMCL and DSL). Both policies yield an increase in the average employment rate by 0.6 p.p., or by 1%. Moreover, the introduction of PMCL causes a 8% (0.3 p.p.) decrease in the unemployment rate, while the restrictions on the demand-side (DSL) decrease the inactivity rate by around 2%. We do not observe any impact of the set of regulations aimed at decreasing the number of deaths such as in the case of NAL and GSL. As with the case of ME units, the compliance of our estimates to the parallel trends assumptions is supported by the event-study analysis shown in Figure A.5. The weakness of the estimated effects is understandable if we consider that the overall rates are computed as a crude measure of labour market performance, since it follows the BLS approach and it is based on all individuals aged 16 or over.

Next, we look at whether these overall effects on labour participation are related to the extent to which a CZ is exposed to the consumption of POs. Columns 2-4 in Table A.4 denote the existence of some heterogeneity, with participation sensibly improving in the CZs with low to medium levels of initial consumption of POs (Panel A and B). Conversely, the CZs with high levels of dispensed ME units per capita in 2000 do not seem to be affected by the enforcement of state opioid laws. These results suggest that the sets of opioid laws successfully stimulate the labour participation in areas characterised by lower levels of initial consumption of POs where, perhaps, the share of heavy opioid users is smaller and therefore it might be that more people manage to escape drug abuse and return to work.

We then break down the impact of the policies on labour market indicators by gender, race and age group. To do so, however, we cannot run the analysis for the entire period considered in the main specifications. Instead, we use the individual data taken from ACS that we then aggregate at the CZ level. Such information, however, is only available from 2005 onwards, which means that for this part of our study we can only rely on a sample of circa 7,400 observations. When we run the whole analysis on this sub-sample we find that coefficients always match those of the benchmark in terms of sign, magnitude and significance.[25]

The estimates by gender, race and age group are reported in Tables A.7, A.8 and Table A.9, respectively. The overall results for PMCL are consistent with those on the whole population, while DSL seem to rise unemployment and inactivity rates for some groups. In the case of the other policies, which did not display any relationship with labour participation in the main sample, the evidence is now suggesting that, at least for some categories, they do enhance the labour market prospects. However, NALs do not follow the same pattern, perhaps due to their very recent enforcement.

[25] Results omitted and available upon request.

4.4 Crime

This section describes the effect of the supply- and the demand-side interventions and of the mortality prevention state laws on crime rates. Theoretically, it is unclear whether the contraction of the legally dispensed POs due to the implementation of the laws will increase or decrease crime. On the one hand, criminal activities might rise if drug burglary, rather than the typical consensual doctor-user transaction, becomes the preferred way to divert POs (Meinhofer, 2017). Moreover, a restriction on the legal suppliers might influence crime through its impact on the illegal drug market as the demand for substitute illegal drugs increases. On the other hand, it is possible that some users might quit their addiction as a consequence of better monitoring of POs from the health care system. They will, then, be less prone to commit crime especially once their labour market participation improves. We provide empirical evidence of the impact of the five sets of state laws on various illegal activities. We evaluate whether these laws have any unintended effects on the participation to criminal activities using both crime and incarceration rates.

Table 6 shows the relationship between POs and total crimes (Panel A). In particular, we distinguish between violent, property and drug-related crimes, while in column 5 we assess the correlation with the incarceration rate computed from the Vera Institute of Justice dataset. Violent crimes consist in the "most aggressive" component of criminal activity, where offenders use or threaten force upon their victims. These include murder, rape, robbery and aggravated assault. Nevertheless, some criminal acts, such as robberies, are included among the violent category even though their final aim is more related to economic crimes. On the contrary, property crimes generally involve taking the property of other people (burglary, larceny and vehicle theft) while drug felonies relate to the possession and/or the sale of illegal substances. Drug users often crave for higher doses over time and this may increase their likelihood to

Table 6: Effect on Crime

Dependent variable	(1) Total Crimes	(2) Violent Crimes	(3) Property Crimes	(4) Drug Crimes	(5) Incarceration Rate	(6) Police
Panel A: POs						
MMEs	0.036	0.022	0.043	0.020	-0.102	0.366
	(0.072)	(0.067)	(0.070)	(0.073)	(-0.268)	(0.382)
Panel B: Laws						
PDMP	-0.164	-0.153	-0.156	-0.102	-0.540	-0.075
	(0.135)	(0.119)	(0.131)	(0.107)	(0.540)	(0.127)
PMCL	1.098**	0.962***	1.050**	1.185***	2.300***	-0.388
	(0.413)	(0.344)	(0.407)	(0.418)	(0.790)	(0.311)
DSL	-1.330	-1.064	-1.309	-1.321	1.670	-0.851
	(0.813)	(0.697)	(0.793)	(0.818)	(1.458)	(0.577)
NAL	0.014	0.037	0.008	0.092	-1.330	-0.023
	(0.256)	(0.245)	(0.245)	(0.268)	(0.937)	(0.271)
GSL	-1.340**	-1.235***	-1.284**	-1.500***	-1.082	0.329
	(0.533)	(0.451)	(0.520)	(0.547)	(0.748)	(0.342)
Observations	11,115	11,115	11,115	11,115	10,800	11,115

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

commit property-related crimes, especially when they need to steal valuables that would allow them to meet their habits.

The empirical evidence describes the absence of a correlation between prescription drugs and crime rates (Panel A). In Panel B, we report the impact of the state laws as from the difference-in-difference framework. The corresponding event-study analysis is shown in Figures A.6 and A.7. We find that PMCLs have a positive and significant impact on all types of crime and on the incarceration rates, while GSLs significantly reduce the reported criminal activities. According to the estimated coefficients, the enactment of PMCLs yields a two-fold increase in all types of crime and a significant rise in the incarceration rate. Enforcing GSLs, instead, determines almost 8 less property or violent crimes and 6.4 less drug-related arrests every 1,000 inhabitants. From this perspective, it seems that the state laws affecting the supply for opioids (i.e. PMCLs) are not effective in terms of social desirability, while GSLs are. Nevertheless, it worth noting that this result is partially expected because GSLs provide for immunity or mitigation in sentence for people who reach out for emergency services in case of an overdose episode, therefore the negative effect that we find is somewhat mechanical. The other sets of laws, namely PDMPs, DSLs and NALs, do not appear to have any statistically relevant overall effect on crime. The final column of Table 6 is a relevant test for the analysis of the impact of the state laws on crime, since it may be that POs consumption, criminal activities and arrest rates are affected by unobserved differences in policing public expenditure across areas. We check whether this is the case by estimating Equation 1 on the share of police officers per 1,000 inhabitants. Column 6 shows the absence of any correlation between ME units per capita or opioid state laws on the police force employed in each CZ, suggesting that such issue does not apply to our setting.[26]

As with the outcomes discussed previously, we break up the effect of the state laws on crimes distinguishing between CZs with low (Panel A), medium (Panel B) and high (Panel C) exposure to POs based on the distribution of ME units per capita in 2000 (Table A.10). Here, we observe consistently and coherently stronger positive effects in the CZs with higher exposure to POs, while little impact is detected in the less exposed CZs. As a matter of fact, some of the coefficients in Panel A indicate that the enforcement of the laws reduces drug-related crimes in some cases. This is somewhat expected, given the earlier discussion of the effects on labour market participation. If we combine the two sets of results, the evidence supports the hypothesis that the implementation of opioid state laws leads people out of drug abuse and fosters the engagement in the labour market in the CZs that present lower levels of dispensed POs per capita. Vice versa, the areas where the consumption of opioids has always been very high are less likely to be positively affected by the enforcement of the laws, which eventually produce an increase drug-related crimes. Such result is particularly relevant in terms of policy as it implies large local unintended effects of supply-side regulations on crime in those CZs that are characterised by the highest levels of drug consumption at the beginning of the period.

In Table 7 we assess the effect of the laws on each sub-category of drug-related crimes. The

[26] We also check for differentiated impacts across all categories of violent and property crime and find that the estimates confirm results outlined above (results omitted).

Table 7: Effect on Crime: Drug Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Possession				Sale			
Dependent variable	Opium	Synthetic	Marijuana	Other	Opium	Synthetic	Marijuana	Other
PDMP	-0.086	-0.104	-0.203*	-0.094	-0.094	0.013	-0.041	-0.037
	(0.086)	(0.083)	(0.103)	(0.072)	(0.081)	(0.106)	(0.072)	(0.081)
PMCL	0.498***	0.068	0.277	-0.041	0.326*	0.119	0.086	-0.053
	(0.167)	(0.151)	(0.168)	(0.130)	(0.179)	(0.134)	(0.137)	(0.116)
DSL	0.062	0.395*	0.063	0.199	0.098	0.567***	-0.019	0.170
	(0.246)	(0.218)	(0.316)	(0.167)	(0.216)	(0.166)	(0.166)	(0.174)
NAL	0.253	0.535**	-0.077	0.164	0.219	0.359*	0.326	0.526***
	(0.223)	(0.217)	(0.235)	(0.144)	(0.172)	(0.194)	(0.197)	(0.151)
GSL	-0.595***	-0.848***	-0.672***	-0.436***	-0.405**	-0.714***	-0.485***	-0.242
	(0.218)	(0.240)	(0.193)	(0.095)	(0.179)	(0.243)	(0.167)	(0.188)
Observations	11,115	11,115	11,115	11,115	11,115	11,115	11,115	11,115

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. The category 'Opium' comprises cocaine, opium and their derivatives; 'Other' encompasses all other non-narcotics.
* p<.10 ** p<.05 *** p<.01.

positive impact of PMCLs is clearly driven by the possession and the sale of opium, cocaine and their derivatives such as morphine, heroin and codeine (columns 1 and 5), for which arrest rates rise by half and by a third, respectively. The increase that follows the enactment of DSLs is due to highly-addictive synthetic narcotics such as pethidine and methadone (columns 2 and 6). Here, arrests go up by around 40-50%. A roughly similar effect occurs with the introduction of NALs, which also brings about an increase in the sale of other non-narcotics. Conversely, GSL yields a substantial decrease in the reported crimes related to all types of illegal substances as expected.

Finally, when we investigate the different reactions by age group (Table A.11), we find a more prominent effect for the young adults in the age bands 16-24 and 25-44. This result is in line with the statistics on the relative use of opioids by age. Moreover, the overall absent effect of PDMPs on crime becomes now negative and statistically significant, particularly for opium and synthetic drug crimes of the youngest group, while increasing the arrests due to the sale of other non-narcotics. These also rise following the enforcement of GSLs.

5 Discussion

The United States are currently struck by an unprecedented epidemic of drug overdoses. This phenomenon has began in the 1990s due to a dramatic increase in the use of prescription opioids for chronic pain and is still causing tens of thousands of deaths across the country every year. In fact, drug overdose deaths in the United States more than tripled from 1999 to 2015. According to the Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, 2017), in 2006 doctors wrote 72.4 opioid prescriptions per 100 persons. The prescription rate has been increasing by 4.1% annually until 2008 and by 1.1% annually from 2008 to 2012 and has finally started to decrease since 2012, reaching a rate of 66.5 per 100 persons in 2016. That year, 19.1 per 100 persons received one or more opioid prescriptions, with 3.5 prescriptions per patient on average.

Our analysis suggests that the recent declining trends in opioid prescriptions might be due to the new sets of policies that have been implemented at the state level in recent years and that were designed to contain the opioid crisis. Among these we find two main types of laws. One aims at the reduction in the quantity of opioids prescribed by physicians or dispensed by pharmacists and tackles both the supply (with PDMP and PMCL) and the demand (through DSL) of opioids. The other one consists of laws that were enacted to contain opioid mortality (NAL and GLS). We assess the effects of these policies on grams of opioids sold, on labour market participation and on crime.

We find that the state laws targeting the supply for opioids yield an overall reduction in the quantity of ME units per capita, particularly in the case of PCMLs, which have brought to the closure of a considerable number of the so-called “pill mills”. As a consequence, the overall labour market participation increases, but the shock on the availability of POs also leads people to the illicit market for drugs. PDMPs, instead, are less effective in reducing the ME units sold and in affecting the labour market indicators. Their enforcement is followed by a slight decrease in the drug-related crime rates among those aged below 25, suggesting that PDMPs might hit the illicit market for drugs that targets the youngsters. Per contra, regulating the demand for opioids through DSLs appears to be inadequate, as they determine a slight increase in MEs and in crime rates, especially for the sale and the possession of synthetic drugs.

As regards the state laws contrasting drug-related mortality, they generally induce a drop in the amount of drug sold, especially GSLs. As in the case of the supply-side regulations, labour participation increases after the implementation of GSLs. The effect for NALs is statistically null, but this is not surprising when considering that NALs have been introduced very recently and that their effects on the labour market might be delayed. Moreover, crime rates increase particularly for the sale and possession of opium and synthetic drugs following the enactment of NALs, while the drop in all types of criminal activities coming after GSLs is somewhat expected given the features of these regulations.

Our results suggest important policy implications. First, the policies that reduce the amount of prescriptions on the supply-side and those aiming at reducing the mortality from opioids do have a negative effect on the quantity of prescription drugs sold. DSLs, on the contrary, are clearly ineffective.

Second, we show that the power of these laws is stronger in the absence of cross-bordering effects. This implies that if they were to be applied across all states, their impact on the amount of prescribed drug would possibly be even higher.

Third, the policies that reduce prescriptions have an important indirect effect on labour market participation and on crime. On the one hand, they induce higher participation rates in the labour market, particularly in the areas where people make less use of opioids in the pre-treatment period. On the other hand, they yield an increase in criminal offenses and arrest rates, especially in the case of drug-related crimes. In most cases, this rise is driven by the sale and the possession of opium and synthetic drugs, suggesting that even if these laws do in fact reduce POs in the legal market, they also have an unintended fallout on the market for illicit substances. These increases are more likely to occur in areas with higher initial levels of POs per capita.

Finally, developing effective tools to regulate and alleviate the costs of opioid crisis and its unintended effects should be a high priority on the agenda of policy makers and economists. This is especially relevant when these costs translate into less job opportunities and higher rates of criminal activities. Policy makers should consider the collateral cost of restriction laws that may create some rooms for the illegal sectors and smuggling in the black market.

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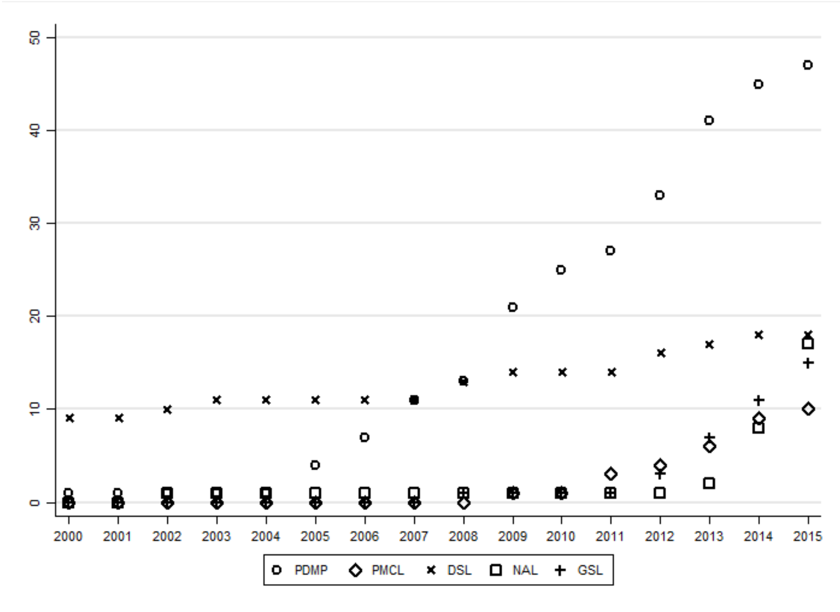
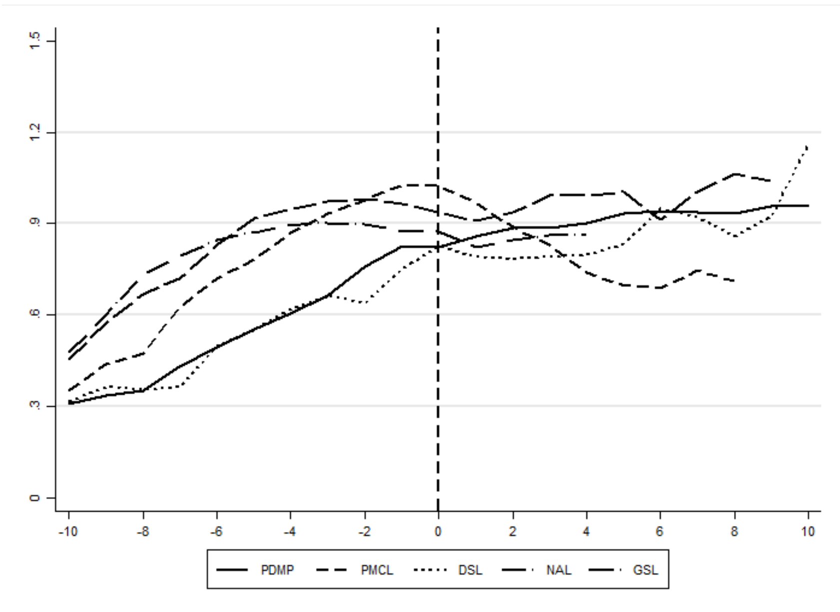
Appendix

Figure A.1: Onset of Opioid-Related Policies by Year



Note: Each marker corresponds to the total number of states in which a given policy is in effect in a given year.

Figure A.2: Average MEs Dispensed by Year since/to the Introduction of the Policies



Note: The labels in the x-axis are such that the zero, the negative and the positive values correspond to the year of, the years before and the years after the introduction of each policy, respectively. Treated states only.

Figure A.3: Geographical Distribution of MEs in 2000 (top) and in 2014 (bottom)

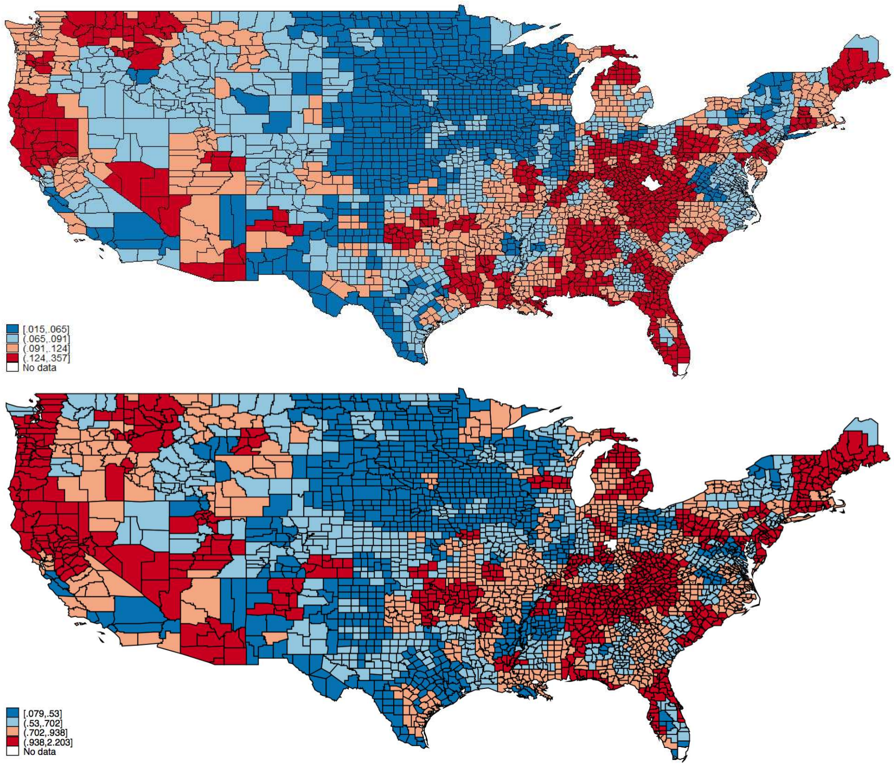
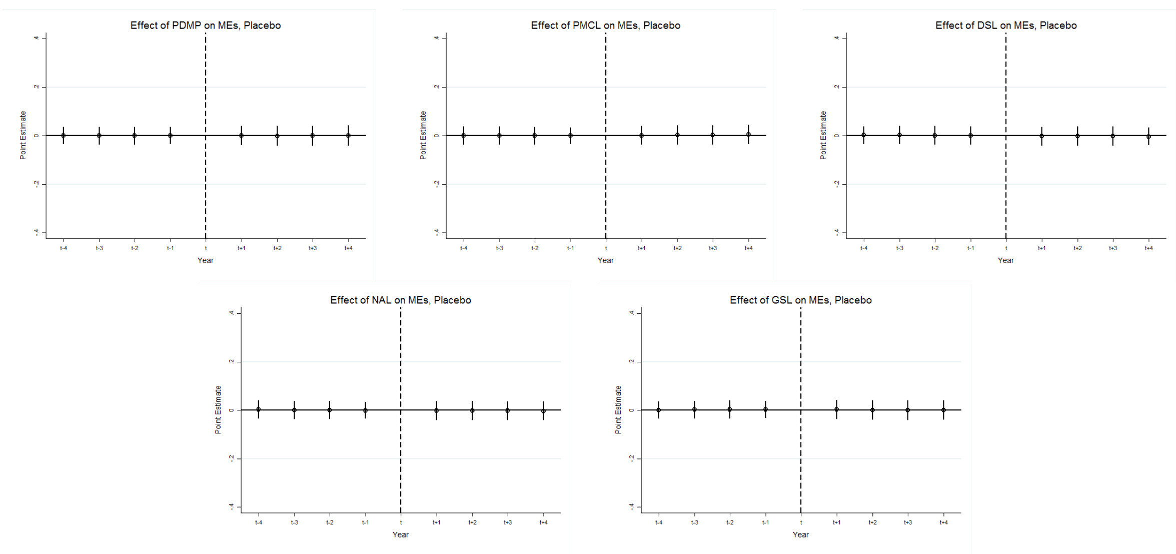
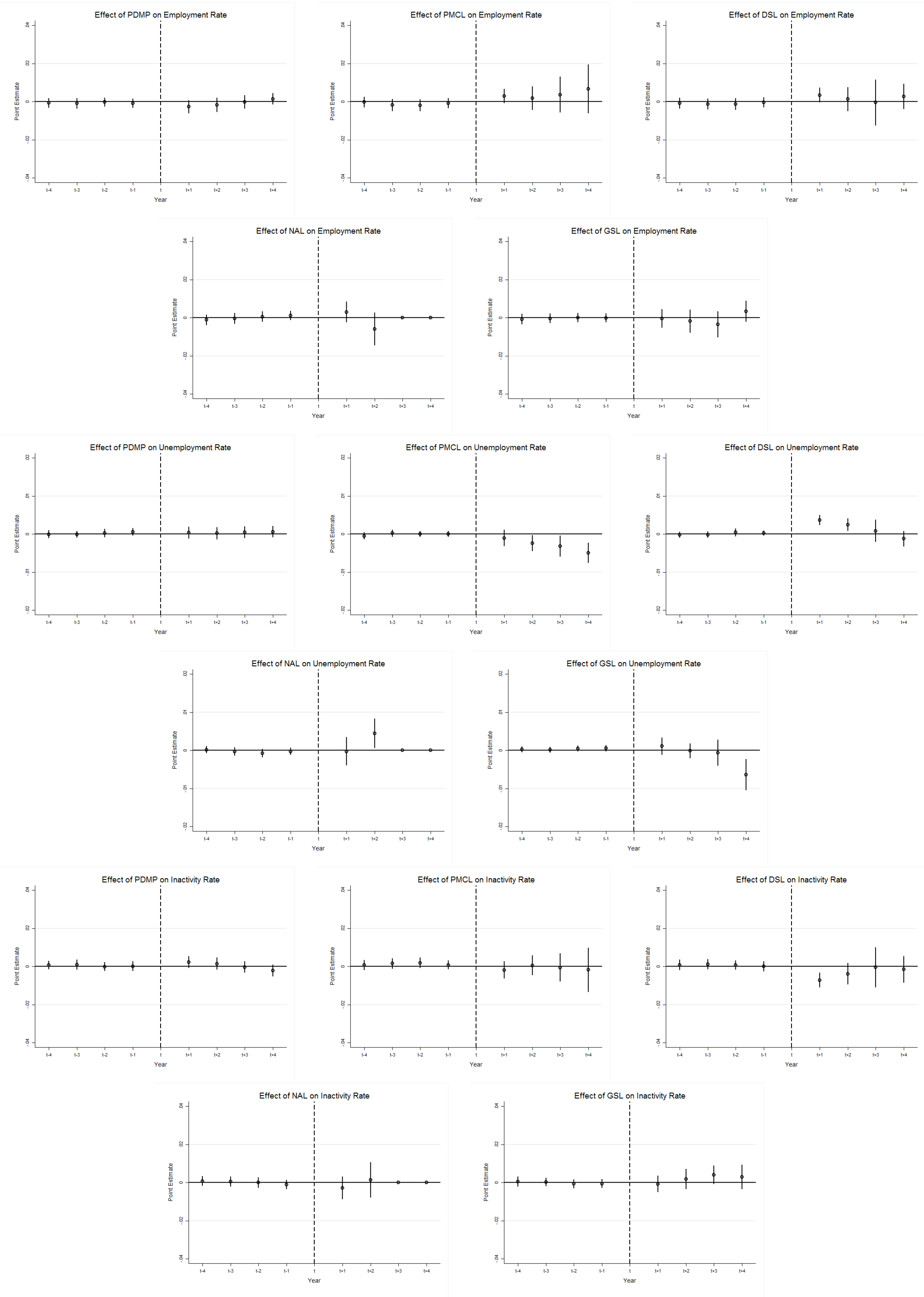


Figure A.4: Event Study: Placeboes on Drug Quantities



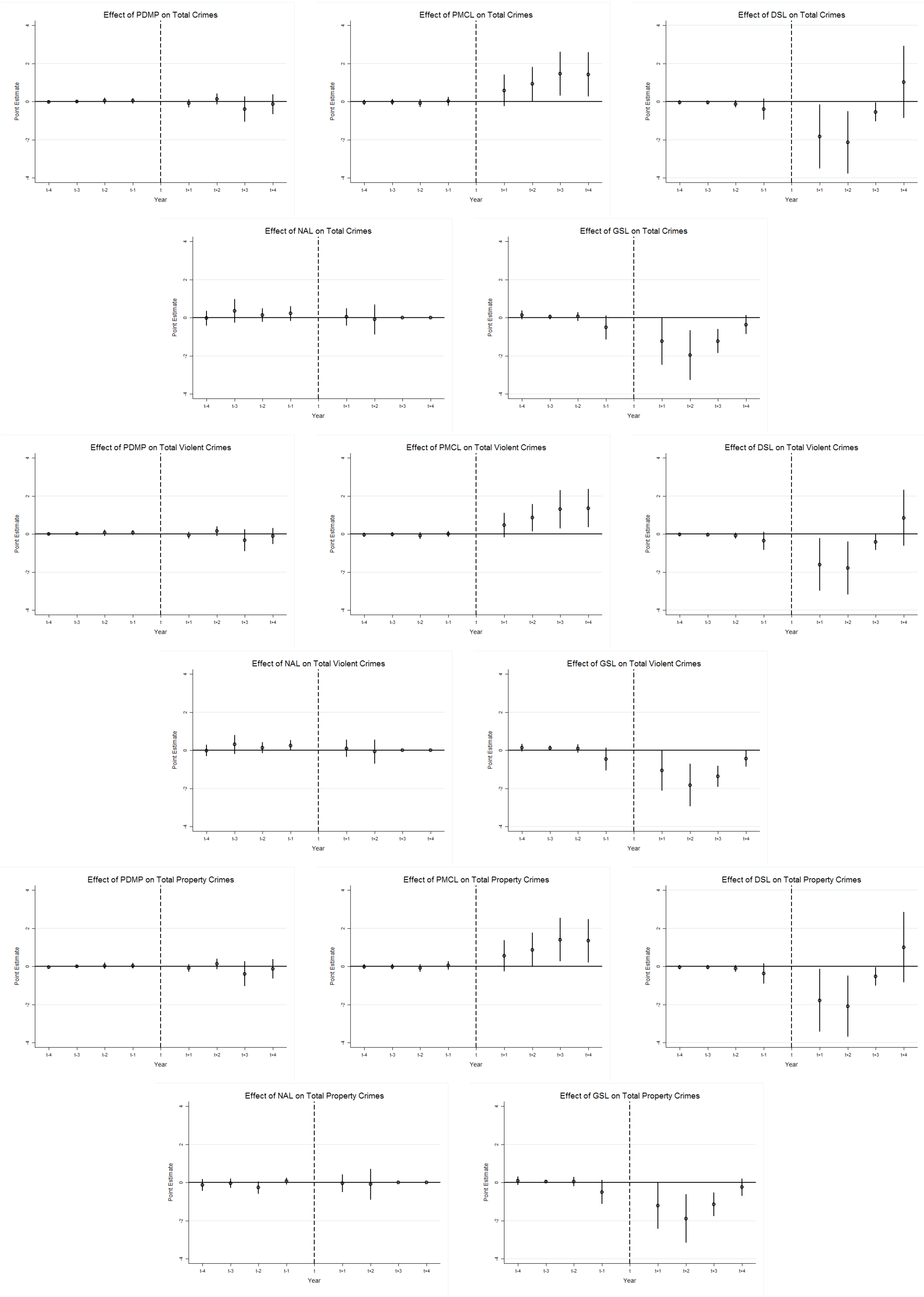
Note: Coefficients are estimated as in Equation 2. 95% confidence intervals are shown and standard errors are clustered at the state level.

Figure A.5: Event-Study Analysis: Effect on Labour Participation



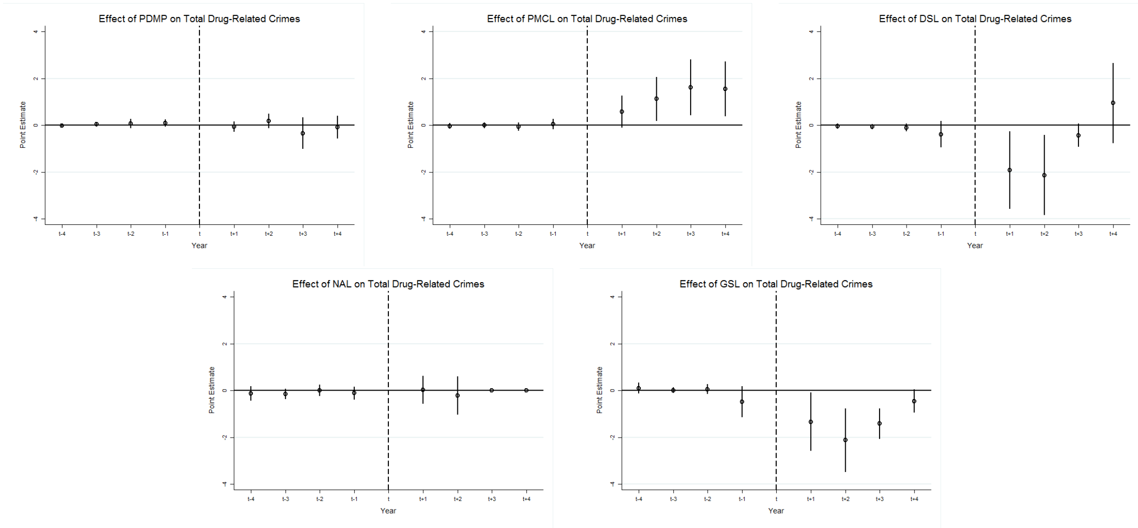
Note: Coefficients are estimated as in Equation 2. 95% confidence intervals are shown and standard errors are clustered at the state level.

Figure A.6: Event-Study Analysis: Effect on Crime (I)



Note: Coefficients are estimated as in Equation 2. 95% confidence intervals are shown and standard errors are clustered at the state level.

Figure A.7: Event-Study Analysis: Effect on Crime (II)



Note: Coefficients are estimated as in Equation 2. 95% confidence intervals are shown and standard errors are clustered at the state level.

Table A.1: Descriptive Statistics

Variable Name	Mean	St. Dev.
Prescription Opioids (in grams per capita):		
Morphine Equivalent units (MEs)	0.564	0.398
Hydromorphone	0.003	0.003
Methadone	0.024	0.032
Meperidine	0.012	0.011
Oxycodone	0.115	0.087
Hydrocodone	0.110	0.078
Fentanyl	0.001	0.001
Morphine	0.053	0.037
Labour Market:		
Employment rate	0.575	0.076
Unemployment rate	0.037	0.014
Inactivity rate	0.388	0.071
Crime rates (per 1,000 inhabitants):		
Total crimes	5.804	5.015
Violent crimes	1.336	1.659
Property crimes	4.468	3.588
Total Drug crimes	4.277	4.027
Drug possession	3.413	3.345
- Opium/Cocaine	0.474	0.886
- Synthetic	2.121	2.174
- Marijuana	0.243	0.402
- Other	0.564	0.798
Drug sales	0.783	0.940
- Opium/Cocaine	0.219	0.416
- Synthetic	0.280	0.385
- Marijuana	0.097	0.213
- Other	0.179	0.321
Incarceration Rate	1.708	3.593
Other Variables:		
Population	402,428	1,104,949
Share of females	0.502	0.017
Share of people aged 18-64	0.649	0.034
Share of people aged 65+	0.154	0.041
Share of whites	0.853	0.156
Share of manufacturing sector	0.086	0.080
State GDP§	0.943	0.146
Marijuana recreational use laws	0.005	0.072
Marijuana medical use laws	0.162	0.369
Share of police force	0.003	0.002
Mortality rate (per 100,000 inhabitants):		
All causes	905.589	132.308
Substance use/Mental disorders	10.939	5.714
Injuries	73.730	18.571
Neoplasms	208.572	27.077
Other non-communicable diseases	7.064	1.368
Forces of nature	0.537	0.619

Note: The number of observations is 11,115 (741 CZs and 15 years). § Relative to the average state GDP in the US.

Table A.2: Effect on Drug Quantities: Robustness Checks

Dependent variable	(1) MEs	(2) MEs	(3) MEs
PDMP	-0.013	-0.016	-0.017
	(0.029)	(0.026)	(0.026)
PMCL	-0.171***	-0.201***	-0.210***
	(0.026)	(0.031)	(0.032)
DSL	0.079**	0.088**	0.099**
	(0.038)	(0.039)	(0.040)
NAL	-0.012	-0.001	0.005
	(0.033)	(0.038)	(0.038)
GSL	-0.124**	-0.135**	-0.124**
	(0.049)	(0.053)	(0.055)
Share of 65+ * post 2006		2.769***	
		(0.739)	
Oxycodone in 2000 * post 2010			0.711**
			(0.353)
Observations	11,115	11,115	11,115
Specification	Population Weights	Medicare Part D	OxyContin Reformulation

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level.
* p<.10 ** p<.05 *** p<.01.

Table A.3: Effect on Drug Quantities: Adjacent Counties

Dependent variable	(1) MEs	(2) MEs	(3) MEs	(4) MEs
PDMP	-0.012	-0.013	-0.001	-0.003
	(0.032)	(0.037)	(0.021)	(0.036)
PMCL	-0.163***	-0.147***	-0.100***	-0.220**
	(0.035)	(0.036)	(0.028)	(0.108)
DSL	0.095**	0.122**	0.104*	0.031
	(0.044)	(0.052)	(0.052)	(0.064)
NAL	0.012	0.077**	0.026	-0.147*
	(0.039)	(0.034)	(0.042)	(0.084)
GSL	-0.140***	-0.172***	-0.024	-0.066**
	(0.043)	(0.038)	(0.040)	(0.026)
Observations	46,978	29,237	7,899	9,763
Sample Counties	All	Inner	Outer	Outer
Laws in Adjacent State	.	.	Any	None

Note: Population-weighted OLS estimates. Includes year, county and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. The sample in column 3 contains outer counties where the adjacent state has enacted at least one opioid law; the sample in column 4 contains outer counties where the adjacent state does not have any of such laws enforced.
* p<.10 ** p<.05 *** p<.01.

Table A.4: Effect on Drug Quantities and Labour Market Participation: by Exposure to POs

Dependent variable	(1) MEs	(2) ERate	(3) URate	(4) IRate
Panel A: Low POs in 2000				
PDMP	-0.010	0.008**	0.002	-0.010***
	(0.017)	(0.004)	(0.002)	(0.003)
PMCL	-0.087***	0.002	-0.006***	0.004
	(0.017)	(0.003)	(0.001)	(0.003)
DSL	-0.075***	0.014**	0.006***	-0.020***
	(0.019)	(0.006)	(0.002)	(0.007)
NAL	0.011	0.006	-0.004**	-0.002
	(0.020)	(0.012)	(0.002)	(0.012)
GSL	0.031	-0.011*	-0.002	0.013*
	(0.021)	(0.006)	(0.002)	(0.007)
Observations	3,705	3,705	3,705	3,705
Panel B: Medium POs in 2000				
PDMP	0.002	0.000	-0.000	-0.000
	(0.022)	(0.003)	(0.001)	(0.003)
PMCL	-0.158***	0.000	-0.001	0.001
	(0.020)	(0.004)	(0.001)	(0.004)
DSL	0.103*	0.010***	0.002***	-0.012***
	(0.061)	(0.003)	(0.001)	(0.003)
NAL	-0.041*	0.009**	-0.002	-0.008*
	(0.022)	(0.004)	(0.002)	(0.004)
GSL	-0.010	-0.010**	0.001	0.009**
	(0.025)	(0.004)	(0.001)	(0.004)
Observations	3,705	3,705	3,705	3,705
Panel C: High POs in 2000				
PDMP	-0.023	-0.003	0.001	0.002
	(0.048)	(0.002)	(0.001)	(0.002)
PMCL	-0.268***	0.003	-0.002*	-0.001
	(0.047)	(0.004)	(0.001)	(0.003)
DSL	0.114*	0.006	-0.000	-0.005
	(0.062)	(0.004)	(0.001)	(0.004)
NAL	-0.005	-0.001	0.000	0.001
	(0.062)	(0.005)	(0.003)	(0.005)
GSL	-0.267**	0.003	-0.002	-0.001
	(0.109)	(0.003)	(0.001)	(0.003)
Observations	3,705	3,705	3,705	3,705

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. 'Low', 'Medium' and 'High' exposure to POs is defined on the amount of ME units in the CZ in 2000 relative to its distribution.
* p<.10 ** p<.05 *** p<.01.

Table A.5: Effect on Drug Quantities: All Substances

Dependent variable	(1) Hydromorphone	(2) Methadone	(3) Meperidine	(4) Oxycodone	(5) Hydrocodone	(6) Fentanyl	(7) Morphine
PDMP	0.001	-0.013	-0.000	-0.017	0.005	0.001	0.003
	(0.001)	(0.015)	(0.000)	(0.016)	(0.005)	(0.001)	(0.002)
PMCL	0.007*	-0.078***	0.000	-0.034***	-0.032***	-0.003***	-0.001
	(0.003)	(0.016)	(0.000)	(0.013)	(0.005)	(0.001)	(0.007)
DSL	-0.003*	0.030	-0.000	0.027	0.011	0.001	0.003
	(0.002)	(0.021)	(0.000)	(0.017)	(0.009)	(0.001)	(0.007)
NAL	-0.005***	0.007	0.000***	0.018	-0.008*	-0.002*	-0.008**
	(0.001)	(0.029)	(0.000)	(0.016)	(0.004)	(0.001)	(0.003)
GSL	0.003*	-0.041	0.000	-0.054***	-0.005	-0.002	-0.003
	(0.002)	(0.025)	(0.000)	(0.020)	(0.005)	(0.002)	(0.004)
Observations	11,115	11,115	11,115	11,115	11,115	11,115	11,115

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. Substances are rescaled as follows: hydromorphone by 4, methadone by 7.5, meperidine by 0.1, oxycodone by 1, hydrocodone by 1, fentanyl by 75, morphine by 1.
* p<.10 ** p<.05 *** p<.01.

Table A.6: Effect on Mortality Rate

	(1)	(2)	(3)	(4)	(5)	(6)
		Opioid-Related			Non Opioid-Related	
Dependent variable	All Causes	Substance Use Disorders	Injuries	Neoplasms (All Cancers)	Other Diseases	Forces of Nature
Panel A: POs						
MEs	3.913**	1.067***	0.826***	0.290	0.005	-0.008
	(1.667)	(0.290)	(0.222)	(0.381)	(0.024)	(0.064)
Panel B: Laws						
PDMP	-0.258	-0.101	-0.161	0.321	0.014	0.010
	(1.483)	(0.215)	(0.181)	(0.464)	(0.014)	(0.022)
PMCL	-0.688	0.778*	-0.124	0.087	-0.006	0.004
	(2.442)	(0.448)	(0.363)	(0.694)	(0.021)	(0.024)
DSL	-5.201**	-0.482	-0.318	-0.588	-0.048	0.075
	(2.317)	(0.500)	(0.362)	(0.501)	(0.036)	(0.061)
NAL	-5.364*	0.569	0.082	-1.192	-0.031*	-0.000
	(3.010)	(0.370)	(0.343)	(0.948)	(0.018)	(0.035)
GSL	-2.869	-0.767**	-0.607**	-0.761	-0.021	-0.082
	(2.608)	(0.330)	(0.227)	(0.670)	(0.020)	(0.058)
Observations	11,115	11,115	11,115	11,115	11,115	11,115

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. 'Substance Use Disorders' includes mental disorders; 'Other Diseases' includes non-communicable diseases such as skin, eye and oral diseases and congenital defects; 'Forces of Nature' includes conflicts and terrorism.
* p<.10 ** p<.05 *** p<.01.

Table A.7: Effect on Labour Participation: by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
Dependent variable	ERate	URate	IRate	ERate	URate	IRate
PDMP	0.001	0.000	-0.001*	0.001	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
PMCL	0.002*	-0.000	-0.002	0.001	0.000	-0.001
	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)
DSL	-0.001	0.001**	0.002*	0.000	0.001**	0.001
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
NAL	-0.002	0.000	0.004	-0.003*	0.001	0.004
	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)
GSL	0.006***	-0.001**	-0.007***	0.006***	-0.001*	-0.006***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	7,404	7,404	7,404	7,404	7,404	7,404

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. Years 2005-2014 only.
* p<.10 ** p<.05 *** p<.01.

Table A.8: Effect on Labour Participation: by Race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		White			Black			Other	
Dependent variable	ERate	URate	IRate	ERate	URate	IRate	ERate	URate	IRate
PDMP	0.001	0.000	-0.002**	-0.002**	0.000	0.002**	0.001	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
PMCL	0.001	0.000	-0.002	-0.002	0.002***	-0.000	-0.002	-0.000	-0.004***
	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
DSL	-0.001	0.001***	0.003**	0.002	0.000	0.001	0.002	0.000	-0.001
	(0.001)	(0.000)	(0.002)	(0.003)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)
NAL	-0.003*	0.000	0.004*	-0.005	0.001	0.003	-0.002	0.001	0.000
	(0.002)	(0.000)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
GSL	0.006***	-0.000	-0.008***	0.007***	-0.002***	-0.005**	0.003	-0.001**	-0.001
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. Years 2005-2014 only.
* p<.10 ** p<.05 *** p<.01.

Table A.9: Effect on Labour Participation: by Age Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Aged 16-24			Aged 25-44			Aged 45-64	
Dependent variable	ERate	URate	IRate	ERate	URate	IRate	ERate	URate	IRate
PDMP	0.000	-0.000	-0.000	-0.000	-0.000	0.001	0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
PMCL	0.003	0.000	-0.003*	0.003*	-0.000	-0.003**	0.003**	0.000	-0.003**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)
DSL	0.001	0.002	-0.002*	0.001	0.001*	-0.003	-0.001	0.001***	-0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
NAL	-0.003	0.001	0.002	-0.002	0.001	0.001	-0.002*	0.001	0.001
	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GSL	0.006***	-0.001	-0.005***	0.003**	-0.002***	-0.001	0.004***	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. Years 2005-2014 only.
* p<.10 ** p<.05 *** p<.01.

Table A.10: Effect on Crime: by Exposure to POs

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Possession:				Sale:			
	Cocaine	Synthetic	Marijuana	Other	Cocaine	Synthetic	Marijuana	Other
Panel A: Low POs in 2000								
PDMP	-0.157	-0.171	-0.242	-0.316**	-0.088	-0.225	-0.205	-0.401**
	(0.225)	(0.133)	(0.226)	(0.130)	(0.197)	(0.193)	(0.174)	(0.145)
PMCL	-0.343	0.012	-0.589	0.310	-0.612	-0.239	-0.746**	-0.288
	(0.262)	(0.270)	(0.382)	(0.375)	(0.413)	(0.507)	(0.349)	(0.340)
DSL	-0.847*	-0.719	-0.884	0.033	-0.034	0.424	-0.233	-0.018
	(0.414)	(0.458)	(0.525)	(0.421)	(0.462)	(0.631)	(0.409)	(0.442)
NAL	0.402	0.906***	0.738	-0.113	0.219	0.952**	1.270***	0.238
	(0.355)	(0.280)	(0.488)	(0.339)	(0.305)	(0.402)	(0.309)	(0.346)
GSL	-0.906*	-0.469	-1.410**	-0.949**	-1.286***	-0.855	-1.045**	-0.641
	(0.462)	(0.492)	(0.584)	(0.425)	(0.451)	(0.558)	(0.382)	(0.438)
Observations	3,705	3,705	3,705	3,705	3,705	3,705	3,705	3,705
Panel B: Medium POs in 2000								
PDMP	-0.058	0.012	-0.243**	-0.073	0.031	0.040	-0.072	-0.057
	(0.080)	(0.113)	(0.093)	(0.077)	(0.110)	(0.130)	(0.071)	(0.088)
PMCL	0.045	0.077	-0.019	-0.391**	0.015	0.173	-0.288**	-0.088
	(0.197)	(0.175)	(0.191)	(0.155)	(0.182)	(0.134)	(0.132)	(0.134)
DSL	0.399**	0.636***	0.408*	0.414**	0.324***	0.527***	0.147	0.282
	(0.172)	(0.160)	(0.238)	(0.178)	(0.119)	(0.156)	(0.135)	(0.232)
NAL	0.295**	0.239**	-0.060	-0.040	0.323**	0.581***	0.347***	0.573***
	(0.127)	(0.098)	(0.107)	(0.108)	(0.149)	(0.145)	(0.085)	(0.107)
GSL	-0.432**	-0.583***	-0.246*	0.002	-0.388*	-0.410	-0.319***	-0.248
	(0.173)	(0.180)	(0.141)	(0.122)	(0.226)	(0.266)	(0.099)	(0.154)
Observations	3,705	3,705	3,705	3,705	3,705	3,705	3,705	3,705
Panel C: High POs in 2000								
PDMP	-0.093	-0.185**	-0.128*	-0.087	-0.093	0.073	0.033	0.005
	(0.070)	(0.085)	(0.067)	(0.066)	(0.087)	(0.130)	(0.057)	(0.110)
PMCL	0.529***	-0.070	0.280*	-0.020	0.312**	0.205	0.136	-0.040
	(0.162)	(0.157)	(0.164)	(0.162)	(0.138)	(0.175)	(0.105)	(0.172)
DSL	0.297	0.542**	0.397*	0.500***	0.329	0.537**	0.096	0.265
	(0.192)	(0.243)	(0.219)	(0.100)	(0.267)	(0.216)	(0.180)	(0.205)
NAL	0.241	0.580	-0.229	0.114	0.351	0.096	0.288	0.589*
	(0.220)	(0.356)	(0.157)	(0.136)	(0.281)	(0.431)	(0.238)	(0.322)
GSL	0.025	0.102	-0.291***	-0.093	0.123	-0.368	-0.042	0.309
	(0.120)	(0.113)	(0.107)	(0.103)	(0.103)	(0.408)	(0.107)	(0.273)
Observations	3,705	3,705	3,705	3,705	3,705	3,705	3,705	3,705

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. 'Low', 'Medium' and 'High' exposure to POs is defined on the amount of ME units in the CZ in 2000 relative to its distribution.
* p<.10 ** p<.05 *** p<.01.

Table A.11: Effect on Crime: by Age Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Possession:				Sale:			
Dependent variable	Opium	Synthetic	Marijuana	Other	Opium	Synthetic	Marijuana	Other
Panel A: Age Group 16-24								
PDMP	-0.107**	-0.181**	-0.178***	-0.039	-0.057	-0.617***	-0.045	0.483**
	(0.044)	(0.088)	(0.057)	(0.057)	(0.085)	(0.203)	(0.085)	(0.232)
PMCL	0.204	0.020	0.032	-0.018	0.102	0.450	-0.563***	-0.415*
	(0.122)	(0.114)	(0.071)	(0.088)	(0.147)	(0.300)	(0.136)	(0.214)
DSL	-0.072	0.325*	0.110	0.074	0.217	0.135	0.121	0.040
	(0.146)	(0.193)	(0.125)	(0.081)	(0.181)	(0.243)	(0.184)	(0.260)
NAL	0.269*	0.430*	-0.244*	-0.313**	0.395**	-0.019	0.097	-0.192
	(0.138)	(0.217)	(0.128)	(0.154)	(0.167)	(0.201)	(0.085)	(0.222)
GSL	-0.441***	-0.723**	-0.120	0.365***	-0.543	-0.686***	-0.272	0.609**
	(0.118)	(0.312)	(0.098)	(0.070)	(0.375)	(0.229)	(0.164)	(0.238)
Panel B: Age Group 25-44								
PDMP	-0.095**	-0.105	-0.183***	-0.041	-0.119	-0.690***	-0.005	0.609**
	(0.044)	(0.073)	(0.064)	(0.056)	(0.085)	(0.198)	(0.072)	(0.248)
PMCL	0.254**	0.284**	0.110	-0.047	0.054	0.510*	-0.539***	-0.233
	(0.117)	(0.138)	(0.082)	(0.110)	(0.162)	(0.294)	(0.173)	(0.212)
DSL	0.038	0.272	0.072	0.147	0.332*	0.147	0.127	-0.006
	(0.149)	(0.191)	(0.124)	(0.109)	(0.179)	(0.249)	(0.185)	(0.266)
NAL	0.198	0.513***	-0.232	-0.063	0.343*	0.133	0.098	-0.127
	(0.133)	(0.171)	(0.146)	(0.159)	(0.174)	(0.223)	(0.088)	(0.258)
GSL	-0.386***	-0.608*	-0.083	0.201***	-0.449	-0.471**	-0.370**	0.710***
	(0.116)	(0.311)	(0.105)	(0.067)	(0.359)	(0.212)	(0.159)	(0.229)
Panel C: Age Group 45-64								
PDMP	-0.026	-0.031	-0.161**	-0.014	-0.116	-0.469**	-0.085	0.449**
	(0.036)	(0.061)	(0.061)	(0.057)	(0.079)	(0.178)	(0.073)	(0.214)
PMCL	0.138	0.262**	0.012	-0.039	-0.085	0.432*	-0.544***	-0.346**
	(0.102)	(0.109)	(0.078)	(0.116)	(0.148)	(0.244)	(0.186)	(0.163)
DSL	0.081	0.271*	0.111	0.133	0.371**	0.168	0.115	0.063
	(0.139)	(0.159)	(0.110)	(0.084)	(0.142)	(0.217)	(0.148)	(0.213)
NAL	0.157	0.296*	-0.197	0.045	0.354***	0.240	-0.006	-0.327
	(0.119)	(0.153)	(0.129)	(0.139)	(0.131)	(0.195)	(0.099)	(0.242)
GSL	-0.274**	-0.979***	-0.117	0.110	-0.237	-0.581***	-0.276*	0.905***
	(0.114)	(0.313)	(0.136)	(0.083)	(0.305)	(0.190)	(0.156)	(0.208)
Observations	8,706	8,298	9,930	9,279	9,068	8,365	8,365	7,392

Note: Population-weighted OLS estimates. Includes year, CZ and division-year fixed effects. Other controls include indicators for: see note to Table 4. Errors are clustered at the state level. The category ‘Opium’ comprises cocaine, opium and their derivatives; ‘Other’ encompasses all other non-narcotics.
* p<.10 ** p<.05 *** p<.01.