Adam Soliman
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Duke University, PhD in Economics (May 2023)
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Re: Review of Economics and Statistics Fellowship for NBER Summer Institute

Dear Selection Committee,

I am a doctoral candidate in the Department of Economics at Duke University with research interests in public, health, and crime economics. With regards to eligibility, I will graduate in May 2023 and join the Department of Economics at Clemson University as an Assistant Professor after a one-year post-doc. Second, my family was born and raised in Cairo, Egypt, and moved to the United States after my older sister was born. Lastly, my research lies primarily in the economics of crime, and thus I would be most interested in the Crime session, but my research interests also align with the Health Economics, Economics of Children, Law and Economics, and Public Economics sessions.

My job market paper examines the role of supply-side enforcement in addressing drug abuse. Its primary contribution is providing some of the first evidence on the effectiveness of a targeted supply-side approach within a legal drug market, where most drug epidemics originate. High-quality administrative data allow me to examine how these targeted interventions generate spillovers across space, substance, and time, which is unique within research on enforcement and public health. I find that cracking down on a single rogue doctor significantly decreases the supply of prescription opioids; this effect persists across a wide geographic region and for an extended period of time. While some users substitute to heroin, overall mortality decreases, indicating that there is a tradeoff between having existing users substituting to more harmful substances and reducing the flow of new users.

My research agenda attempts to understand the role of different actors involved in issues related to drug abuse, such as the police and health care professionals, and how they interact with the demand-side, such as heavy users and patients. I use mainly publicly available or restricted administrative data with quasi-experimental methods, where my broad goal is to improve community health and public policy. In addition to my job market paper, I have two solo-authored publications and several co-authored works in progress focusing on either the management and consequences of drug epidemics or discretion in the criminal justice system.

Please find my CV and job market paper attached below.

Thank you for your consideration,
Adam Soliman

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Education

Ph.D., Economics, Duke University, 2023

M.A., Economics, University of California, San Diego, 2019

M.S., Agricultural, Food, and Resource Economics, Michigan State University, 2016

B.A., Economics & B.S., Health Science, Boston University, 2009

Fields of Specialization

Public, Health, Urban, and Crime

Research

Publications

Crime and (a Preference for) Punishment: The Effects of Drug Policy Reform on Policing Activity, *The Journal of Law and Economics*, 2022.

Prescriptive Drought Policy and Water Supplier Compliance, *Ecological Economics*, 2022.

Working Papers

Disrupting Drug Markets: The Effects of Crackdowns on Rogue Opioid Suppliers

Rebel Funding Strategies: Illicit Activities, Natural Resources, and Substitution Behavior

Works in Progress

Pill Mills and Corner Crews: Estimating the Elasticity of Substitution between Legal and Illegal Markets (with Stephen Billings, Jesse Bruhn, and Kevin Schnepel)

School Funding, Accountability, and the Opioid Epidemic (with Jason Baron and Brian Jacob)

The Effects of Changing Felony Theft Thresholds (with Steve Billings and Kevin Schnepel)

The Impacts of Physician License Suspensions on Peer Behavior and Health Outcomes (with Janet Currie, Molly Schnell, and Jonathan Zhang)

The Role of Controlled Substance Distributors in the Opioid Epidemic (with Aljoscha Janssen and Xuan Zhang)

Honors and Awards

Research Fellowship, The Graduate School, Duke University, Summers 2020, 2021, & 2022

Graduate Fellowship, Department of Economics, Duke University, 2019 - 2020

Graduate Research and Travel Award, International Institute, UC San Diego, Summer 2019

San Diego Fellowship, Program for Interdisciplinary Environmental Research, UC San Diego, 2017 - 2019

Schmid Fellowship in Institutional Economics, Michigan State University, 2015

Best Primary School Mathematics Teacher, International School of Choueifat, Dubai, United Arab Emirates, 2010 - 2011

Presentations

2023: LSE-CEP Policing and Crime Workshop, Workshop on the Economics of Crime for Junior Scholars, Conference on the Economics of Crime and Justice at the Becker Friedman Institute

2022: Southern Economic Association, UNC Wilmington, Association for Mentoring and Inclusion in Economics: 2nd Workshop in Applied Microeconomics, UNC Greensboro, NBER Summer Institute (Invited), Western Economic Association International, Carolina Region Empirical Economics Day, ASSA 2022 Annual Meeting (Poster Presenter, Online)

2021: Workshop on the Economics of Crime for Junior Scholars (Online), 2021 APPAM Fall Research Conference, Urban Economics Association (Online), Carolina Region Empirical Economics Day (Online), Eastern Economic Association (Online)

Professional Development and Teaching

Duke University

Preparing Future Faculty Program, 2022 - 2023

Teaching on Purpose Fellowship, 2022

Certificate in College Teaching, 2022

Instructor of Record, Stata for Economics PhD Students (Graduate Course), Summer 2022

Head Teaching Assistant, Probability and Statistics (Undergraduate Course), Fall 2019

International School of Choueifat, Dubai, United Arab Emirates

Teacher, Mathematics (Grades 3 - 7) & Economics (Grade 11), 2009 - 2011

Workshops

Summer School in Marine Biodiversity, Conservation, and Global Change, UC San Diego, Summer 2018

Summer School in Environmental and Energy Economics, UC Berkeley, Summer 2016

Languages

English (Native), Spanish (Proficient), Arabic (Conversational)

Policy Work

Water Policy Center Intern, Public Policy Institute of California, Summer 2015

"Reducing the Costs of Drought: Lessons from Australia," September 2015

"What if California's Drought Continues," August 2015

"The 'Inexact Science' of Water Pricing," July 2015

Field Work

Accra, Ghana (Scoping Visit), November 2019

Huambo, Angola (10 enumerators, 404 households, 3 weeks), January 2015

Durban, South Africa (20 enumerators, 4007 households, 11 weeks), Summer 2013

Disrupting Drug Markets:
The Effects of Crackdowns on Rogue Opioid Suppliers*

Adam Soliman†

March 7, 2023

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Abstract

More than 564,000 Americans have died from an opioid-related overdose since 1999. In this paper, I estimate the impacts of enforcement actions taken against doctors on the supply of prescription opioids, black-market prices, and health outcomes. Exploiting plausibly exogenous variation in the timing and location of controlled substance license audits, I find that cracking down on a single doctor decreases county-level opioid dispensing by 10%. This decline in legal supply persists across space and time and results in a 44% increase in the black-market pill price. Significant heroin substitution also occurs, yet for each additional heroin overdose death, there are two fewer non-heroin opioid overdose deaths. The mortality declines are strongest among young and prime-aged men. These results highlight a novel tradeoff policymakers should consider when attempting to address drug abuse through targeted supply-side enforcement: reductions in the flow of new users must be balanced against the harm that arises when existing users substitute to more dangerous drugs.

JEL Codes: H12, I10, K42

Keywords: enforcement, drug epidemic, overdose, spatial crime dynamics

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1 Introduction

Since 1999, over 60% of all drug overdose deaths in the United States involved opioids (CDC, 2021). Reducing drug abuse is an important domestic policy goal, where the majority of federal drug control spending is on enforcement efforts targeting supply (Dobkin and Nicosia, 2009). Supply-side crackdowns are intended to reduce drug availability and use, but two types of demand-side spillovers can reduce their efficacy: 1) substitution to different suppliers and 2) substitution to more harmful substances (Caulkins and Reuter, 2010; Alpert et al., 2018; Evans et al., 2019). This is especially concerning for controlled substances, which have a large pool of potential users and where initial use is often driven by medical need (Volkow and McLellan, 2016). Although four of the last five nationwide drug epidemics began with legally-produced drugs, there is almost no research on the impacts of targeted supply-side enforcement in a controlled substance market (Moore and Pacula, 2020).

Non-medical use of prescription opioids is the primary cause of the current opioid crisis (Currie and Schwandt, 2021). The Drug Enforcement Administration (DEA) attempts to prevent this diversion of controlled substances out of the medical system by requiring medical professionals to obtain a controlled substance license in addition to any state license requirements. They also detect and investigate diversion, such as doctors prescribing to patients who do not have a legitimate medical need, where enforcement actions range from fines to loss of license and prison time. The DEA often targets doctors and pharmacies, as they are the source of over 80% of all prescription drug diversion (Inciardi et al., 2007). This practice is especially relevant in the prescription opioid market: 60% of abused opioids begin with a prescription, and 1% of the doctors who prescribe opioids account for almost 50% of all domestic opioid doses prescribed (Lembke, 2012; Kiang et al., 2020).

In this paper, I identify the impacts of prescription opioid supplier crackdowns on legal drug supply, black-market prices, and health outcomes. Dell (2015) states that the primary challenge in studying this topic is that enforcement agencies do not randomly decide where to crack down. To address this, I isolate plausibly exogenous variation in the timing and location of enforcement stemming from the DEA's audit process of controlled substance license holders. While the exact algorithm that triggers an audit is not available to researchers, I observe that conditional on DEA field division, the timing of these audits is as-good-as random. I begin by constructing a new dataset on the universe of these DEA investigations of doctors and pharmacies from the Federal Register, which I merge with all US pharmacy opioid pill dispensing records from the DEA, all US death records from the CDC, and a sample of black-market opioid pill prices from StreetRx. This novel dataset, spanning 2006 to 2014, allows me to study not only the spatial and temporal dynamics associated with supply-side enforcement, but how these actions reverberate into the illicit market. Such high-quality administrative data is unique within the literature on drug enforcement, as its focus is often on illegally-produced drugs.

Using a difference-in-differences framework, I find that DEA investigations of individual doctors significantly decrease city- and county-level opioid dispensing relative to cities and counties without such investigations. I also observe increases in black-market opioid pill prices and heroin overdose deaths but decreases in net overdose mortality: for each additional heroin overdose death, there are two fewer overdose deaths from non-heroin opioids. These results

are robust to methods from Callaway and Sant'Anna (2021) and Arkhangelsky et al. (2021), and to a variety of control groups, including not-yet-treated areas, synthetic areas, and ones generated by forensic accounting methods that detect suspicious dispensing behavior, which suggests that prescription opioid diversion is quite pervasive and relatively unchecked during my sample period. For context, crackdowns are relatively infrequent with less than one in ten thousand doctors found in violation in any year.

Rogue doctors often run high-volume practices with little patient interaction or concern for patient health (Quinones, 2015). They are colloquially known as "drug dealers in lab coats," working directly with addicts and exchanging prescriptions for cash or sexual favors (Kristof, 2017). I find that cracking down on a single doctor decreases city-level opioid dispensing by 10% after three months and 25% after two years. The declines are larger for smaller cities, where the increasing effects over time are consistent with dynamic deterrence for non-sanctioned doctors that prescribe more conservatively after a local colleague is sanctioned. The dynamics at the county-level are similar, where the average decline in dispensing is 9.5%, or a reduction of approximately 4 pills per person per year.

The city- and county-level declines in legal opioid supply lead to over 40% increases in both black-market opioid pill prices and heroin overdose deaths. Virtually all opioid pills found in the black market begin in the legal market during my sample period (Powell and Pacula, 2017). Black-market prices should thus increase when the supply of legal prescriptions decreases, the demand for diverted pills in the black market should increase, or both. Quinones (2015) suggests that it is often difficult to find a doctor willing to write a prescription for a non-medical purpose in one's local community. The increase in heroin overdose deaths is thus likely due to existing users substituting from prescription opioids to heroin for access and/or cost reasons.

Having established the local impacts of crackdowns on doctors, I then examine their effects at a larger geographic scale. Caulkins (1992) indicates that enforcement either displaces illegal activity or reduces its overall frequency. To determine the extent of spatial displacement, I approximate larger markets around a crackdown by generating different size buffers and then studying how opioid dispensing behavior changes within them. I find that doctor crackdowns lead to persistent declines in dispensing across space and time, which again suggests that targeted enforcement deters non-sanctioned doctors.

The persistent decline in dispensing following a doctor crackdown is especially important, as I find evidence of spatial displacement when the DEA separately cracks down on pharmacies. More specifically, while the effects are similar between doctor and pharmacy crackdowns at the city- and county-level, I find large increases in dispensing in areas farther from a sanctioned pharmacy.[1] Using outlier detection methods from forensic accounting, I find that several small independent pharmacies in the same market become suspicious for the first time soon after a pharmacy crackdown. On average, the rapid increases from their normal ordering patterns negate the local reduction achieved from removing a single rogue pharmacy. I provide suggestive evidence that this is not mechanical and may be driven by drug traffickers diversifying their

[1] In addition to differences in both the opportunity cost of crime between doctors and pharmacists and their respective customers, interviews with current and former DEA agents suggest that rogue pharmacies are often part of a larger criminal enterprise; rogue doctors often are not. These pharmacies often fill forged prescriptions and thus are not connected to a rogue doctor.

supply along interstate highways.

In addition to substance substitution and crime displacement, important considerations are the type of user impacted by a supply-side intervention and overall mortality. This is relevant because drug epidemics occur when a sufficient number of light users create feedback loops that encourage further initiation and escalation until a "tipping point" is passed (Moore and Pacula, 2020). Young and prime-aged men are considered the most susceptible to drug abuse (Grecu et al., 2019), and I find that mortality for this group decreases by almost 10% following a doctor crackdown. The effects are smaller for women, likely due to differences in risk-taking behavior and occupational choice (Kloos et al., 2009), and the reductions are driven by decreases in both non-heroin opioid overdoses and non-opioid drug overdoses. These crackdowns also net reduce overdose mortality: for each additional heroin overdose death, there are two fewer non-heroin opioid overdose deaths. Therefore, these interventions likely reduce the flow of new addicts and can prevent people from becoming regular drug users (Strang et al., 2012).

This paper contributes to several literatures. My primary contribution is providing some of the first empirical evidence on the effectiveness of individual supplier crackdowns in a legal drug market. To the best of my knowledge, the only other paper to study enforcement actions within a controlled substance market is by Meinhofer (2016). Meinhofer studies a coordinated enforcement effort to shut down pain clinics in Florida and finds striking state-level opioid supply decreases with limited aggregate effects on crime and drug substitution. A related paper by Dobkin and Nicosia (2009) studies the impacts of a federal effort to reduce the supply of methamphetamine precursors in 1995. Using data from California, they find that enforcement causes state-level prices to rise, drug abuse and purity to fall, and methamphetamine arrests to drop. Notably, all of these effects are temporary. These seminal papers focus on broad interventions and leverage aggregate measures of drug supply and usage. I instead focus on local supply shocks and outcomes using administrative data on the universe of dispensed opioid pills, enforcement actions, and death records. This strategy allows me to study not only the more granular direct impacts of enforcement, but the potential spillovers across space, substance, and time.

This paper builds on the economic literature studying the causes and consequences of the opioid epidemic by focusing on individual actor interventions. Related research often examines the role of preventative state- or federal-level policies, which can affect both illegitimate *and* legitimate actors. One of the most popular of these supply-side interventions is a prescription drug monitoring program (PDMP). These state-based electronic databases track controlled substance prescriptions and are intended to identify or deter misuse and diversion, but evidence on their effectiveness is mixed (Meara et al., 2016; Mallatt, 2018; Meinhofer, 2018). Doctor access in most states is voluntary and thus participation rates are often low, but broad interventions that restrict supply may still cause harm to patients with a legitimate medical need (Islam and McRae, 2014; Kim, 2021). Researchers have also examined changes in Medicare coverage (Alpert et al., 2015; Powell et al., 2020), the reformulation of OxyContin (Alpert et al., 2018; Evans et al., 2019), triplicate prescription programs (Alpert et al., 2022), and pharmaceutical marketing (Arteaga and Barone, 2022).

I also complement a growing body of work examining the role of physician behavior in

contributing to the opioid epidemic by focusing instead on a single doctor's removal from the medical system. Eichmeyer and Zhang (2021) find that patients randomly assigned to high-prescribing doctors are more likely to be addicted to opioids, underscoring the role a single doctor can play in initiating drug abuse. These authors also highlight significant heterogeneity in opioid prescribing patterns across doctors, which Schnell and Currie (2018) find is partly driven by differences in training. Schnell (2017) estimates a model of physician behavior in the presence of an illegal secondary market, which shows that the potential for diversion will make strict doctors prescribe more conservatively and lenient doctors to loosen their prescription thresholds.

Lastly, this paper contributes to a large literature on drug enforcement, which generally focuses on the effectiveness of traditional policing methods in illegally-produced drug markets and often finds evidence of displacement. For example, Dell (2015) finds large increases in drug-related violence following close mayoral election victories for a conservative party in Mexico that was tougher on drug traffickers.[2] The purely illicit nature of these markets and the associated data constraints have limited the ability of researchers to granularly test for both spatial and substance substitution following targeted enforcement actions. In particular, there is limited evidence on the second margin of a potential demand-side response to crackdowns.

I find evidence of spatial displacement, similar to the literature on drug enforcement in purely illicit markets, but only for pharmacy crackdowns. For doctor crackdowns, the persistent decline in prescription opioid dispensing across space and time suggests that certain supply-side interventions can be effective at reducing diversion and generating deterrence. There is scope for complementary demand-side interventions to address the unintended consequence of heroin substitution, such as targeted treatment programs or harm reduction strategies, but stopping the flow of new addicts leads to net reductions in overdose mortality and suggests there are significant long-run benefits of these crackdowns. Even in the short run and under the assumption that the primary costs and benefits of such interventions stem from their effects on human life, the most conservative back of the envelope estimate is an average county net benefit of $27 million annually per crackdown.

The remainder of this paper is organized as follows. Section 2 provides background information that helps contextualize and interpret the main empirical findings. Section 3 describes the primary data sources. Section 4 determines the extent of substance and spatial substitution following doctor crackdowns. Section 5 examines pharmacy crackdowns. Section 6 concludes.

2 Background Information

This section helps frame and interpret the empirical results found in Sections 4 and 5. Section 2.1 provides information on controlled substances and the role of doctors and pharmacies. Section 2.2 presents facts associated with the opioid epidemic. Section 2.3 describes diversion in the prescription opioid market and contains a conceptual framework for each substitution margin. Section 2.4 highlights relevant institutional details regarding DEA enforcement. Section 2.5

[2] Additional papers examining this type of enforcement include Caulkins (1992), Caulkins and Reuter (2010), Dobkin et al. (2014), Pollack and Reuter (2014), Castillo et al. (2020), and Blattman et al. (2021).

presents an outlier detection method from forensic accounting which I use to identify suspicious pharmacy behavior.

2.1 Controlled Substances

Prescription drugs are produced and distributed in a highly regulated medical system. The Food and Drug Administration (FDA) decides first whether a pharmaceutical can be sold based on whether the pharmaceutical company has provided adequate scientific evidence of its efficacy and therapeutic benefit. If approved, the Controlled Substances Act (CSA) states that controlled substances are subject to additional rules and regulations from the DEA. Only authorized veterinarians, dentists, optometrists, physicians, and advanced practice nurses can prescribe such drugs. While there are state-specific requirements to practice, medical professionals who want to prescribe or dispense controlled substances must also receive a special federal license from the DEA (Powell and Pacula, 2017).

The DEA assigns controlled substances a 'schedule' of I through V. Scheduling is determined by considering both the medical benefits of a drug and the potential for misuse or addiction. Schedule I drugs are prohibited and considered to have no medical benefits and a high potential for misuse and addiction; there are fewer restrictions on access to drugs in lower schedules. For example, heroin is a schedule I drug while prescription opioids, such as oxycodone, fentanyl, and hydrocodone, are schedule II pharmaceuticals (Maclean et al., 2022).

The Code of Federal Regulations (21 CFR 1306.04) states that

> [a] prescription for a controlled substance to be effective must be issued for a *legitimate medical purpose by an individual practitioner acting in the usual course of his professional practice* [emphasis added]. The responsibility for the proper prescribing and dispensing of controlled substances is upon the prescribing practitioner, but a *corresponding responsibility rests with the pharmacist who fills the prescription* [emphasis added]. An order purporting to be a prescription issued not in the usual course of professional treatment or in legitimate and authorized research is not a prescription within the meaning and intent of section 309 of the Act (21 U.S.C. 829) and the person knowingly filling such a purported prescription, as well as the person issuing it, shall be subject to the penalties provided for violations of the provisions of law relating to controlled substances.

The mission of DEA's Diversion Control Division is then to "prevent, detect, and investigate the diversion of controlled pharmaceuticals and listed chemicals from legitimate sources while ensuring an adequate and uninterrupted supply for legitimate medical, commercial, and scientific needs." Penalties for violating any aspect of the DEA's regulations range from fines and the loss of their prescribing license to prison time.

Unlike other addictive substances, controlled substances serve an important medical purpose. For example, prescription opioids effectively treat severe post-operative pain (Wiffen et al., 2016). Therefore, initiation may be driven by a medical need, not just an intention to get high, which means that the pool of potential abusers is often larger than it is for illegally-produced drugs (Volkow and McLellan, 2016). Legally-produced drugs have actually fueled four of the last five nationwide drug epidemics, which include morphine, heroin, amphetamine, and prescription opioids (DeShazo et al., 2018).[3] The primary concern with controlled substances is non-medical use and misuse, where the former is when the user is not the one originally prescribed the

[3]See Figure A.1 for a timeline of these public health crises.

medication and the latter is when it is used in a manner inconsistent with the doctor's orders. Individuals can obtain prescription drugs for non-medical use through several channels including theft, street purchases, from a friend or relative, and "doctor shopping" (Grecu et al., 2019).

The legal standard described in 21 CFR 1306.04 would necessitate a doctor to conduct a medical examination and record the patient's history, as well as the patient to be experiencing severe pain (Cutler and Glaeser, 2021). If a prescription is written, it is often filled at a pharmacy. The pharmacist has a responsibility, among other things, to ensure that the prescription is valid and that the patient is not doctor shopping. In my sample period, rogue doctors were often running high-volume practices that did not see patients for more than a few minutes (Quinones, 2015). Rogue pharmacies often filled forged prescriptions and thus were not always linked to a doctor (Eyre, 2020).

2.2 The Opioid Epidemic

In 2018, an estimated 10.1 million people aged 12 and older misused opioids, and prescription opioid misuse has been linked to higher health care costs (White et al., 2005), lower worker productivity and employment (Harris et al., 2020), more suicides (Borgschulte et al., 2018), increased use of other drugs (Grecu et al., 2019), and worse outcomes for children (Evans et al., 2022). Figure 1 shows the change in the distribution of prescription opioids and the associated mortality rate. OxyContin, the pain reliever produced by Purdue Pharma at the heart of the opioid epidemic, was introduced in 1996. Its main ingredient is OxyCodone, which sees steady increases over time that correspond to increases in the mortality rate. There are several potential explanations for the dramatic rise in opioid dispensing and abuse over time, which include aggressive marketing, changes in willingness to prescribe opioids, over-prescribing, declining costs to customers, and diversion (Powell and Pacula, 2017; McCance-Katz, 2020).

Another contributing factor is (the lack of timely) enforcement. The Office of the Inspector General recently examined the regulatory activities and enforcement efforts of the DEA and found that it was slow to respond to the opioid crisis (Department of Justice, 2019). Eyre (2020) provides additional insight from a May 2018 hearing involving the DEA director and the five largest drug distributors held by the Subcommittee on Oversight and Investigations of the Committee on Energy and Commerce:

> Distributors set limits on pharmacy drug orders but failed to enforce them. They flagged excessive shipments but did not stop them. They sold drugs to pharmacies they knew were breaking the law. They willfully ignored red flags and stark warning signs that the drugs they sold were being diverted to the black market..."Your agency needs to be turned upside down," Rep. Chris Collins, R-N.Y., said. "There is no doubt there is an abject failure in the DEA going back 10 years."

2.3 Opioid Diversion and Potential Spillovers from Enforcement

Within a market-oriented complex of criminal activity, there are important interrelations that involve suppliers, middlemen, and customers (Cook, 1980). For example, with heroin, this includes poppy growers and heroin processors, importers and retailers, and users. In a market for controlled substances, it is manufacturers and distributors, doctors and pharmacies, and patients; Figure A.2 summarizes information gathered on rogue doctors and pharmacies involved

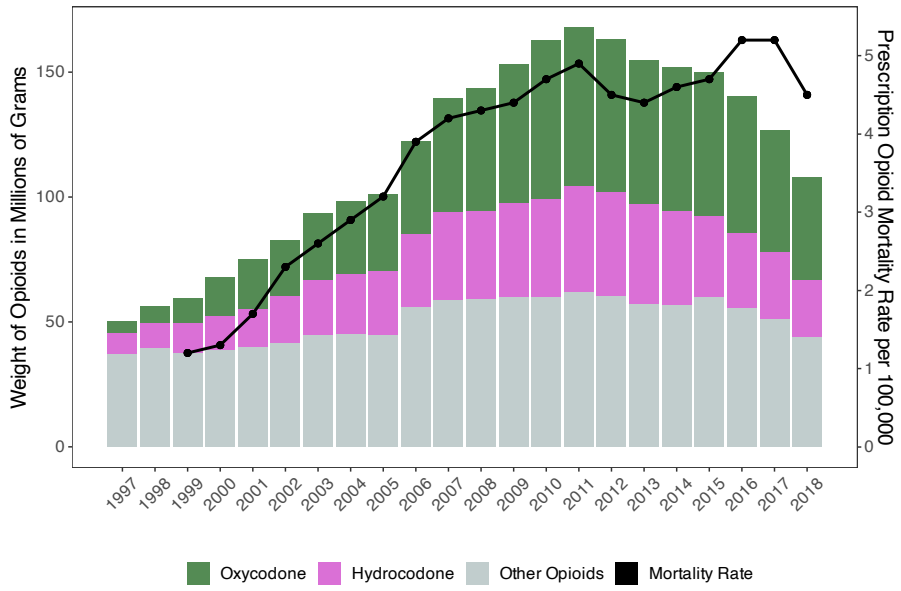


Figure 1: Evolution of Prescription Opioid Distribution and Mortality in the United States

Notes: Oxycodone is the active ingredient in OxyContin. Shipments of prescription opioids are expressed in morphine-equivalent doses on the left axis. The mortality rate from prescription opioids is constructed using data from the National Vital Statistic System and plotted in a black line on the right axis.

in the prescription opioid market. According to the Office of National Drug Control Policy, disrupting a market that supports illegal activity is one of three core priorities for federal drug policy.[4] The motivation for disrupting these markets is that while they operate outside of the law, they do not operate outside of social and economic forces. The implicit assumption is therefore that disrupted markets will be less able to supply customer demand for their product (Brownstein and Taylor, 2007). However, Figure A.3 shows that if a substitute is available, a supply disruption may lead to worse health outcomes: heroin is more lethal than prescription opioids, and for some users, it is a close substitute (Alpert et al., 2018).

Note that while legally- and illegally-produced drugs are pharmacologically similar, the controlled substance market is more like the gun market than an illegal drug market; their market structure, supply chain, and enforcement agency are similar. Enforcement actions in markets for illegal drugs include source-country eradication, interdiction, and those related to traditional policing, while those for controlled substances and guns include regulation and administrative action. Especially relevant for gun violence and opioid abuse is that virtually all guns and opioid pills in the illegal market begin in the legal market.

Determining the extent of displacement is important not only to evaluate the overall effectiveness of a market disruption approach, but because the answer has implications for our understanding of criminal behavior (Blattman et al., 2021). In economic models of criminal decision-making, such as Becker (1968), potential offenders weigh the returns from engaging in illegal activity against the risk of capture and expected sanction. Supply-side interventions should increase the risk of capture in a given area and thus reduce the likelihood of crime commission there. According to Johnson et al. (2014), the degree to which displacement occurs

[4]The other two core priorities are stopping drug use before it begins and healing drug users.

depends on how invested an offender is in committing a crime, the degree to which the extra effort of finding and exploiting an alternative is worthwhile, and the degree to which offenders know of other potential situations that they can manipulate.

If displacement does not occur, Blattman et al. (2021) suggest that at least one of the following hypotheses are true: criminal rents are highly concentrated and unequally distributed within a given area, some offenders are resistant to moving crime locations, and/or the supply of crime is elastic to the actual or perceived risk of apprehension in a small number of areas. To formalize the spatial substitution analysis, consider a market m that has two cities $c \in \{1, 2\}$ and that the probability of apprehension is p_c. If we assume that the market production function for opioids is

$$\text{opioids}_m = \text{opioids}_1(p_1, p_2) + \text{opioids}_2(p_1, p_2),$$

where opioids_c is the amount of opioids dispensed in a given city, then the total effect of an increase in enforcement in one city can be decomposed into

$$\frac{\partial \text{opioids}_m}{\partial p_1} = \underbrace{\frac{\partial \text{opioids}_1}{\partial p_1}}_{\text{local effect}} + \underbrace{\frac{\partial \text{opioids}_2}{\partial p_1}}_{\text{spatial spillover}}.$$

Existing literature suggests that the local effect is likely negative, as prescribing is relatively concentrated and thus a single doctor can play a large role in local drug supply, but I test this empirically. The spatial spillover effect could be zero/negative (market-level deterrence) or positive (market-level displacement) depending on various margins of substitutability, such as the opportunity cost of crime for a supply chain actor, distance to the nearest rogue actor, reputation costs, or informational asymmetries for the user.

The primary underlying consideration, however, is the distribution of rogue behavior within the two types of actors I study (doctors and pharmacies). Assume that there is a threshold of perceived profitability above which a given supply chain actor decides to participate in illegal activity. The crackdown may increase the perceived revenue, as when a competitor is removed, more customers are available. Simultaneously, it may increase the perceived probability of getting caught. These competing forces will affect expected profits and thus the marginal supplier, but the point of indifference and the size of the shift in potential profit following a crackdown may be different for doctors and pharmacies.

As described in Section 2.1, the primary responsibility of a patient's health lies with the doctor. They also have extensive training and a lucrative legal option for work. Therefore, the threshold needed to participate in illegal activity is likely high at baseline. The saliency of the crackdown combined with their legal liability likely means that if the shift in potential profit is not very large, the intervention may not entice marginal doctors to participate. There also may be little mass near the threshold or doctors do not have much scope for additional capacity.

The opportunity cost to commit crime, or the personal cost of illegal activity, is potentially lower for a pharmacist than for a doctor. They can go out of business and only have a corresponding legal responsibility. The threshold of perceived profitability needed to participate in illegal activity is therefore likely lower. Additionally, the clientele of each actor is generally different. Rogue pharmacies often work with drug dealers and criminal organizations, who have

a significant incentive to search for another rogue pharmacy to meet their trafficking needs. Given the scale of such operations, the shift in perceived revenue following a crackdown may be quite large. They may also have more excess capacity than doctors. Taken together, this suggests that a pharmacy crackdown is more likely to induce spatial displacement.

2.4 DEA Investigations

The DEA conducts audits of controlled substance license registrants, and conditional on DEA field division, the timing of these audits is plausibly exogenous.[5] A lawyer that represents doctors in cases involving the DEA described the audits as being similar to IRS audits, which examine or review information and accounts to ensure individuals are reporting income correctly and following the tax laws. In contrast, a DEA audit examines whether any violation of the Controlled Substance Act (CSA) occurred. For doctors, actions that would lead to a CSA violation include prescribing controlled substances that were either not for a legitimate medical purpose or not in the usual course of professional practice.

If a given registrant is found in violation of the CSA, the audit report can be sent to the Office of Administrative Law Judges to conduct a formal hearing and adjudication. There are two Administrative Law Judges, appointed for life, that hear cases from all 23 DEA field divisions. The Deputy Administrator of the DEA then issues the final Agency decision after the hearing is complete, where sanctions can range from fines to loss of license and prison time. There are relatively few cases, with less than one in ten thousand doctors found in violation in any year of my sample, and Department of Justice (2019) states that

> ...the DEA was slow to respond to the significant increase in the use and diversion of opioids since 2000. We also found that DEA did not use its available resources, including its data systems and strongest administrative enforcement tools, to detect and regulate diversion effectively. Further, we found that DEA policies and regulations did not adequately hold registrants accountable or prevent the diversion of pharmaceutical opioids. Lastly, we found that while the Department and DEA have recently taken steps to address the crisis, more work is needed.

2.5 Suspicious Behavior Detection

In addition to submitting information on all controlled substance shipments to the DEA, the CSA requires drug distributors to "design and operate a system to disclose all suspicious orders of controlled substances." Given the richness of the data that was available to the DEA and that their data systems were cited as a primary issue in Department of Justice (2019), I use their data to flag suspicious behavior of non-sanctioned pharmacies. I then use this information to generate control groups for the main analysis and to examine how non-sanctioned pharmacies respond to a crackdown.

Suspicious orders are considered deviations from a normal ordering pattern, and I flag suspicious behavior using the "twice the trailing 12-month average pharmacy dosage units for each pharmacy" method. This detection method is referenced in court documents from Ohio

[5]The exact algorithm that predicts an audit is not currently known, but for the analysis, all that is needed is exogenous variation in the timing of the audit, which I test for in Section 4. Note that the DEA also pursues anonymous tips to determine CSA compliance; they lead to less than 15% of all subsequent enforcement actions during my sample and the associated units are removed from the analysis.

lawsuits against opioid distributors (Ohio MDL 2804).[6] Figure A.4 shows what this method looks like graphically, where a pharmacy is suspicious any time one of their monthly orders (gray bar) exceed two times the rolling average (red line). The pharmacy in the left panel has their first suspicious order in the beginning of 2009. Their ordering continues to increase until around August 2010. The pharmacy in the right panel does not have any significant deviations in its ordering and thus would not be flagged as suspicious. For reference, the total share of pharmacies in the US that are suspicious in any given month is approximately 0.5%.

3 Data

In order to examine both the direct and spillover effects of supplier crackdowns in a prescription opioid market, I combine four sources of data. First, as part of the CSA, distributors and manufacturers of controlled substances are required to report all transactions to the DEA. The Automation of Reports and Consolidated Orders System (ARCOS) database contains the record of every controlled substance sold in the United States. The complete database for opioids, from 2006 to 2014, was recently released by a federal judge as a result of a trial in Ohio against manufacturers and distributors. The ARCOS database has been previously used to study opioids, but generally only using the publicly available quarterly aggregate weight of drugs sold or via special request to the DEA (Zhang and Guth, 2021). The newly released database allows me to examine supply dynamics at any level of geographic or temporal aggregation. For example, Figure A.5 shows that there is significant variation in both the levels and trends in yearly per capita opioid dispensing across states. Figure A.6 provides a heat map of per capita dispensing at the county-level showing similar spatial and temporal variation.

For each of these over 180 million transactions, I have the DEA number, address, name, and business type for both the reporter and the buyer, as well as information on each transaction, such as the transaction date, opioid drug name, quantity, strength, and Morphine Milligram Equivalent (MME) conversion factor. I consider only retail pharmacies, where approximately 90,000 unique chain and independent pharmacies dispensed over 100 billion pills during my sample period. An observation in the raw data is therefore a single transaction between a retail pharmacy and a distributor or manufacturer. I aggregate these data to the pharmacy-month level and convert the dosage into MME so that different opioid pills can be compared. For the primary analysis, I aggregate this further to a certain unit of geography in a given month or year, which includes city, county, or market depending on the outcome.

For the second source, I construct a dataset on every DEA investigation of a doctor or pharmacy using Federal Register notices and the DEA's Diversion Control Division reports. These notices and reports contain information on the registrant's DEA number, operating location, details of the investigation, and the outcome of the investigation. They represent the universe of investigations with a disposition. I examined all reports and notices from 2000 until 2019 involving doctors or pharmacies and focus on potential revocations of the registrant's DEA license. This includes a doctor voluntarily surrendering their DEA license or the state revoking

[6]Such a method does not capture, for example, pharmacies that always dispense a very high amount of opioids. Therefore, I also explore high per-capita dispensing (99th percentile for the year) and other outlier detection methods from forensic accounting. They show qualitatively similar results and are in the appendix.

their medical license before the investigation is completed.[7] Figure A.7 shows that few investigations occurred and that they were not spatially concentrated. Figure 2 provides examples of their impact on prescription opioid supply, where the finding of a violation against a single doctor, stemming from an audit, immediately decreases monthly city-level opioid dispensing.

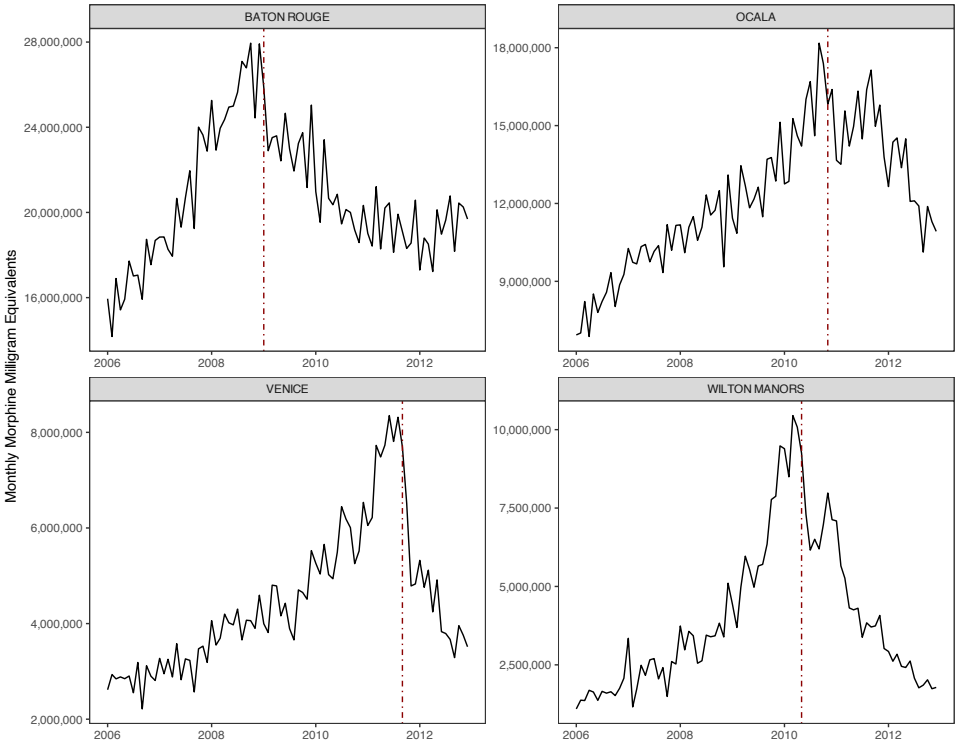


Figure 2: The Impact of Doctor Crackdowns on Monthly City-Level Opioid Dispensing

Notes: The vertical axis is the total monthly MME dispensed in a city that experienced a doctor crackdown, while the red vertical dashed line is the month when a doctor operating in the city was found in violation of the Controlled Substance Act stemming from a DEA audit. These examples represent the first stage impact of crackdowns on prescription opioid dispensing shown analytically in Section 4.

For the third source, I use information on black-market opioid pill prices from StreetRx, which is a partnership between the Denver Health and Hospital Authority and Lexigraph. It is an ongoing observational public health surveillance study based on crowdsourcing, where their website gathers user-submitted information on black-market prices of diverted prescription and illicit drugs (Denver Health and Hospital Authority, 2022). Visitors can anonymously view, post, and rate submissions in a format that offers transparency to an otherwise opaque market. Variables in the data include the city and date of purchase, source, product name, drug classification, and dosage since 2000. While the data are not available for the entire US, other than occasional cross-sectional surveys for a single geographic area, the only reliable data on illicit drug prices are single yearly nationwide ones for marijuana, cocaine, heroin, and methamphetamine from the Office of National Drug Control Policy. These data correlate well with those yearly averages, but are able to go considerably further both temporally and spatially: during my sample period, there are 113,274 unique submissions in the US, and Figure A.8 provides an example of the cross sectional county-level variation in black-market pill prices.

[7] I exclude DEA license applications, which are the remainder of the notices, as they unrelated.

For the fourth data source, I obtain micro-data from the CDC's Restricted-Use Vital Statistics Data, which are also known as the Multiple Cause of Death (MCOD) research files. They provide a comprehensive collection of information on all deaths in the United States. They include details on the decedent, the county of occurrence, the county of residence, the underlying cause of death, and multiple conditions (if applicable) since 2000. This allows me to isolate opioid-related overdose deaths, heroin overdose deaths, homicides, suicides and other relevant classifications, which can be broken down by gender and age group. Figure A.9 shows significant cross-sectional variation in opioid-related overdose death rates across counties, as well as that the vast majority of counties experience an increases in these rates over time. Figure A.10 shows the distribution of county-level changes in opioid overdose deaths from 2006 to 2014, where the average was an increase of 74%, while Figure A.11 shows the age profiles of those that overdose from opioids by gender. Tables A.1 to A.3 provide county-level summary statistics.

4 The Impacts of Crackdowns on Rogue Doctors

4.1 Substance Substitution

The potential for substitution to more harmful substances following a supply-side crackdown is a primary concern when taking this approach to reduce drug abuse. To examine whether this occurs and/or if legal opioid dispensing is impacted, my primary research design exploits plausibly exogenous variation in the timing and location of DEA enforcement actions in a difference-in-differences framework. I use the data sources described in Section 3 and begin by estimating a two-way fixed effects model of

$$Y_{it} = \beta \text{Post_DEA_Action}_{it} + \lambda_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the outcome of interest in geographic unit i in time t, $\text{Post_DEA_Action}_{it}$ is an indicator denoting the period after a treated unit experiences a DEA enforcement action, λ_i are unit fixed effects, γ_t are time fixed effects, and ε_{it} is the error term. The geographic unit depends on data availability for the outcome and can be either a city or a county; standard errors are clustered at the geographic unit. β is the coefficient of interest, which captures the average impact of a doctor crackdown on legal opioids dispensed, black-market pill prices, or heroin overdose deaths relative to control units. To examine whether using a two-way fixed effects approach is appropriate, I begin by implementing the difference-in-difference decomposition found in Goodman-Bacon (2021). Figure A.12 shows that all weights are non-negative and that the vast majority of the weighting comes from the treated versus untreated comparison.

While the full sample includes every geographic unit in the contiguous United States, I use three additional approaches to ensure that the estimates are unbiased. First, as treatment effect heterogeneity is a primary concern when using a two-way fixed effects approach, I use the dynamic aggregation method from Callaway and Sant'Anna (2021) with both not-yet-treated and never treated control units.[8] The second uses outlier detection methods from forensic

[8] An additional test from Jakiela (2021) is to examine the relationship between the residualized treatment and each residualized outcome. In Figure A.13, I find that this relationship is linear, which suggests that the treatment effects are homogeneous.

accounting described in Section 2.5 to generate control units that are similarly "suspicious" but did not experience a crackdown. The third uses the synthetic difference-in-differences method from Arkhangelsky et al. (2021). The results are robust to these additional approaches. Therefore, I present the two-way fixed effects estimates and the event studies from Callaway and Sant'Anna (2021) in the main text for consistency, but the results from additional specifications and those with different control groups are referenced in footnotes and located in the appendix.

The identifying assumption is that the average untreated potential outcomes for the group of units first treated with a violation in a given time period would have followed parallel trends in outcomes to the control group for all post-treatment periods. As this is not directly testable, I examine the implications of this assumption in three different ways. First, Table A.4 suggests that this assumption holds for observable characteristics: when I regress a dummy variable for whether the violation occurred in the first half of my sample on characteristics of counties that experienced a crackdown, I find no significant predictors and the effect sizes are small. Table A.5 repeats this exercise with a continuous treatment timing measure at the city-level and arrives to the same conclusion. These tests suggest that the DEA does not appear to select or target certain areas earlier, such as those with higher levels of opioid-related overdose deaths. Lastly, there are no pre-trends in the event study analysis of this section and Section 5. For the primary treatment variable, $\text{Post_DEA_Action}_{it}$, I use the date a case is first registered in the Federal Register, which is a standardized date for when the doctor definitively knows of their CSA violation and when it is public record. The results should therefore be interpreted as an intent-to-treat (ITT) effect, as this is often before any formal punishment is delivered.

I begin with the legal opioid supply impacts of crackdowns on rogue doctors in an event study framework. Figure 3 shows how monthly city-level opioid dispensing evolves, where we see statistically significant decreases of approximately 10% within 3 months of the initial enforcement action.[9] Refills are not allowed for schedule II controlled substances and the supply limit for any single prescription is 90 days. Additionally, pharmacists should not fill a prescription from a doctor if their registration was revoked or suspended. Therefore, any prescriptions filled after 3 months should not be attributed to the sanctioned doctor, or that the declines are no longer mechanical beyond 3 months of the finding of a CSA violation.

The effect continues to grow to approximately 25% after two years, which is likely due to two factors.[10] Interviews with DEA agents suggest it is dynamic deterrence for non-sanctioned doctors, who are "scared straight" or prescribe more conservatively after a local colleague is sanctioned. Figures A.15 and A.16 show that this dynamic decline is both driven by and larger for smaller cities, which may be due to tighter information networks and that a single doctor can contribute a larger share of dispensing in a smaller city. However, the raw data is at the pharmacy-level and thus I cannot determine how individual doctor prescribing habits change. The second factor involves substitution to other substances or death. I examine this formally in the following paragraph, but conceptually, rogue doctors want to both maximize the number

[9] I use the first crackdown that occurred in a city, and there are almost no cities that are treated more than once during my sample period. Figure A.14 instead uses the not-yet-treated cities as the control group, where I also limit the sample to cities where a crackdown eventually occurs; the results are similar.

[10] To ensure that the dynamics are not due to changes in the composition of the control group, I examine only enforcement actions that occurred before 2013. This provides at least two years of post-treatment dispensing data for each treated city. The results are qualitatively similar if I use the entire sample.

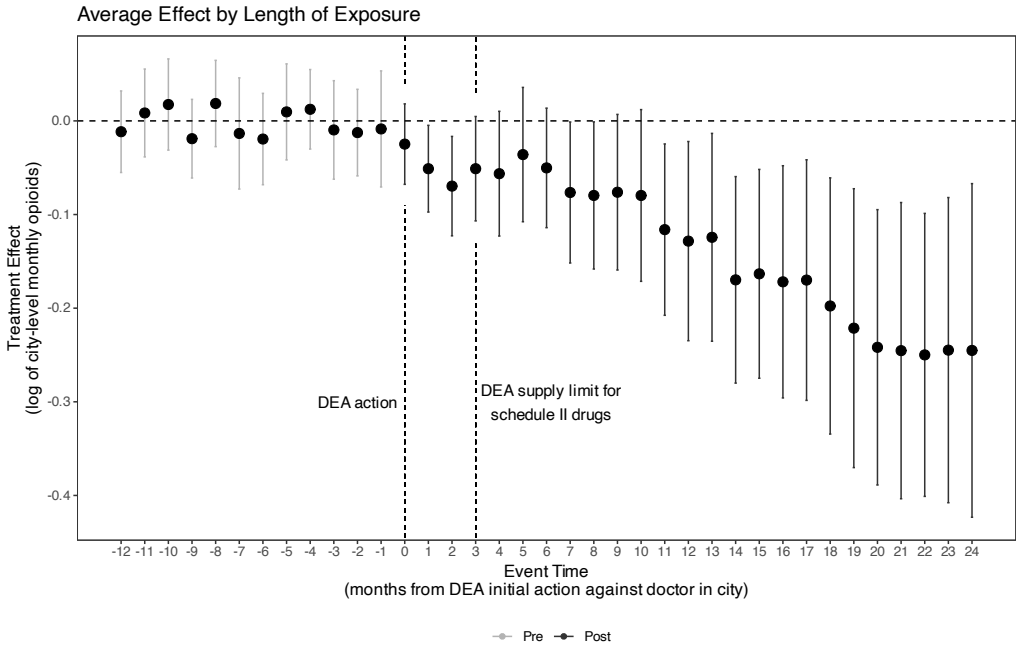


Figure 3: Dynamic Impact of Doctor Crackdowns on Opioid Dispensing

Notes: The outcome is the logarithm of monthly city-level opioids dispensed, where the treatment is the DEA action against taken against a doctor. The control group consists of never treated cities. Figure A.14 instead uses not-yet-treated cities and limits the sample to only cities that were treated. Standard errors are clustered at the city-level and computed using a multiplier bootstrap, and the estimation method is doubly robust from Callaway and Sant'Anna (2021). The first dotted line captures the treatment date, while the second captures the 90-day supply limit of any schedule II controlled substance prescription. Prescriptions filled after the 90-day limit should not be attributable to the sanctioned doctor.

of prescriptions written to current patients, as well as initiate new addicts. Sanctioning them affects both margins. In other words, if we assume that the counterfactual flow of consumers into addiction would be very high, past reduction in equilibrium quantity could also change consumer tastes and eventually lower demand for legal opioids.

Given the large and persistent negative legal supply shock following a crackdown, I examine their impacts on black-market opioid pill prices and heroin substitution. The results for estimating equation (1) at the county-year level are in Table 1.[11] In my sample, treated cities are smaller than their associated counties, and column (1) provides the point estimate for the average county decline in yearly dispensing: 9.4%. Columns (2) and (3) show 44% increases in both average street pill prices per milligram and heroin overdose deaths.[12] Note that all opioid pills entering the illegal market begin in the legal market, and a single rogue doctor can play a significant role in supplying addicts directly and the black market indirectly. Supply to both channels decreases once a rogue doctor is removed. However, I cannot determine whether the rise in street prices is due to reduced supply to the black market, increased black market demand from addicts because they no longer have a valid prescription, or both.

The increase in heroin overdose deaths is likely due to end user substitution following the negative supply shock. This aligns with the findings of Alpert et al. (2018), Evans et al. (2019), and Mallatt (2022), where state- or federal-level policies meant to curb prescription opioid

[11]The corresponding estimates using Callaway and Sant'Anna (2021) are in Table A.6, and the county-year event studies for county dispensing, overdoses, and prices (Figures A.17 to A.19) all show dynamic changes.

[12]There are fewer observations in column (2) because street prices are available only for a subset of the country.

Table 1: Impacts of Doctor Crackdowns on Dispensing, Street Prices, and Substitution

	Opioids Dispensed	Pill Price	Heroin Deaths
	(1)	(2)	(3)
Post-DEA Action	-0.094^{***}	0.444^{***}	0.439^{***}
	(0.017)	(0.110)	(0.087)
Control Mean	3.218	1.441	1.386
Observations	26,765	5,057	26,765
R^2	0.990	0.430	0.800

Notes: *p<0.1; **p<0.05; ***p<0.01
Outcomes are county-year and log transformed
County and year FEs in all specifications
Standard errors are clustered at county level

abuse induce heroin substitution. Additionally, Cicero et al. (2015) find that the incidence of heroin initiation is 19 times higher among those who reported prior non-medical pain reliever use than among those who did not. This represents a significant shift from historical trends. Of people entering treatment for heroin addiction who began abusing opioids in the 1960s, more than 80 percent started with heroin. Of those who began abusing opioids in the 2000s, 75 percent reported that their first opioid was a prescription drug; nearly 80 percent of heroin users reported using prescription opioids prior to heroin (Cicero et al., 2014).

Table 2 shows that for each additional heroin overdose death per 100,000 residents (column 2), there are two fewer non-heroin opioid overdoses (column 3). There are also reductions in non-opioid drug overdoses and suicides, but they are smaller in magnitude and insignificant. This suggests that there is a tradeoff between existing users substituting to more harmful substances and stopping the flow of new users. Decomposing this further, Table A.9 finds a reduction in young male mortality, which suggests that heroin substitution is limited to heavy users, while the number of new recreational users is reduced. I begin with young men because they are the group that is most likely to be exposed to drugs and thus initiate use (Grecu et al., 2019). I then transition to middle-aged men, who see a larger decline in overall mortality. In additional to risk-taking behavior and occupational choice, Kloos et al. (2009) suggest that cultural ideas of masculinity may contribute to male substance use. Women of the same age groups also experience declines in overall mortality, but the effects sizes are smaller; substance abuse in women often starts later and involves lighter and/or less frequent use. As a placebo test, I examine mortality of those 85 and older and find a small and insignificant effect on death rates.

The results in this section suggest that a single rogue doctor's reach is quite far: sanctioning them not only leads to large city-level declines in opioid dispensing, but to a county-level decline of almost 10% (Table 1). The dynamic declines found in Figure 3 further suggest that other doctors are at least partially deterred by the enforcement action. Moreover, while substitution to more dangerous substances is especially concerning, net mortality in these communities decreases. These mortality declines are strongest among young and prime-aged men.

Table 2: Impacts of Doctor Crackdowns on Mortality Rates

	Per Capita Pill Volume	Heroin	Non-Heroin Opioids	Non-Opioid Drugs	Suicide
	(1)	(2)	(3)	(4)	(5)
Post-DEA Action	-3.889^{***}	0.531^{***}	-1.033^{***}	-0.441	-0.169
	(0.808)	(0.200)	(0.386)	(0.429)	(0.307)
Control Mean	39.541	0.633	11.356	10.409	14.846
Observations	26,765	26,765	26,765	26,765	26,765
R^2	0.939	0.458	0.517	0.535	0.271

Notes: *p<0.1; **p<0.05; ***p<0.01
Mortality outcomes are in yearly rates per 100,000
County and year FEs in all specifications
Standard errors are clustered at county level

4.1.1 Robustness Checks

To examine stability of the main results, I first randomize the treatment date and plot the resulting t-statistics and coefficients from estimating equation (1) 1000 times in Figures A.20 and A.21, respectively.[13] This exercise suggests that the results in Table 1 are unlikely due to chance. Two additional checks include generating alternative control groups with outlier detection methods described in Section 2.5 and utilizing the synthetic difference-in-differences approach from Arkhangelsky et al. (2021). The results for these approaches are in Table A.7, Figure A.22, and Table A.8, and they all align with the findings of Table 1.

4.2 Spatial Substitution

Displacement of illicit activity following a crackdown is also a critical consideration when evaluating the effectiveness of a supply-side intervention. To examine the extent of spatial displacement following a doctor crackdown, I study their pharmacy-level impacts within larger geographic areas. More formally, I estimate

$$Y_{pt} = \sum_{d} \phi_d(\text{Post_DEA_Action}_{pt} \times \text{Distance_Group}_{p \in d}) + \delta_j + \lambda_t + \mu_{pt}, \tag{2}$$

where Y_{pt} is the log of legal opioid dispensed by pharmacy p in time t, $\text{Post_DEA_Action}_{pt}$ is a dummy variable equal to one after a treated market is exposed to a crackdown, $\text{Distance_Group}_{p \in d}$ is a categorical variable that splits up each pharmacy p's distance to the rogue doctor into 10-mile bins d, δ_j are market fixed effects, λ_t are time fixed effects, and μ_{pt} is the error term. The reference category are pharmacies that are greater than 100 miles from the crackdown.[14] Therefore, ϕ_d captures the average effect of a crackdown for a pharmacy located in distance bin d relative to these control pharmacies.

[13] I randomize 1) first which units get treated, then conditional on receiving treatment, I randomize the treatment year, as well as 2) treatment years across only treated units. The two approaches produce qualitatively similar results, and I present the first for the sake of consistency.

[14] The results are not sensitive to the choice of buffer size within 15 miles and so I use 100 miles to align with the literature and to ensure there is no overlap of buffer zones. I also separately replace market fixed effects with market-by-distance bin fixed effects and pharmacy fixed effects, and the results are qualitatively similar. Lastly, I cannot estimate equation (2) for prices or overdoses, as these data sources are only available at the county-level.

Figure 4 presents the estimates of ϕ from equation (2), where we observe large decreases within 10 miles of the doctor crackdown: the average decline in pharmacy dispensing in this distance bin is 17%. The effect becomes less negative until 40 miles, crossing the zero at 20 to 30 miles from the crackdown. It then remains insignificant and small thereafter. The overall effect is a small but significant decrease in dispensing. This suggests that deterrence plays a significant role in the behavior of nearby doctors following a crackdown, as the decline in dispensing persists with no negating increases.

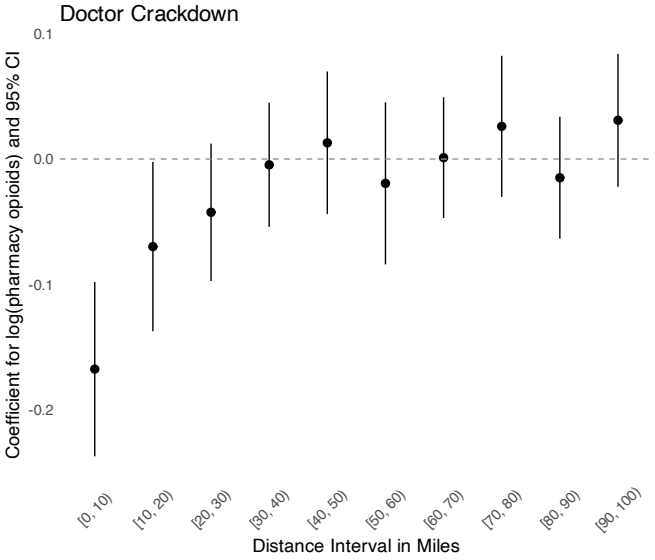


Figure 4: Pharmacy-Level Opioid Dispensing Impacts of Doctor Crackdowns

Notes: Market and year fixed effects are included, and standard errors are clustered at the DEA action. The plotted coefficients are the interaction between each 10-mile distance bin and the DEA enforcement action. Pharmacies farther than 100 miles from the enforcement action are the omitted category.

5 Pharmacy Interventions and Spatial Dynamics

Doctors are the primary focus of this paper, as they are the source of all legal prescriptions, but pharmacies also play a critical role in circulating opioids. For example, Janssen and Zhang (2023) find that independent pharmacies dispense more opioids and that acquisitions by pharmacy chains reduce dispensing, which suggests that pharmacies can operate at least partially independent of local demand. While there are considerably fewer enforcement actions taken against pharmacies than doctors, which limits statistical power if repeating the analysis found in Section 4, I can conduct a more granular examination of crackdowns because the data is at the pharmacy-level. For the sake of comparison, I repeat the exercises from the previous section, which show similar results between doctor and pharmacy crackdowns at the city- and county-levels: prescription opioid supply decreases, heroin overdose death increases, and net mortality decreases. These results are in the appendix and include Figures A.23 to A.30 and Tables A.10 to A.15.

To examine the extent of spatial displacement, I re-estimate equation (2) for pharmacies in Figure 5. We see large declines for pharmacy crackdowns until 30 to 40 miles, then significant

increases thereafter. I cannot reject the null hypothesis that any of the first five coefficients are equal to each other, but they are each statistically different than the last five, and the overall effect is a small and insignificant decrease. This spatial displacement contrasts to Figure 4, which finds persistent and significant declines following a doctor crackdown.

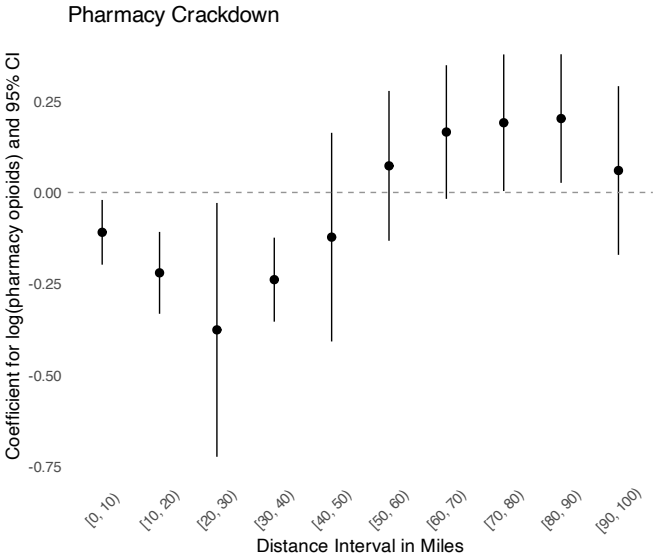


Figure 5: Pharmacy-Level Opioid Dispensing Impacts of Pharmacy Crackdowns

Notes: The outcome is the log of pharmacy-level opioid dispensing. Market and year fixed effects are included in all models, and standard errors are clustered at the DEA action. The plotted coefficients are the interaction between each 10-mile distance bin and the DEA enforcement action. Pharmacies farther than 100 miles from the enforcement action are the omitted category.

As an alternative test of displacement, I aggregate the data to the market-level, remove markets that did not experience a crackdown, and then estimate

$$Y_{jt} = \pi \text{Post_DEA_Action}_{jt} + \delta_j + \lambda_t + \nu_{jt}, \tag{3}$$

where Y_{jt} is the outcome of interest in market j in month t, $\text{Post_DEA_Action}_{jt}$ is a dummy variable equal to one after a given market is exposed to a sanctioned doctor or pharmacy, δ_j are market fixed effects, λ_t are year fixed effects, and ν_{jt} is the error term.[15] The parameter of interest, π, captures the average impact of a crackdown at the market-level relative to markets that have yet to have a crackdown.

Table 3 shows the results from estimating equation (3) in a market that is within 100 miles of a crackdown.[16] In columns (1) and (3), we see that there is no meaningful change in overall opioid dispensing after a pharmacy crackdown and that the share of suspicious pharmacies increased by approximately 8%. The typical 100-mile area has approximately 300 pharmacies, with 0.5% of them being suspicious in any given month, so this represents a large increase relative to the baseline. For doctor crackdowns, columns (2) and (4) of Table 3 show no meaningful change in suspicious behavior and instead a persistent decline in overall opioid

[15] I cannot estimate equations (2) or (3) for prices or overdoses, as these data sources are only available at the county-level.

[16] Similar to estimating equation (2), the results are not sensitive to the choice of buffer size within 15 miles and so I use 100 miles to align with the literature and to ensure there is no overlap of buffer zones.

dispensing, similar to Figure 4. Taken together, the results of this section suggest that spatial displacement is a concern for pharmacy crackdowns, while non-sanctioned doctors are at least partially deterred by a crackdown against another doctor.

Table 3: Impacts of Opioid Supplier Crackdowns at 100-Mile Market Level

	Monthly Opioids		Share Suspicious	
	Pharmacy	Doctor	Pharmacy	Doctor
	(1)	(2)	(3)	(4)
Post-DEA Action	−0.015	−0.056***	0.083***	0.010
	(0.050)	(0.021)	(0.016)	(0.028)
Control Mean	67.343	51.408	0.605	0.576
Observations	3,672	13,608	3,672	13,608
R^2	0.988	0.983	0.109	0.249

Notes: *p<0.1; **p<0.05; ***p<0.01
DEA crackdown and year FEs in all specifications
Standard errors are clustered at the DEA crackdown
Outcomes are market-month and log transformed

For pharmacy crackdowns, Figure A.31 shows that the average decrease in prescription opioids achieved from the supply-side intervention is almost fully negated by several initially low-volume independent pharmacies that significantly increase their post-crackdown dispensing. More specifically, on average 8 pharmacies per crackdown become suspicious within the first 3 months and 100 miles of an enforcement action; the average baseline number of suspicious pharmacies per 100 miles is 1.6. The average increase in dispensing the year after the crackdown for each of these 8 newly suspicious pharmacies is 70,000 opioid doses, or a 110% increase above their pre-crackdown dispensing. Therefore, the total dose increase of 560,000 from these 8 pharmacies almost completely negates the 740,000 dose decrease achieved from sanctioning a single rogue pharmacy.

This displacement is not likely due to legitimate users moving to these newly suspicious pharmacies, as they are on average 40 miles from the sanctioned pharmacy. A newly suspicious pharmacy is never the next closest pharmacy to the sanctioned one, as there is always at least one other pharmacy operating within 6 miles of the crackdown. They are also always close to an interstate highway: in the US, the average distance from a pharmacy to an interstate highway is 8.9 miles, yet newly suspicious pharmacies are on average 4.5 miles from an interstate. This is suggestive evidence that the spatial displacement is not mechanical and is following some economic rationale. Interviews with DEA agents suggest that one possibility is drug traffickers are attempting to diversify their supply or spread their risk across multiple pharmacies. Given that these pharmacy crackdowns are effective at reducing prescription opioid supply locally, the suspicious behavior detection methods used in this section may be helpful to the DEA in order to minimize displacement.

6 Conclusion

Supply-side interventions are the primary policy tool for curbing drug abuse in the United States. When evaluating the effectiveness of this approach, there are two important demand-

side spillovers to consider, namely substitution to other suppliers and substitution to more harmful substances. Despite the substantial costs associated with drug epidemics, which often originate with legally-produced drugs, we have little sense of the impacts of targeted enforcement in legal drug markets. This is especially relevant because regulation has either fallen short or been subverted, and drug treatment has not been a policy priority.

This paper is one of the first to examine the effectiveness of supply-side crackdowns on individual actors within a market for controlled substances. Exploiting plausibly exogenous variation in the timing and location of controlled substance license audits, I find that cracking down on a single rogue doctor causes large decreases in local opioid dispensing that persist across space and time. This sustained reduction in legal drug supply increases both street pill prices and heroin overdose deaths but decreases net overdose mortality. These results suggest that substitution to heroin is limited to existing heavy users and that targeted enforcement reduces the flow of new addicts. Given that these interventions are effective at reducing local drug supply and provide net reductions in mortality, the policy implication is that complementary demand-side interventions could be employed to minimize substance substitution.

Future research should focus on determining supply-side factors that may have accelerated the opioid epidemic, as changes in demand-side factors alone can only explain a small fraction of the increase in opioid use and deaths over time (Currie and Schwandt, 2021; Cutler and Glaeser, 2021). However, our current public health crisis involving opioids is not unique. The failure to consider the addictive potential of legally-produced drugs is a common theme across domestic drug epidemics since the Civil War (Moore and Pacula, 2020). The findings of this paper suggest that using only supply-side interventions after a certain threshold of community-level addiction is reached can be problematic for certain populations. Moving forward, quantifying the optimal mix of enforcement and treatment is critical for properly addressing drug abuse.

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A Additional Figures and Tables

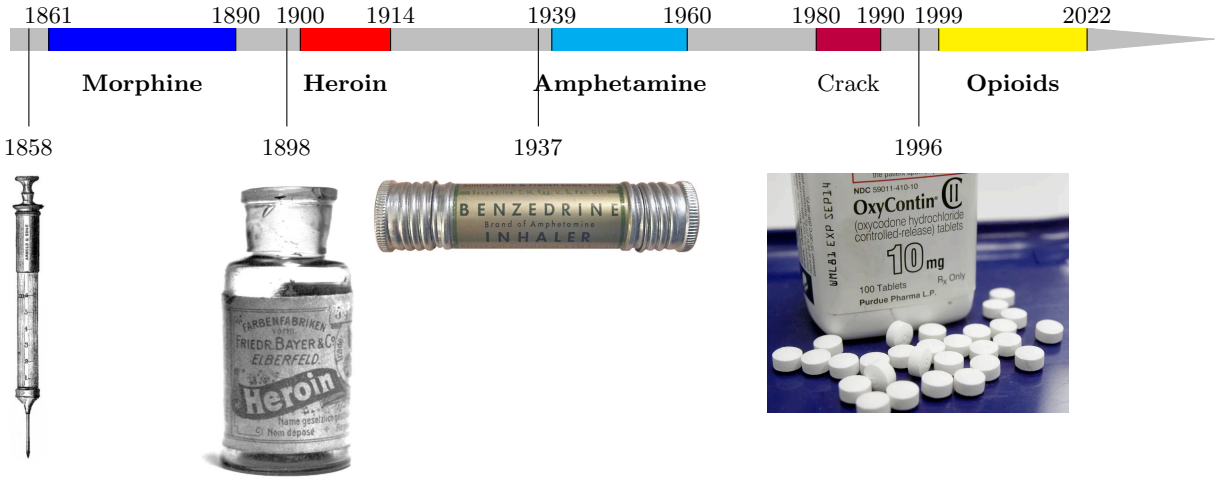


Figure A.1: History of Nationwide Drug Epidemics since the US Civil War

Note: Substances in bold were legally produced at the time.

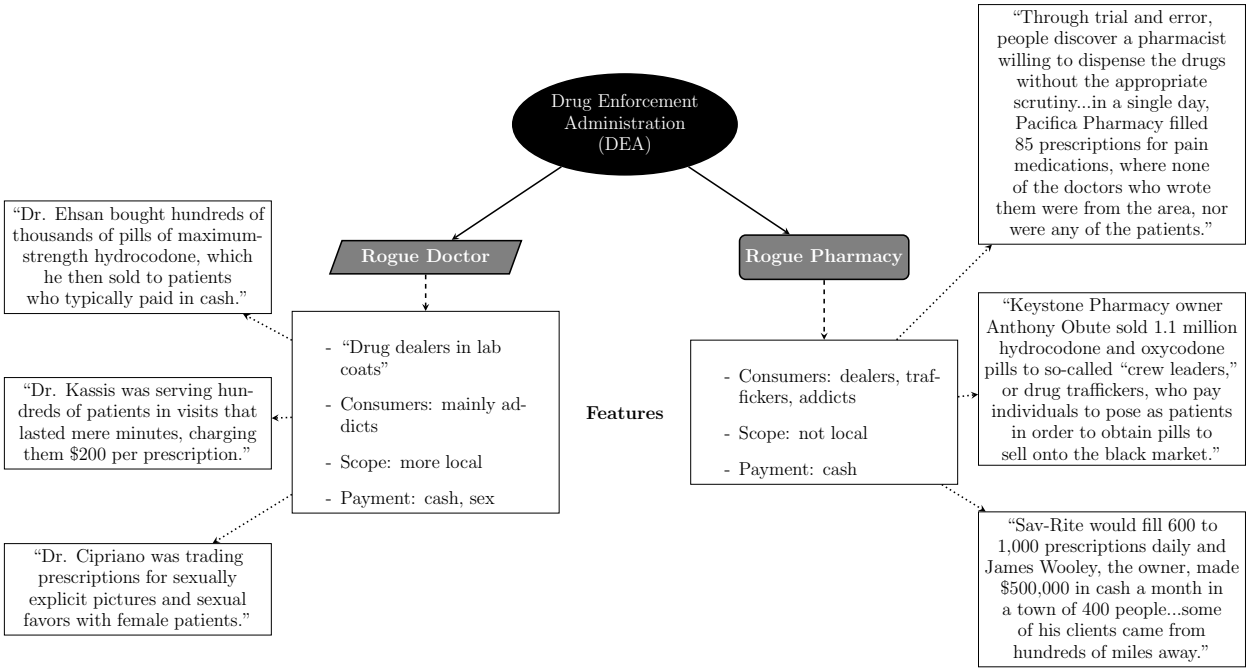


Figure A.2: Excerpts from reports and articles on rogue doctors and pharmacies

Sources: interviews with DEA agents, news media articles, and DEA Diversion Control Division reports

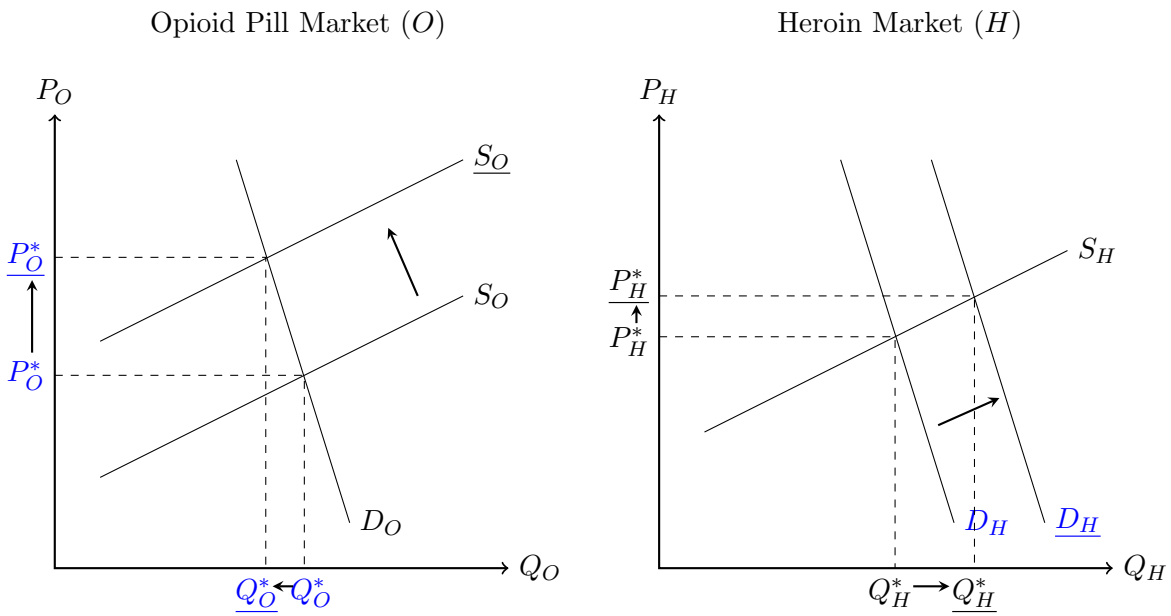


Figure A.3: Supply-Side Drug Policy in the Presence of Substitutes

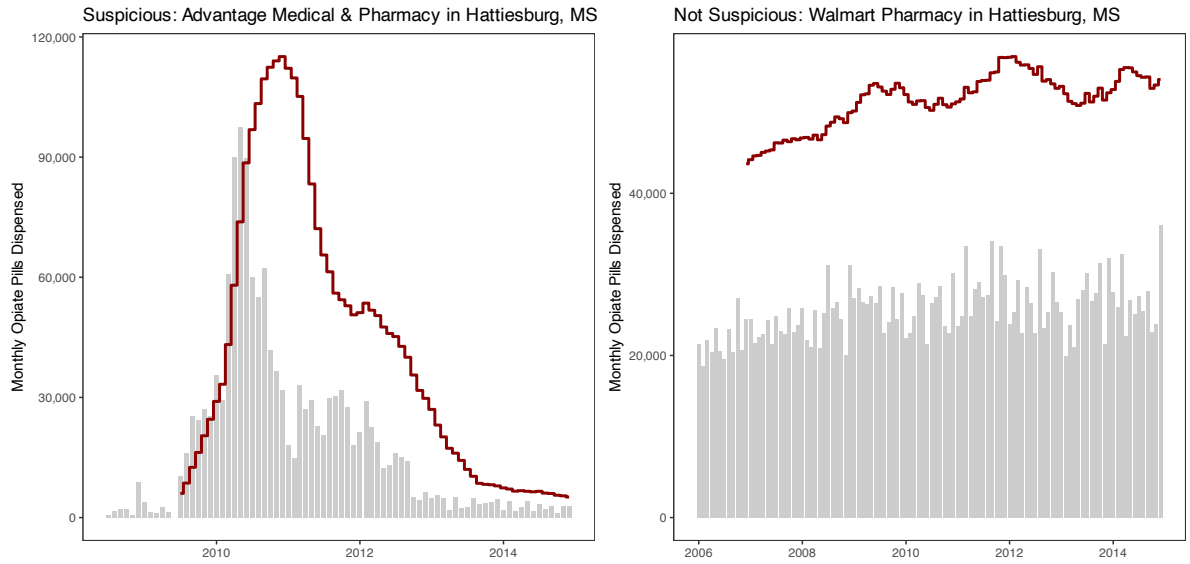


Figure A.4: Examples of Implementing Criteria for Flagging Suspicious Orders

Notes: gray bars show total monthly opioid pill orders and the red line captures the "twice the trailing 12-month average pharmacy dosage units" outlier detection threshold for each pharmacy. The left pharmacy would be flagged as suspicious, as monthly orders during 2009 and 2010 exceed the red line, while the right pharmacy would not be.

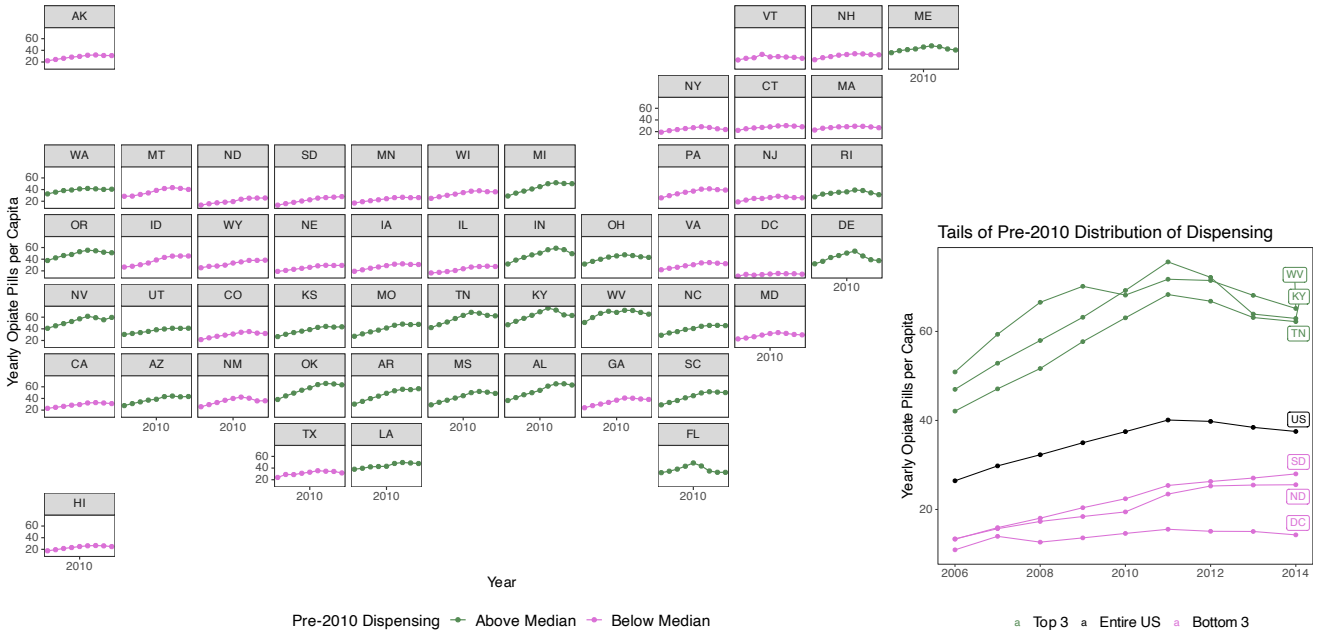


Figure A.5: Yearly per Capita Opioid Dispensing by State (2006 to 2014)

Notes: Per capita opioid dispensing is calculated by dividing the total yearly opioid doses dispensed in a given state by the yearly state population. The states are colored in by whether their pre-2010 average yearly per capita dispensing is above or below the US median. The right panel isolates the top and bottom 3 states. These figures show the significant spatial and temporal variation in a yearly per capita opioid dispensing at the state-level.

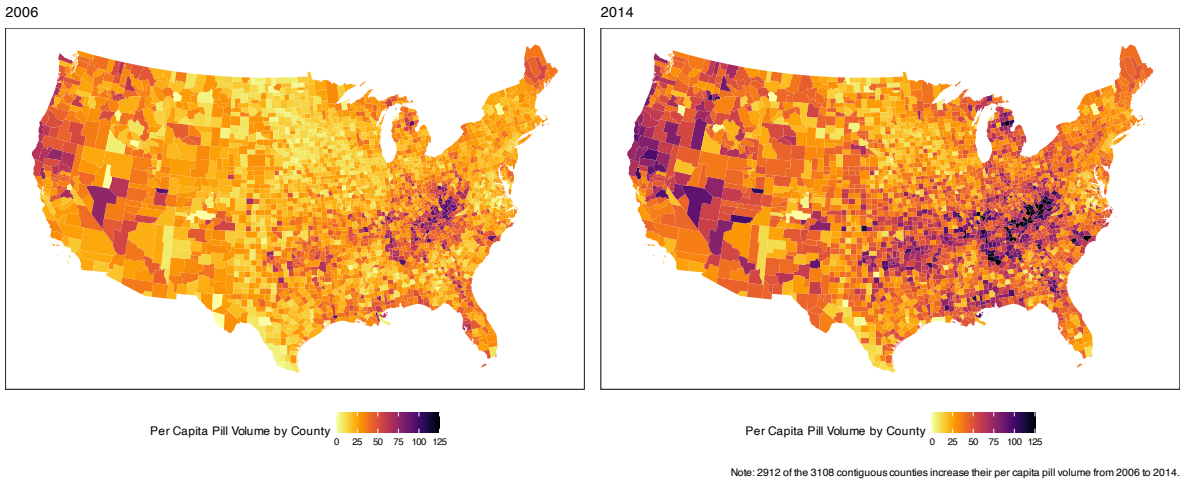


Figure A.6: Variation in per capita pill volume changes by county

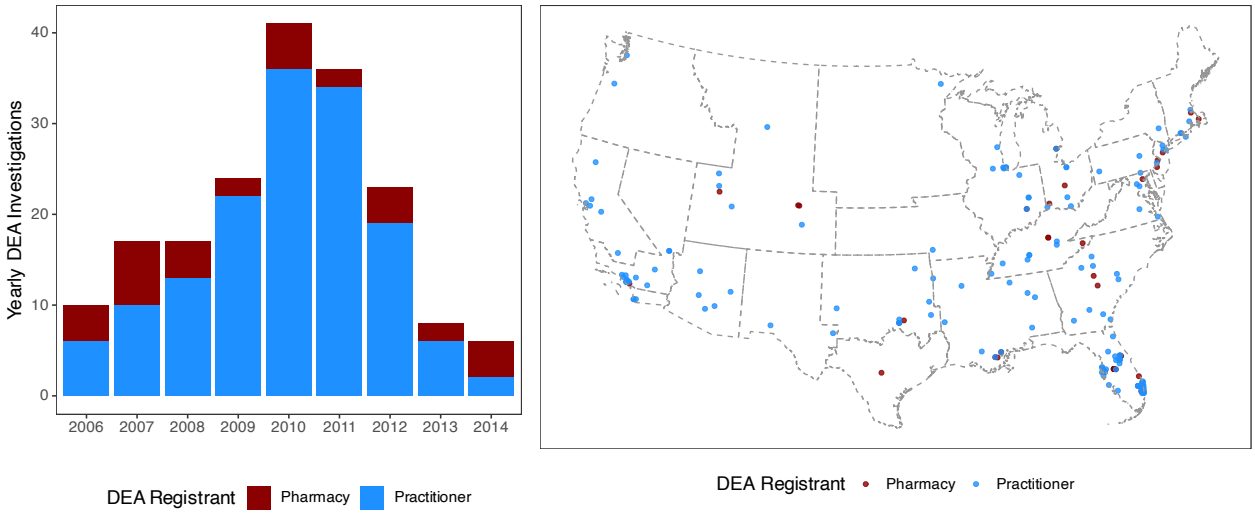


Figure A.7: Yearly DEA Investigations from 2006 until 2014

Notes: The left panel shows the annual violations of the Controlled Substance Act by registrant type. The right panel shows where these violations occur, where dashed grey lines are DEA jurisdiction boundaries.

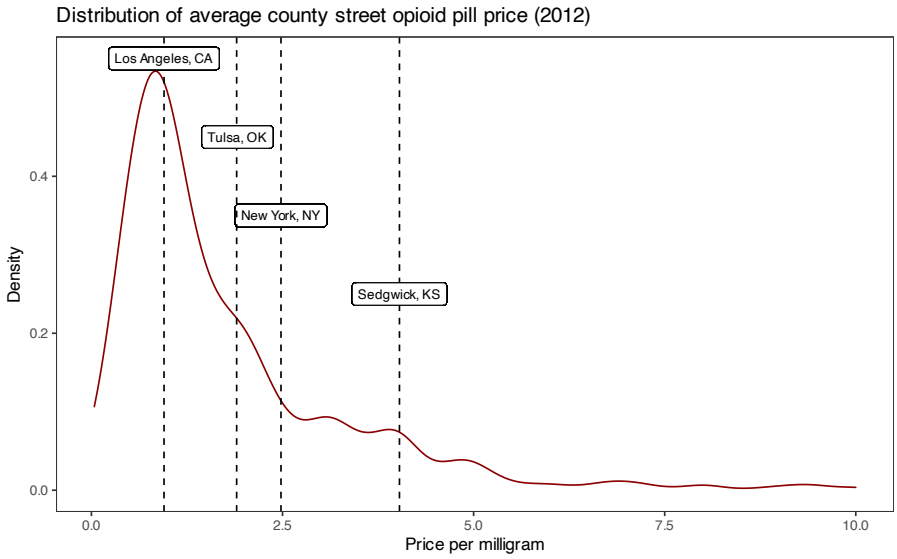


Figure A.8: County-level opioid pill price per milligram

Notes: This figure presents the cross-sectional distribution of street pill price per milligram. Four counties are highlighted to show the significant variation in prices, as generally, the only other available data on illicit drug prices are single yearly nationwide prices for marijuana, cocaine, heroin, and methamphetamine from the Office of National Drug Control Policy.

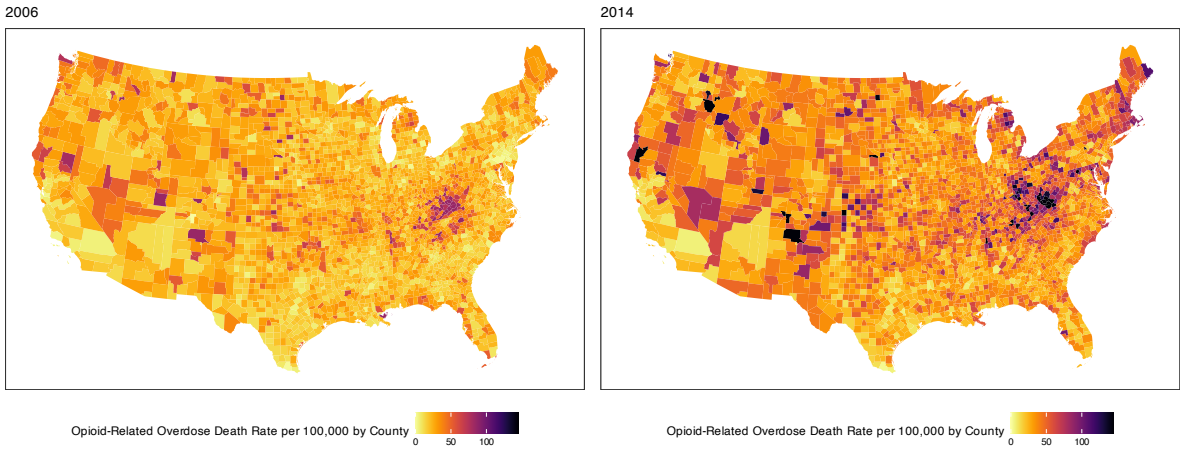


Figure A.9: Variation in the levels and growth of opioid-related death rates by county

Notes: 2628 of the 3108 contiguous counties experience increases in their overdose rate from 2006 to 2014. County rates are calculated by dividing opioid-related overdose deaths from the CDC by population of that year, then scaling by 100,000.

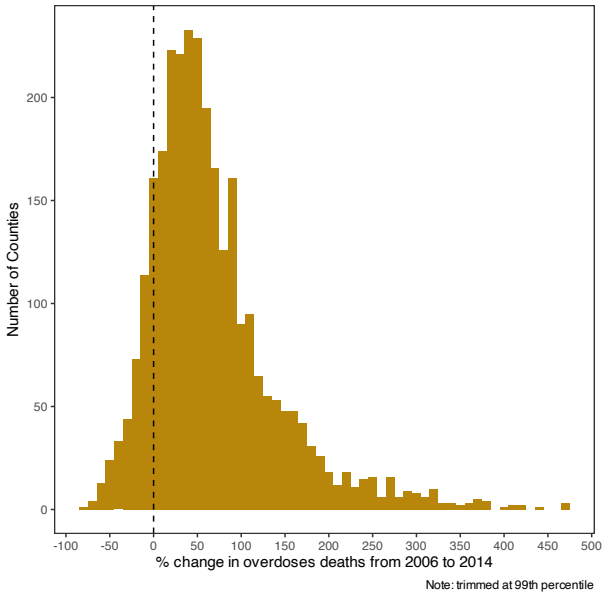


Figure A.10: County-level Variation in Opioid-Related Deaths

Notes: Similar to Griffith et al. (2021), opioid-related deaths were determined using the following ICD-10 codes: T40.0 (Opium), T40.1 (Heroin), T40.2 (Other opioids), T40.3 (Methadone), T40.4 (Other synthetic narcotics), T40.6 (Other and unspecified narcotics), X40-X44 (Accidental poisoning), X60-64 (Intentional self-poisoning), Y10-Y14 (Poisoning) by non-opioid analgesics, antipyretics and antirheumatics; antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified; narcotics and psychodysleptics [hallucinogens], not elsewhere classified; other drugs acting on the autonomic nervous system; other and unspecified drugs, medicaments and biological substances. I also include ICD-10 code X85 (Assault by drugs, medicaments and biological substances).

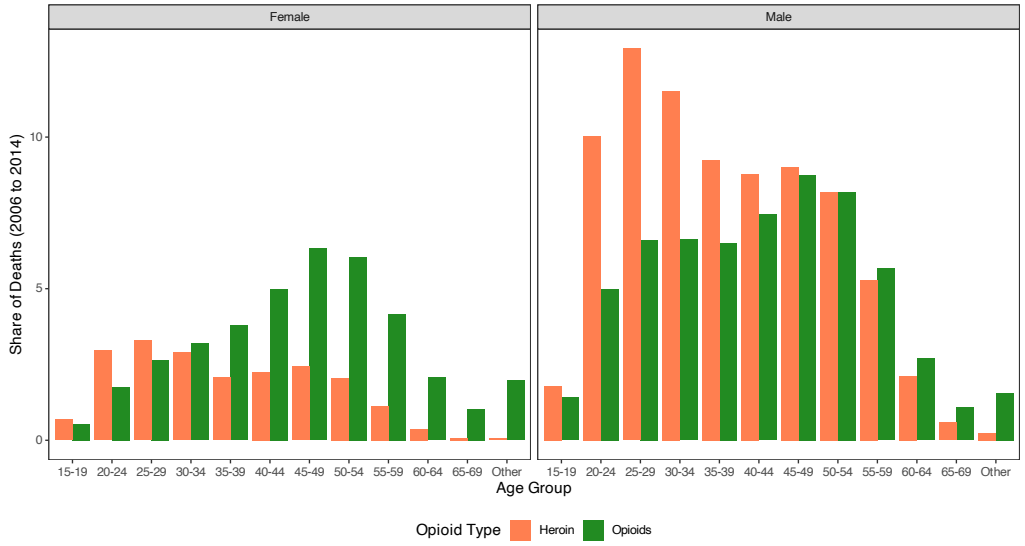


Figure A.11: Differences in age profiles of overdose deaths by opioid type and gender

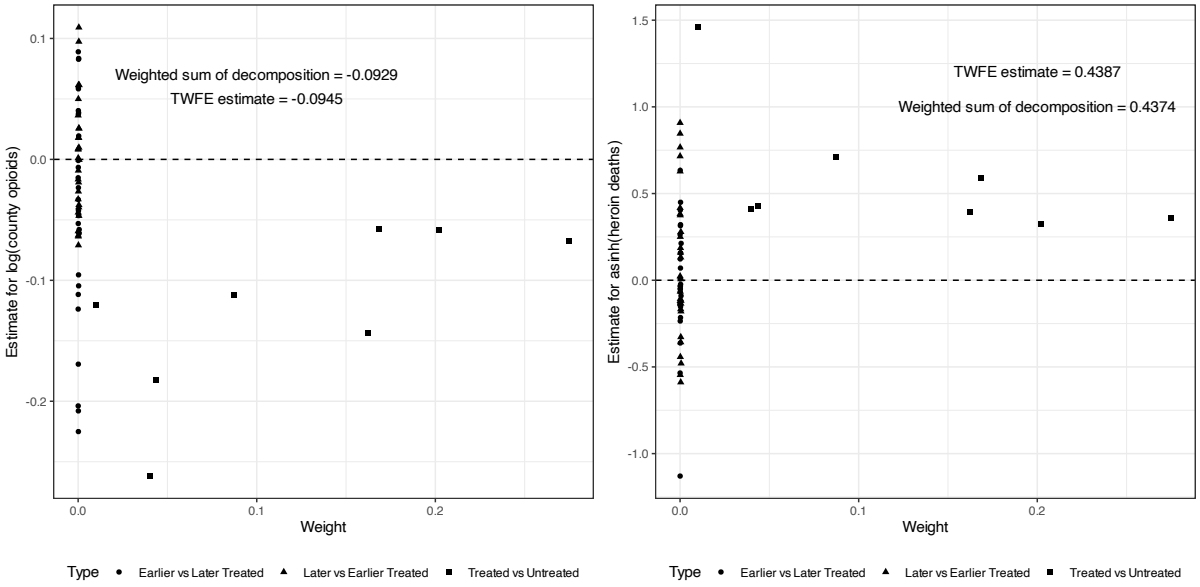
Table A.1: Counties with a Pharmacy Crackdown versus a Doctor Crackdown (2006 to 2014)

	Pharmacy (N=261)		Practitioner (N=837)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
% Medicare	14.2	4.0	16.3	4.1	2.1	0.3
% Black	16.5	16.6	12.4	13.6	-4.1	1.1
Unemployment rate	6.8	2.2	7.6	3.1	0.9	0.2
Doctors per 100K	394.0	267.2	291.7	191.4	-102.3	17.8
Specialists per 100K	127.3	101.0	89.8	67.5	-37.5	6.7
Opioid overdoses	179.4	176.7	162.5	243.3	-17.0	13.8
% Manufacturing	9.6	4.8	10.3	5.5	0.7	0.4
Population density	17.6	25.1	10.7	19.3	-6.9	1.7
Population in 10,000	66.0	58.9	71.5	128.7	5.4	5.8
Pills per capita	37.5	13.4	43.7	20.8	6.2	1.1
Pharmacies	189.3	170.3	205.6	353.9	16.3	16.1

Table A.2: Counties with DEA Crackdown versus those Without (2006 to 2014)

	DEA Action (N=1017)		No Action (N=25766)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
% Medicare	15.9	4.2	19.2	4.6	3.4	0.1
% Black	13.4	14.8	8.1	13.9	-5.3	0.5
Unemployment rate	7.5	3.0	7.1	3.0	-0.4	0.1
Doctors per 100K	316.5	221.4	144.3	167.5	-172.2	7.0
Specialists per 100K	98.8	80.2	34.3	56.4	-64.6	2.5
Opioid overdoses	168.5	236.3	20.8	48.2	-147.7	7.4
% Manufacturing	10.3	5.4	12.7	7.0	2.4	0.2
Population density	12.4	21.8	2.3	17.7	-10.1	0.7
Population in 10,000	69.5	119.2	7.9	19.6	-61.6	3.7
Pills per capita	42.2	20.0	39.5	24.4	-2.6	0.6
Pharmacies	197.0	326.8	24.2	65.7	-172.9	10.3

Panel A: Doctor Crackdowns



Panel B: Pharmacy Crackdowns

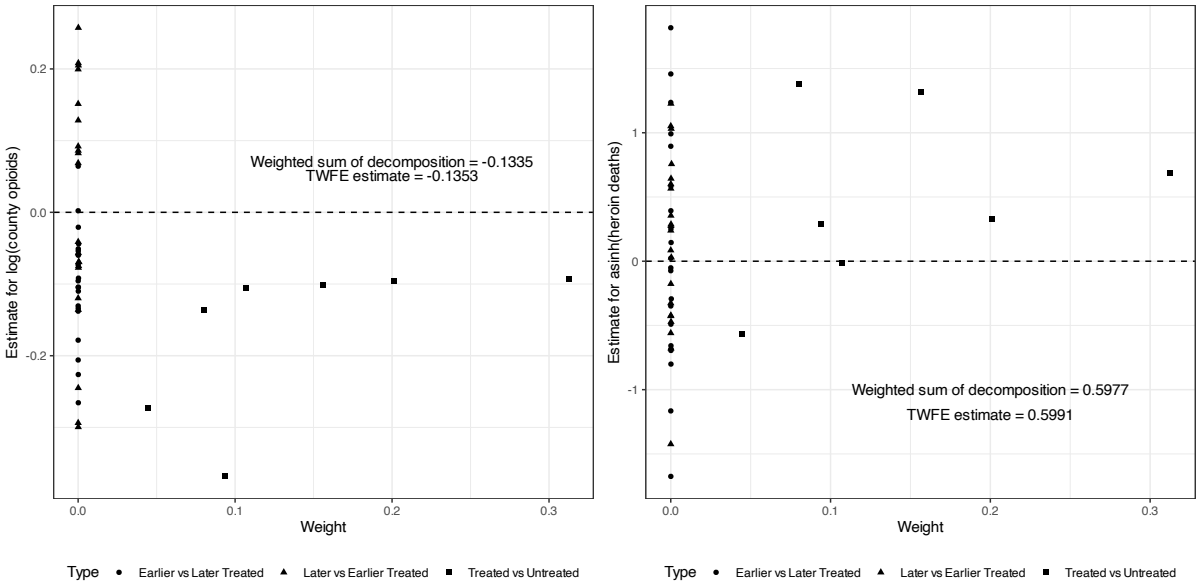


Figure A.12: Bacon Decomposition for the Impacts of Crackdowns

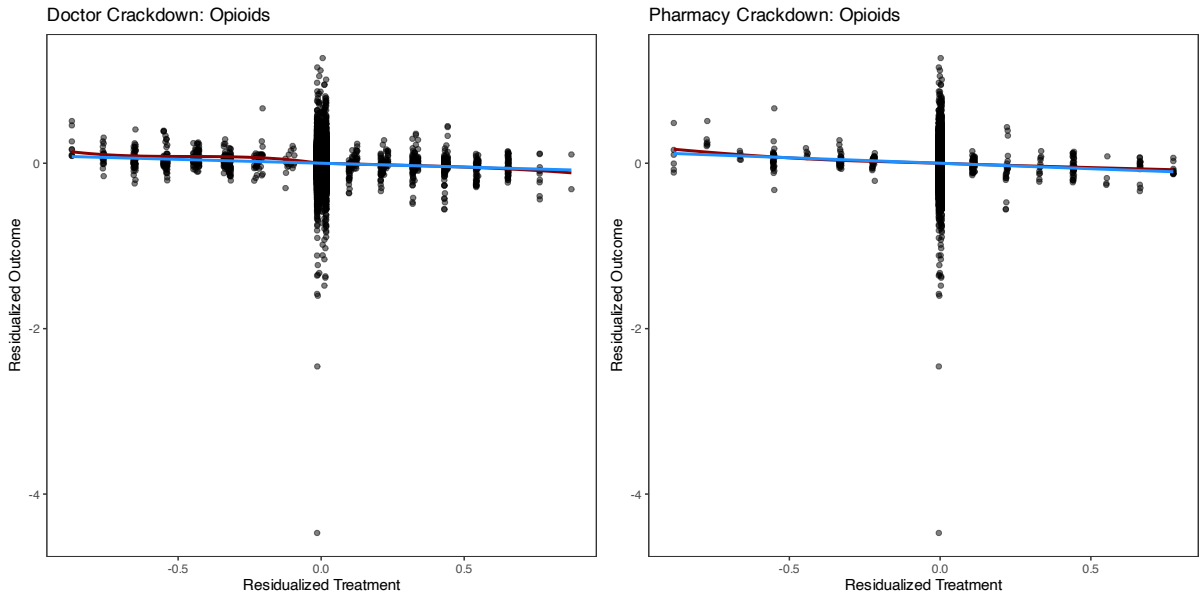


Figure A.13: Test of homogeneity of treatment effects from Jakiela (2021)

Notes: These figures plot the relationship between the residuals from a regression of the log of opioids dispensed on county and year fixed effects and the residuals from a regression of treatment on county and year fixed effects. If treatment effects are homogeneous, the relationship is linear. The line of best fit (loess) is in red and the best linear fit is in blue. The left panel is for doctor crackdowns and the right is for pharmacy ones, where the outcome is the log of county opioids dispensed.

Table A.3: Counties with a Crackdown versus Above Average Suspicious (2006 to 2014)

	Above Average (N=5310)		DEA Action (N=1017)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
% Medicare	17.9	4.4	15.9	4.2	-2.1	0.1
% Black	10.4	14.8	13.4	14.8	3.0	0.5
Unemployment rate	7.2	2.9	7.5	3.0	0.3	0.1
Doctors per 100K	193.1	194.7	316.5	221.4	123.3	7.4
Specialists per 100K	52.6	66.4	98.8	80.2	46.2	2.7
Opioid overdoses	37.2	73.6	168.5	236.3	131.3	7.5
% Manufacturing	12.6	6.5	10.3	5.4	-2.3	0.2
Population density	6.1	36.0	12.4	21.8	6.3	0.8
Population in 10,000	15.8	31.9	69.5	119.2	53.7	3.8
Pills per capita	40.8	24.1	42.2	20.0	1.3	0.7

Table A.4: Testing of implication of identifying assumption at the county-level

	Early DEA Action (Dummy Variable)	
	Doctors	Pharmacies
	(1)	(2)
log(opioids in previous year)	−0.105	−0.133
	(0.131)	(0.243)
log(overdoses in previous year)	0.200	−0.103
	(0.134)	(0.209)
Rural	−0.007	0.039
	(0.056)	(0.132)
Doctors per 100,000	0.059	0.102
	(0.070)	(0.206)
Population Density	0.034	−0.016
	(0.060)	(0.198)
Percent Manufacturing	0.068	−0.155
	(0.060)	(0.131)
Mental health clinics per 100,000	0.002	0.075
	(0.058)	(0.127)
log(median income)	0.023	−0.038
	(0.063)	(0.116)
Joint F-stat	1.168	1.266
Observations	93	29
R^2	0.100	0.336
Note:	All covariates z-score transformed	

Table A.5: Testing implication of identifying assumption at the city-level

	Date of DEA action	
	Doctors	Pharmacies
	(1)	(2)
log(city opioids)	0.054	0.121
	(0.089)	(0.124)
Observations	1,120	346
R^2	0.941	0.967
Notes:	*p<0.1; **p<0.05; ***p<0.01	
	Year FEs included in both specifications	
	Sample limited to year before treatment	
	Outcome is continuous variable (0 to 108)	

Table A.6: Impacts of Rogue Doctor Crackdowns on Dispensing, Street Prices, and Substitution

Parameter	Event	Opioids Dispensed	Pill Price	Heroin Deaths
Overall ATT	Post-DEA Action	-0.111	0.385	0.46
		(0.02)	(0.095)	(0.099)
Control Mean		3.218	1.441	1.386
Observations		26765	5057	26765

Notes:
Outcomes: County-Year and Log Transformed
Estimation Method: Doubly Robust, Callaway and Sant'Anna (2021)
Control Group: Not Yet Treated Counties, Anticipation Periods: 0
Standard Errors: Clustered at County and Computed using Multiplier Bootstrap

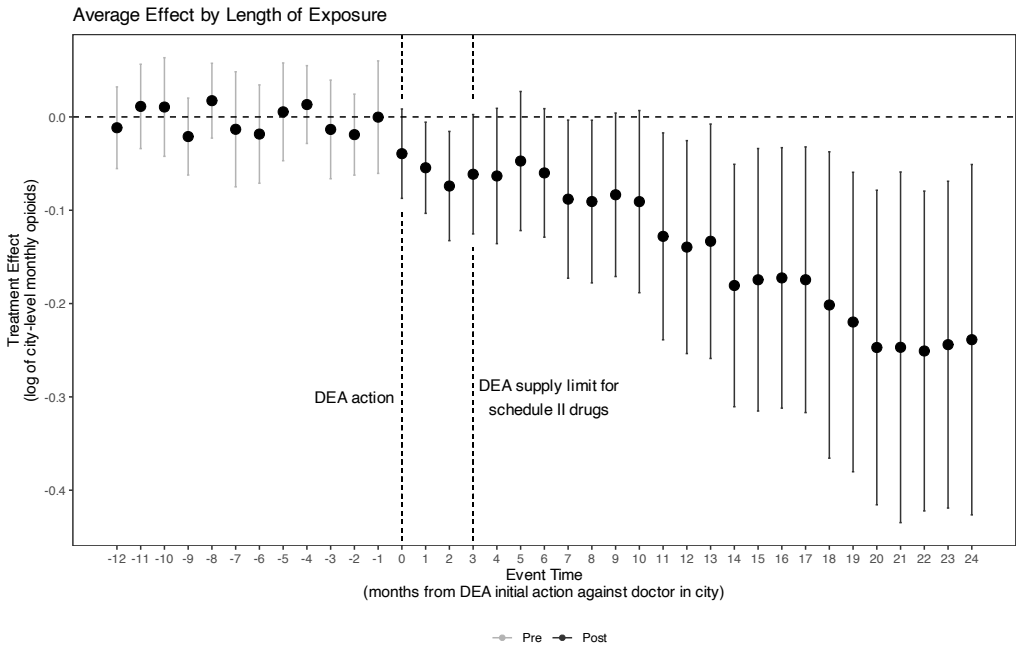


Figure A.14: City-Level Impact of a DEA Action against a Doctor

Notes: The outcome is the logarithm of monthly city-level opioids, where the treatment is the DEA action against taken against a doctor. The sample is limited to cities that had a doctor with a DEA registration revoked, and the control group are the not yet treated cities. Figure 3 instead uses never treated cities. Standard errors are clustered at the city-level and computed using a multiplier bootstrap, and the estimation method is doubly robust from Callaway and Sant'Anna (2021). The first dotted line captures the treatment date, while the second one captures the 90-day supply limit that the DEA places on any controlled substance prescription. Any prescriptions after the 90-day limit should not be attributable to the sanctioned doctor.

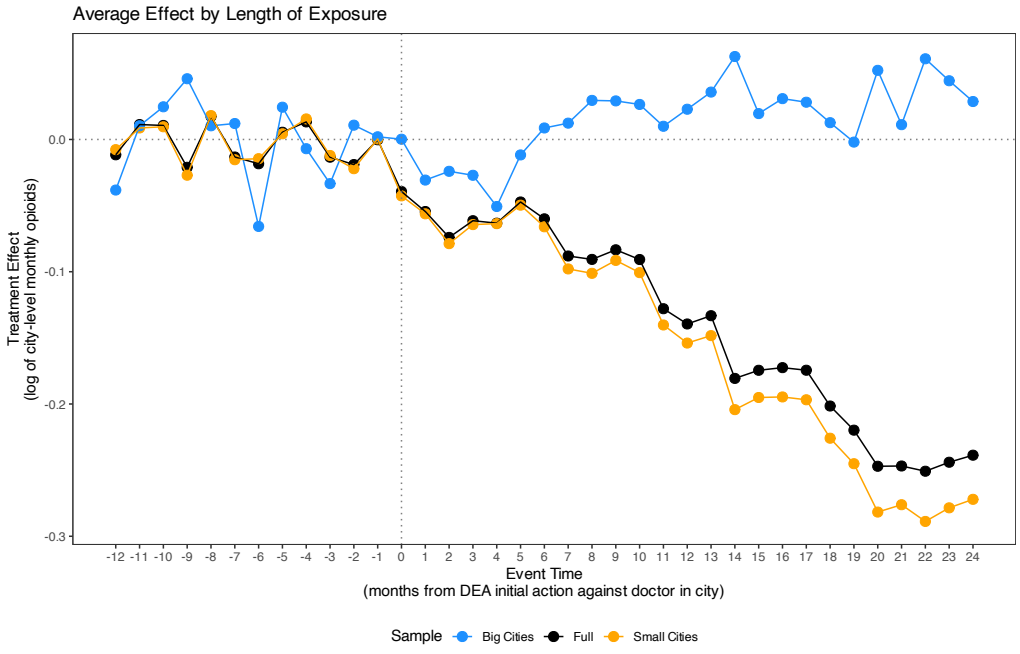


Figure A.15: City-Level Impact of DEA Action against a Doctor

Notes: The outcome is the logarithm of monthly city-level opioids, where the treatment is the DEA action against taken against doctor. The control group consists of the not yet treated cities. Large cities are those in the top 25% of the distribution of city population, but I vary this threshold and the results are not sensitive. I remove standard errors to highlight the trends, given the relatively small sample size in each group, but standard errors are clustered at the city-level and computed using a multiplier bootstrap; the estimation method is doubly robust.

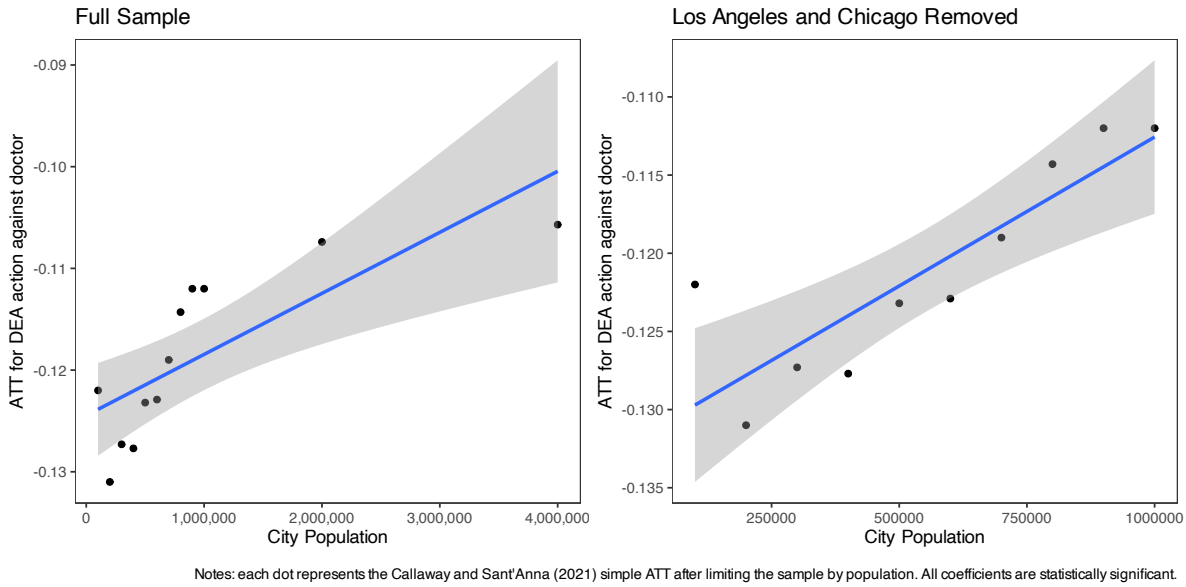


Figure A.16: Decline in Dispensing after Doctor Crackdown is Greater for Smaller Cities

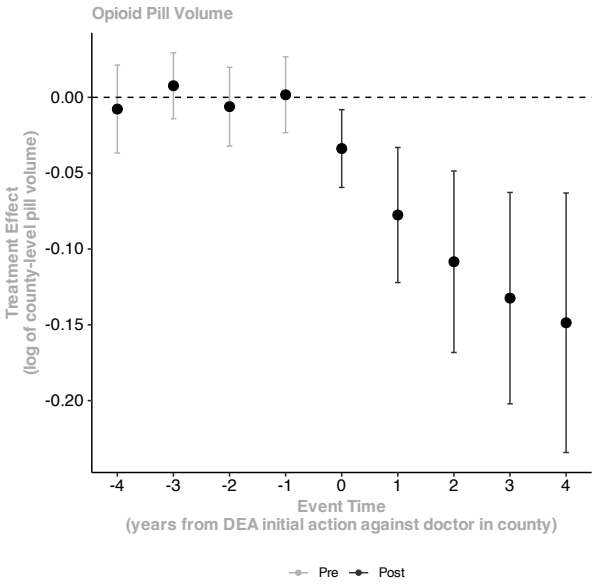


Figure A.17: The Impact of Doctor Crackdowns on County-Year Opioid Dispensing

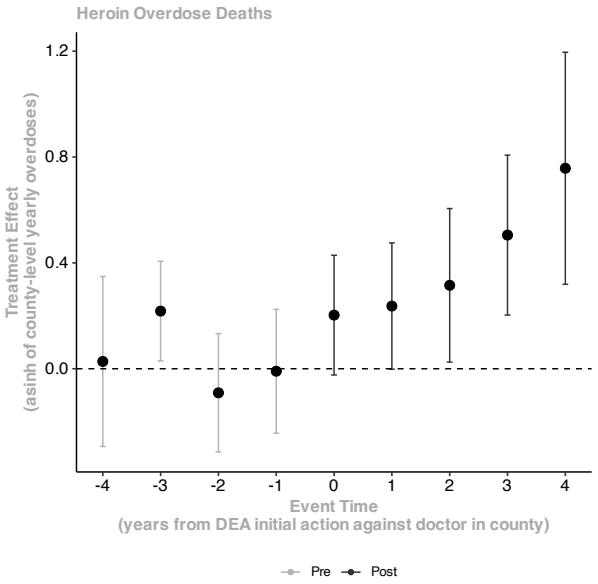


Figure A.18: The Impact of Doctor Crackdowns on Overdose Deaths

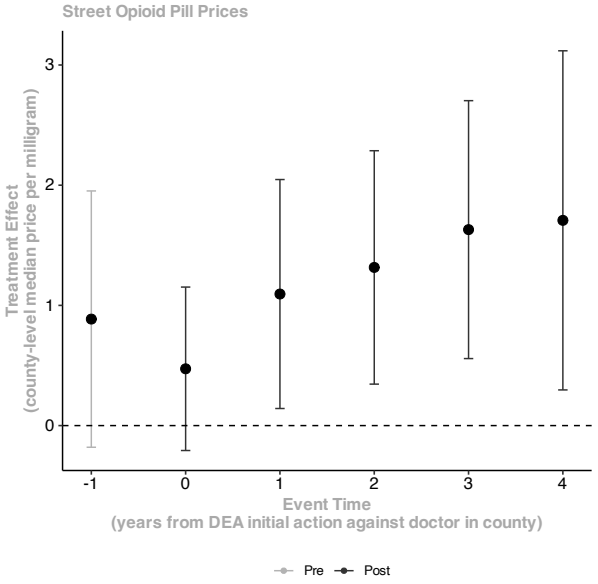


Figure A.19: The Impact of Doctor Crackdowns on Prices

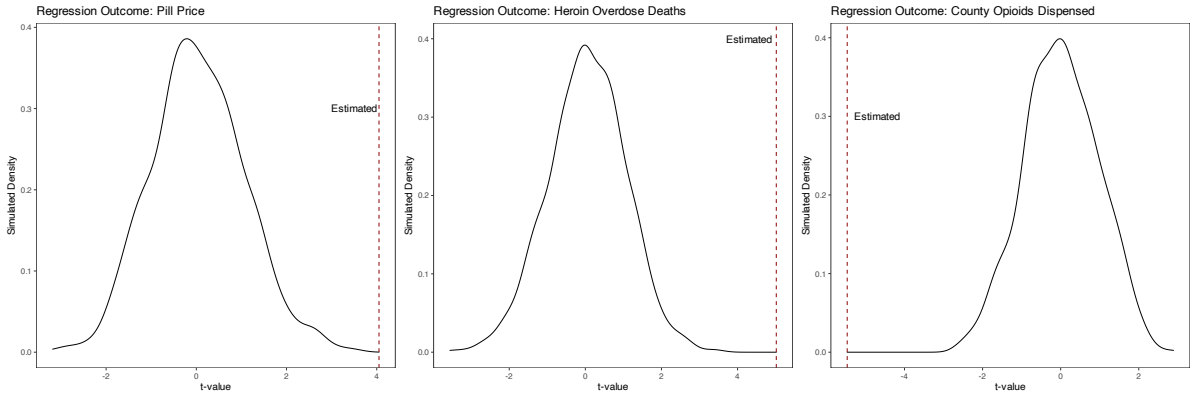


Figure A.20: Permutation Test for Impacts of Doctor Crackdowns (t-statistics)

Notes: I first randomize which unit gets treated, then conditional on receiving treatment, I randomize what year they are treated. I run equation (1) 1000 times using this new sample, where the figures are the distribution of the t-statistics obtained from these regressions. Randomizing treatment dates across only treated units produces similar results.

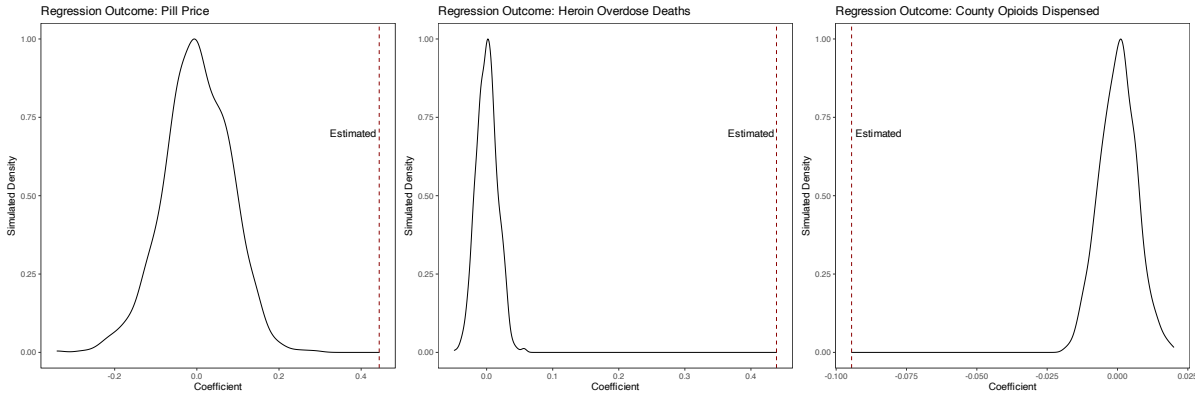


Figure A.21: Permutation Test for Impacts of Doctor Crackdowns (coefficients)

Notes: I first randomize which unit gets treated, then conditional on receiving treatment, I randomize what year they are treated. I run equation (1) 1000 times using this new sample, where the figures are the distribution of the coefficients obtained from these regressions. Randomizing treatment dates across only treated units produces similar results.

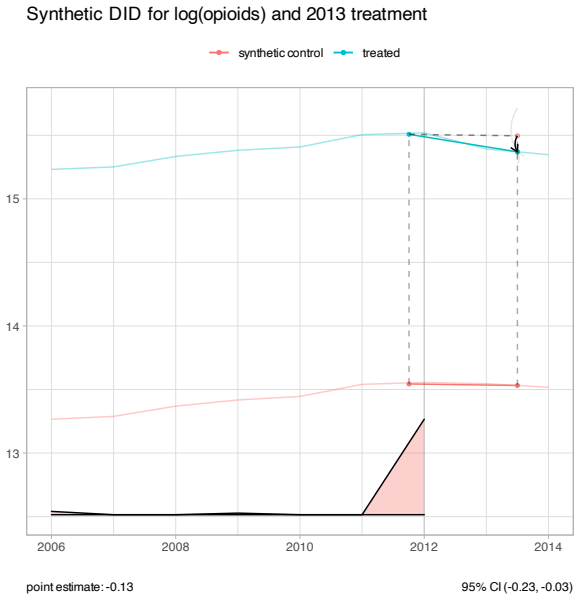
Table A.7: The Impacts of Rogue Doctor Crackdowns on Opioid Overdoses and Dispensing

	Heroin	Opioids	Heroin	Opioids	Heroin	Opioids
	Ever Suspicious		Above Mean Suspicious		Above 90th	per Capita
	(1)	(2)	(3)	(4)	(5)	(6)
Post-DEA Action	0.432^{***}	-0.085^{***}	0.291^{**}	-0.085^{***}	0.290	-0.157^{***}
	(0.093)	(0.018)	(0.127)	(0.023)	(0.234)	(0.047)
Control Mean	11.47	242.073	11.398	255.192	5.36	185.296
Observations	17,994	17,994	5,811	5,811	3,286	3,286
R^2	0.808	0.993	0.874	0.997	0.847	0.993

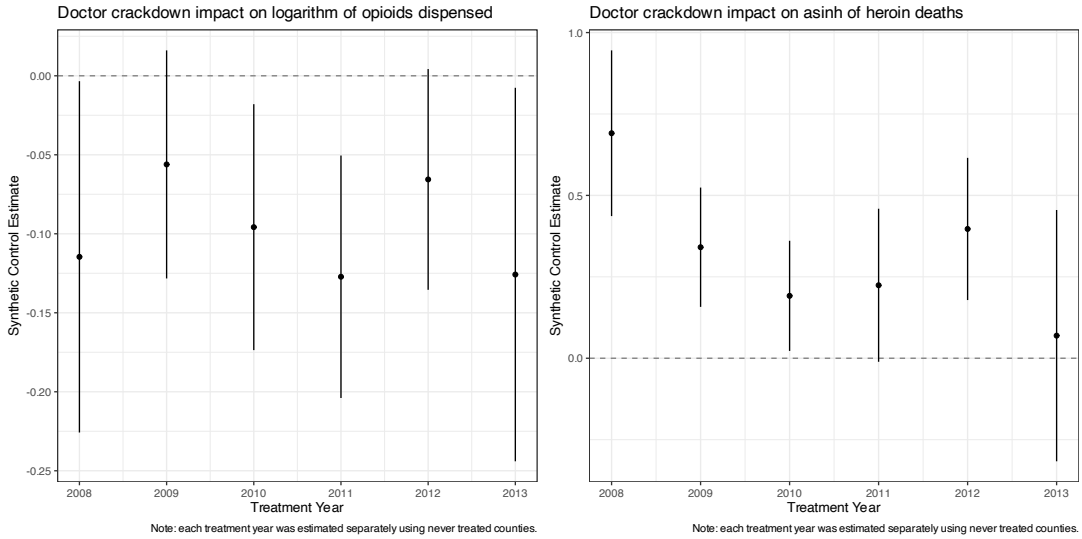
Notes: *p<0.1; **p<0.05; ***p<0.01
Outcomes are county-year and log transformed
County and year fixed effects included in all specifications
Standard errors are clustered at the county level

Figure A.22: Synthetic DID Method for Impacts of Doctor Crackdowns

Panel A: Parallel Trends and Estimated Effect for 2013 Treatment (Example)



Panel B: The Impacts of Crackdowns on Opioid Street Prices, Overdoses, and Dispensing



Notes: Panel A shows an example of what parallel trends look like, as I estimate the synthetic control DID method separately for each treatment year. I do this because the method is for a single treatment date and it is unclear how to aggregate/ weight the coefficients from different treatment years. Standard errors were calculated using the placebo method suggested in Arkhangelsky et al. (2021). Panel B shows the impacts of crackdowns for each treatment year starting in 2008.

Table A.8: The Impacts of Rogue Doctor Crackdowns on Opioid Dispensing and Overdoses

Parameter	Event	County Opioids	Heroin Deaths
Synthetic DID Estimate	Post-DEA Action	-0.0975	0.319
		(0.0419)	(0.1317)

Estimation Method: Arkhangelsky et al. (2021)

Table A.9: Impacts of Rogue Doctor Crackdowns on All Cause Mortality by Age and Gender

	Males (15-29)	Males (30-49)	Females (15-29)	Females (30-49)	All (10-65)	Elderly (85+)
	(1)	(2)	(3)	(4)	(5)	(6)
Post-DEA Action	-1.210^{***}	-4.130^{***}	-0.309^{**}	-1.557^{***}	-6.023^{***}	-0.009
	(0.292)	(0.625)	(0.145)	(0.429)	(2.142)	(0.028)
Control Mean	4.906	14.162	1.88	8.715	81.098	86.651
Observations	26,765	26,765	26,765	26,765	26,765	26,765
R^2	0.584	0.753	0.436	0.706	0.875	0.910

Notes: *p<0.1; **p<0.05; ***p<0.01
County and year fixed effects included in all specifications
Standard errors are clustered at the county level
Outcomes are in rates per 100,000

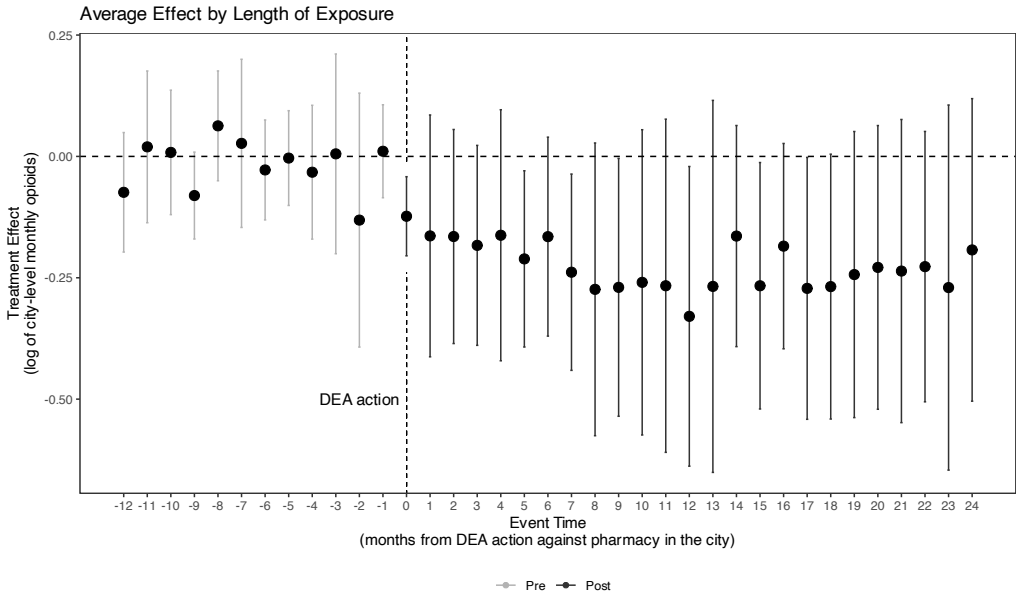


Figure A.23: City-Level Impacts of DEA Action against a Pharmacy

Notes: The outcome is the logarithm of monthly city-level opioids, where the treatment is the DEA action against taken against pharmacy. The sample is limited to cities that had a pharmacy with a DEA registration revoked, and the control group are the not yet treated cities. Standard errors are clustered at the city-level and computed using a multiplier bootstrap, and the estimation method is doubly robust from Callaway and Sant'Anna (2021).

Table A.10: Impacts of Rogue Pharmacy Crackdowns on Dispensing and Mortality

	Opioids Dispensed	Heroin Deaths	Opioid Deaths
	(1)	(2)	(3)
Post-DEA Action	-0.135^{***}	0.599^{***}	-0.039
	(0.034)	(0.168)	(0.048)
Control Mean	3.544	1.519	12.32
Observations	26,765	26,765	26,765
R^2	0.990	0.799	0.888

Notes: *p<0.1; **p<0.05; ***p<0.01
County and year FEs included in all specifications
Standard errors are clustered at the county level
Outcomes are county-year and log transformed

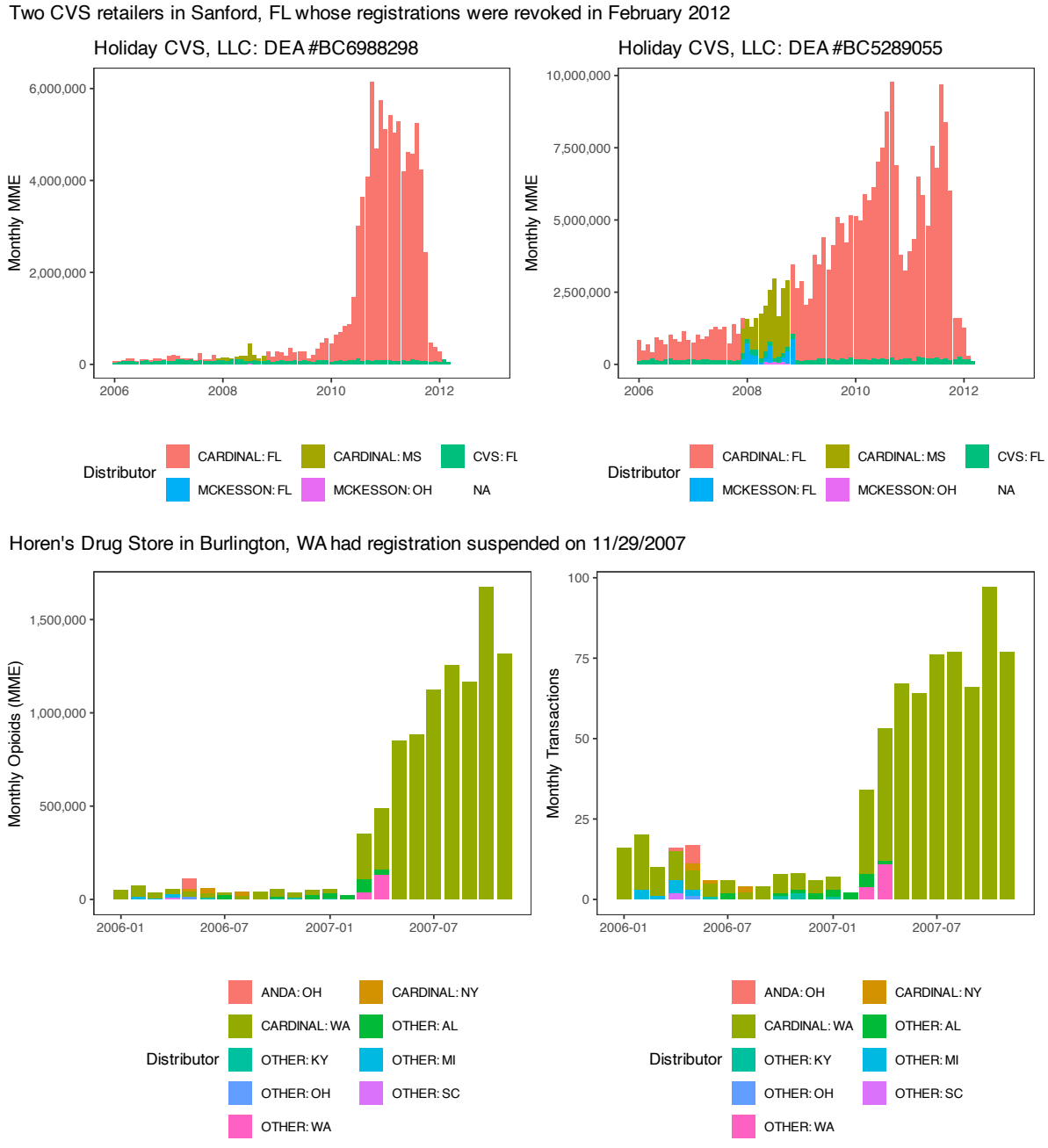


Figure A.24: Examples of Sanctioned Pharmacies

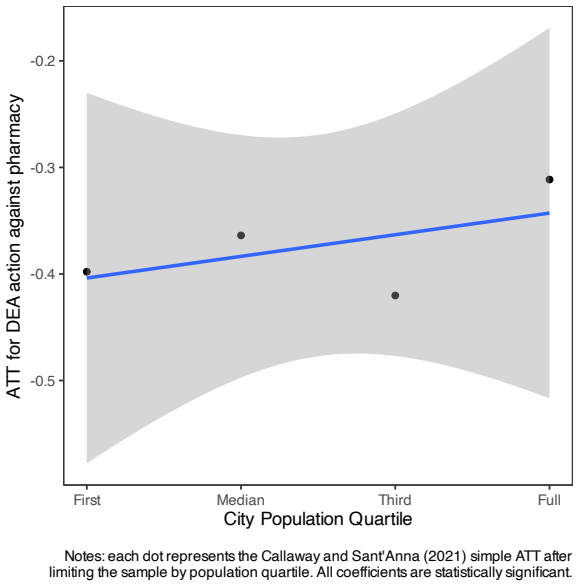


Figure A.25: Decline in Dispensing after Doctor Crackdown is Greater for Smaller Cities

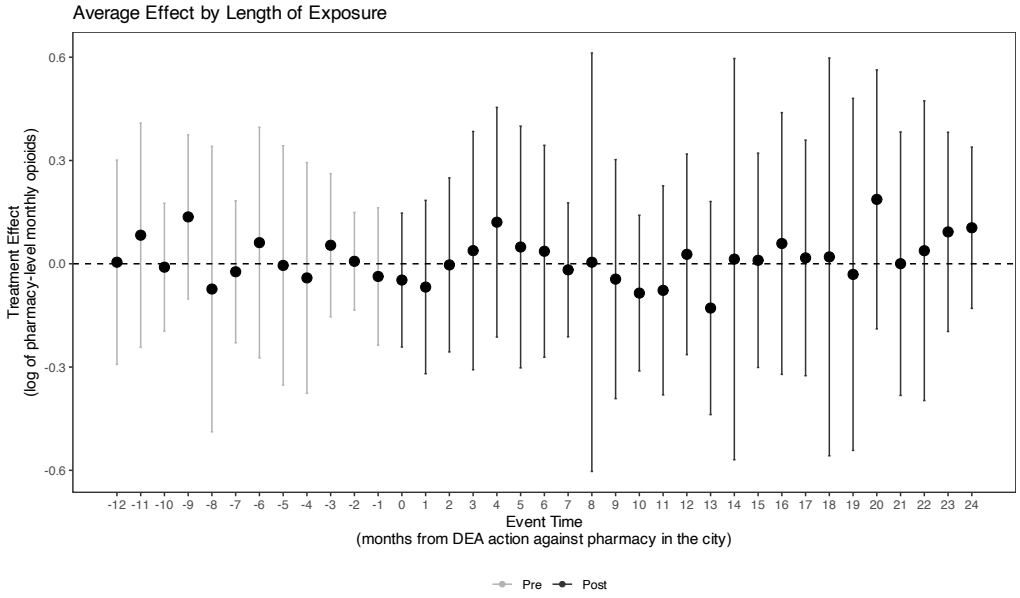


Figure A.26: Pharmacy-Level Impacts of DEA Action against a Pharmacy

Notes: The outcome is the logarithm of monthly pharmacy-level opioids, where the treatment is the DEA action against taken against pharmacy. The sample is limited to pharmacies in cities that had a pharmacy with a DEA registration revoked, and I remove the pharmacies that were sanctioned. The control group consists of the not yet treated pharmacies. Standard errors are clustered at the city-level and computed using a multiplier bootstrap, and the estimation method is doubly robust.

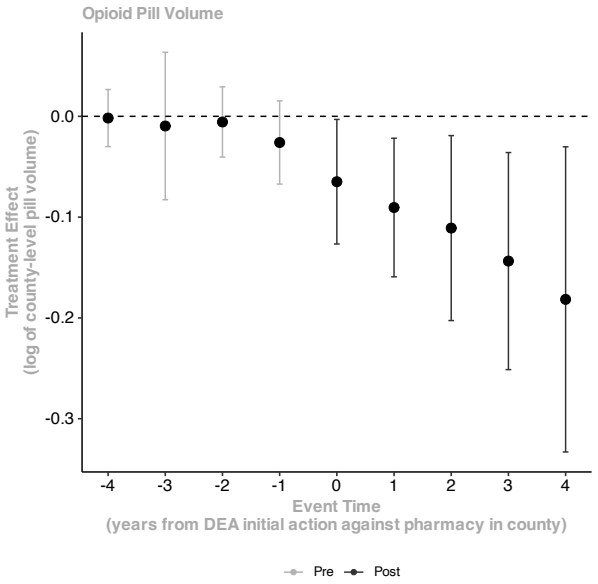


Figure A.27: The Impact of Pharmacy Crackdowns on County-Year Dispensing

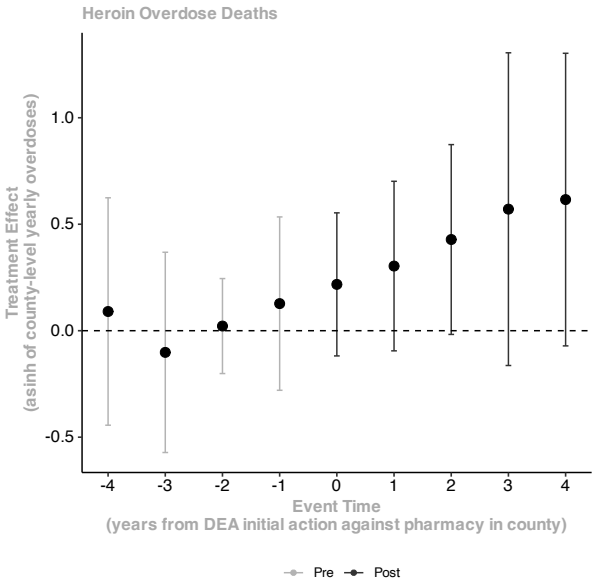


Figure A.28: The Impact of Pharmacy Crackdowns on Overdose Deaths

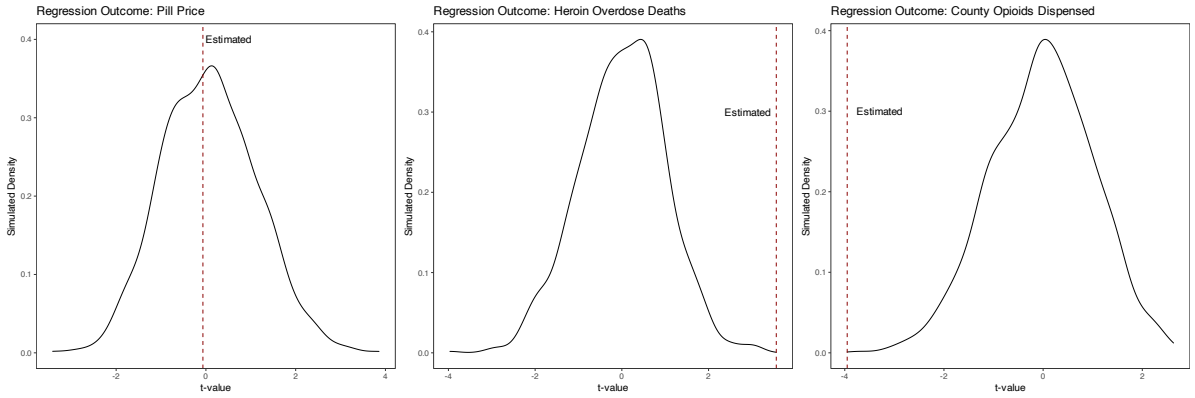


Figure A.29: Permutation Test for Impacts of Pharmacy Crackdowns (t-statistics)

Notes: I first randomize which county gets treated, then I randomize what date they are treated. I then rerun equation (1) 1000 times, where these figures are the distribution of the t-statistics obtained from these regressions. Randomizing treatment dates across only treated units produces similar results.

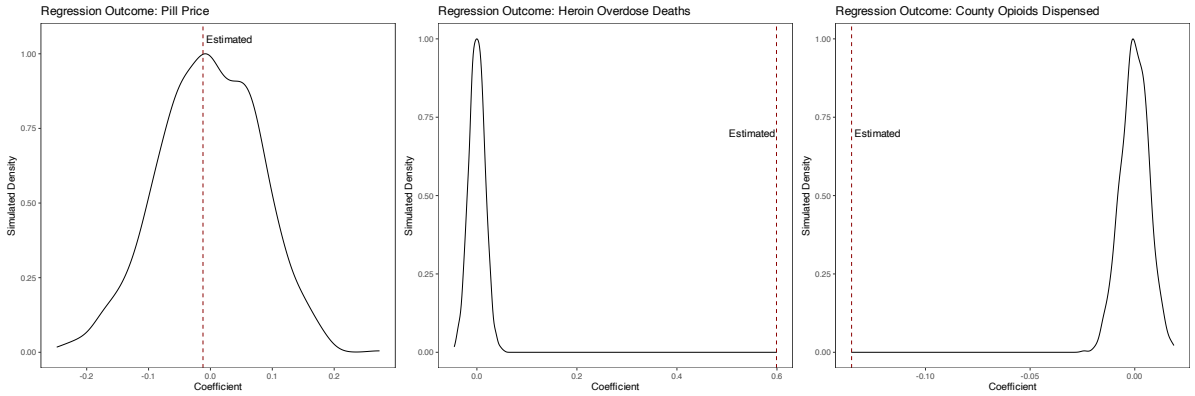


Figure A.30: Permutation Test for Impacts of Pharmacy Crackdowns (coefficients)

Notes: I first randomize which unit gets treated, then I randomize what date they are treated. I then rerun equation (1) 1000 times, where these figures are the distribution of the coefficients obtained from these regressions. Randomizing treatment dates across only treated units produces similar results.

Table A.11: Impacts of Rogue Pharmacy Crackdowns on All Cause Mortality by Age and Gender

	Males (15-29)	Males (30-49)	Females (15-29)	Females (30-49)	All (10-65)
	(1)	(2)	(3)	(4)	(5)
Post-DEA Action	-1.892^{***}	-4.225^{***}	-0.101	-1.854^{***}	-7.936^{*}
	(0.658)	(1.324)	(0.174)	(0.603)	(4.127)
Control Mean	5.019	14.321	1.902	8.818	82.26
Observations	26,765	26,765	26,765	26,765	26,765
R^2	0.584	0.753	0.436	0.706	0.875

Notes: *p<0.1; **p<0.05; ***p<0.01
County and year fixed effects included in all specifications
Standard errors are clustered at the county level
Outcomes are in rates per 100,000

Table A.12: The Impacts of Rogue Pharmacy Crackdowns on Opioid Overdoses and Dispensing

	Heroin Ever Suspicious	Opioids Ever Suspicious	Heroin Above Mean Suspicious	Opioids Above Mean Suspicious	Heroin Above 90th per Capita	Opioids Above 90th per Capita
	(1)	(2)	(3)	(4)	(5)	(6)
Post-DEA Action	0.538^{***}	-0.141^{***}	0.369	-0.108^{***}	0.786	-0.408^{***}
	(0.176)	(0.036)	(0.229)	(0.039)	(0.486)	(0.157)
Treated Mean	19.743	231.521	20.863	239.622	21.811	220.172
Observations	18,413	18,413	5,840	5,840	3,008	3,008
R^2	0.810	0.993	0.872	0.997	0.834	0.991

Notes: *p<0.1; **p<0.05; ***p<0.01
Outcomes are county-year and log transformed
County and year fixed effects included in all specifications
Standard errors are clustered at the county level

Table A.13: The Impacts of Rogue Pharmacy Crackdowns on Opioid Dispensing and Overdoses

Parameter	Event	County Opioids	Heroin Deaths
Synthetic DID Estimate	Post-DEA Action	-0.1724	0.2283
		(0.1027)	(0.2446)

Estimation Method: Arkhangelsky et al. (2021)

Table A.14: Impacts of Rogue Pharmacy Crackdowns on Dispensing, Street Prices, and Mortality

	Opioids Dispensed	Pill Price	Heroin Deaths
	(1)	(2)	(3)
Post-DEA Action	−0.053	−0.348	0.337^{**}
	(0.043)	(0.271)	(0.150)
(Post-DEA Action)X(2nd Wave)	-0.101^{**}	0.336^{*}	0.322^{***}
	(0.048)	(0.204)	(0.115)
Control Mean	35.27	1.441	1.499
Observations	26,765	5,057	26,765
R^2	0.990	0.430	0.799

Notes: *p<0.1; **p<0.05; ***p<0.01
County and year FEs included in all specifications
Standard errors are clustered at the county level
Outcomes are county-year and log transformed

Table A.15: The Impacts of Highway Access on Opioid Overdoses (Pharmacy Crackdowns)

	asinh(Heroin Overdose Deaths)	
	(1)	(2)
Post-DEA Action	0.506**	0.825***
	(0.249)	(0.253)
(Post-DEA Action)X(Within 2 miles)	0.215	
	(0.318)	
(Post-DEA Action)X(asinhmiles)		−0.192*
		(0.108)
Observations	26,765	26,765
R^2	0.799	0.800
Notes:	*p<0.1; **p<0.05; ***p<0.01	
	County and year FEs included	
	Standard errors clustered at county level	

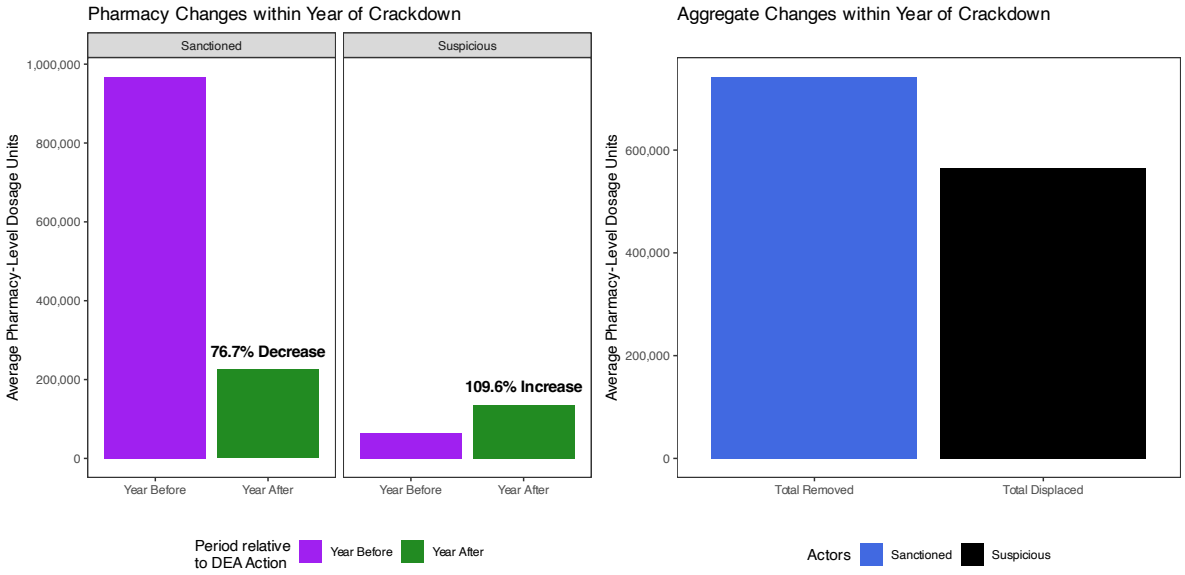


Figure A.31: Displacement following a Pharmacy Crackdown

Notes: The left panel shows the average change in pharmacy-level dispensing one year before and after a pharmacy crackdown for both the average sanctioned pharmacy and the average newly suspicious pharmacy. The right panel multiplies the average increase from a newly suspicious pharmacy by the average number of newly suspicious pharmacies.

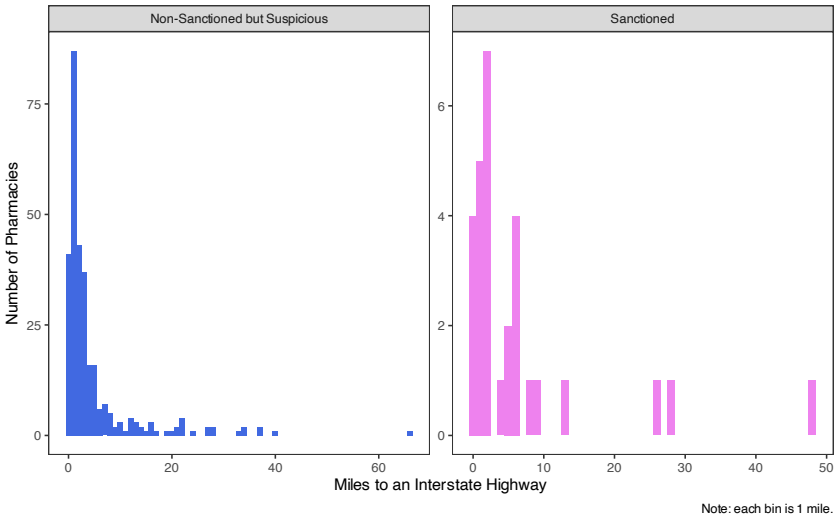


Figure A.32: Distance to the nearest interstate highway

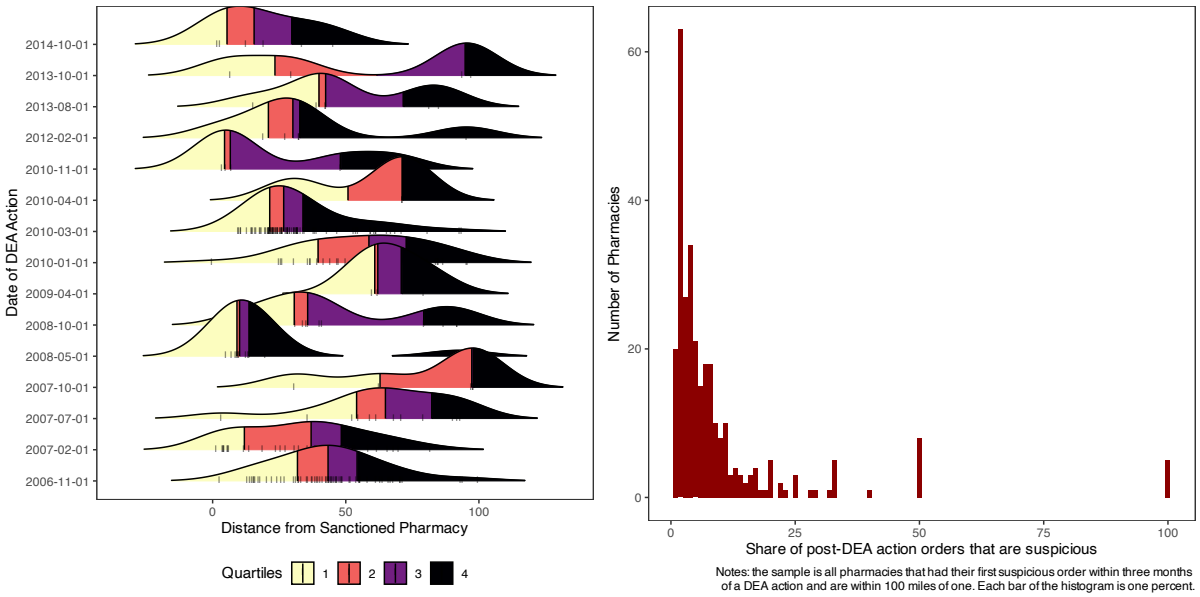


Figure A.33: Distribution of Distances to Sanctioned Pharmacy and Share of Orders that are Suspicious

B Comparison to State- and Federal-Level Interventions

This paper is one of the first to examine the impacts of supply chain actor crackdowns, which generate a targeted or local supply shock. However, there is a large literature examining the impact of more aggregate interventions. These state or federal reforms often affect addicts and rogue supply chain actors, as well as legitimate users and doctors. Researchers primarily focus on prescription drug monitoring programs (PDMPs), pill mill reforms, and the OxyContin reformulation. A PDMP is an electronic database that tracks controlled substance prescriptions in a state and can provide information on prescribing and patient behaviors. All states currently have an operational PDMP, but they were initially optional. Over time, certain states made them must-access; this means that doctors must not only report all controlled substance prescriptions, but also consult the PDMP before writing one. Pill mill laws impose regulations on pain clinics and the OxyContin reformulation introduced an abuse-deterrent form of the blockbuster drug considered to be the main catalyst of the epidemic.

In order to compare the magnitude of my estimates to the literature, I estimate equation (1) but replace the treatment variable of a DEA crackdown with one of the aforementioned interventions. For completeness, I run the regressions separately at the county- and state-level, and the results are in Figure B.1. They show that county- and state-level opioids decrease after all of these interventions, as intended. The supply impacts of doctor and pharmacy crackdowns are generally larger than the those of these policies, but qualitatively similar. Heroin overdose deaths generally increase as well, but at the county-level, they are nowhere near as large as the estimates from the doctor and pharmacy crackdowns. At the state-level, the ecological fallacy is likely an issue.

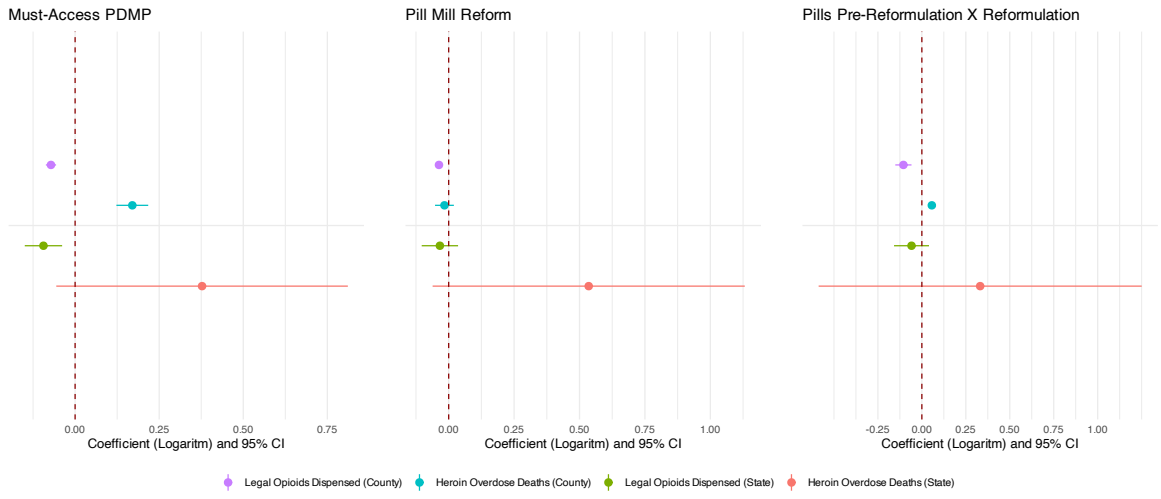


Figure B.1: Impacts of State and Federal Opioid Supply Interventions

Notes: the "County" models included county and year fixed effects, while the "State" models include state and year fixed effects. The former are clustered at the county-level, while the latter are at the state-level.