Anatomy of Opioid Diversion: Examining Supply-Side Curtailment

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Pharmacies are legally required to act as gatekeepers for opioid distribution. However, rogue pharmacies may divert opioids to non-medical users, exacerbating the opioid epidemic. We examine the spatial redistribution of opioids dispensed following targeted shutdowns by the Drug Enforcement Administration, employing comprehensive pharmacy-level opioid shipments and hospital diagnoses data in ten U.S. states. The displacement of local opioid shipments after removing a pharmacy reveals the extent of prior non-medical use: medical users can readily switch to competing local pharmacies, while non-medical users cannot. We develop and estimate a structural model to study medical and non-medical consumers' substitution patterns when facing changes in their consideration sets. We find that 8% of pharmacies dispense opioids for non-medical use with a probability greater than 90%, and over half of pharmacy-dispensed opioids are diverted to non-medical use from 2008 to 2010. Aggressive pharmacy crackdowns, however, drive a substantial portion of non-medical users to the black market, which may lead to the rise of more dangerous narcotics such as heroin and fentanyl.

JEL: L1, L5, I11

Keywords: opioid diversion, supply-side curtailment, pharmacy competition

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I. Introduction

The late 1990s marked the beginning of the opioid epidemic, a widespread public health crisis characterized by the misuse and addiction to opioid drugs. These drugs bind to receptors in the brain responsible for pain and pleasure, creating feelings of euphoria and relaxation, which make them highly addictive. This epidemic has had a devastating impact on communities across the country, with millions of individuals struggling with addiction and thousands losing their lives each year. From 1999 to 2020, opioid-related deaths reached a staggering 718,369 in the U.S. Today, opioid overdoses are the leading cause of death for Americans aged 18 to 45.[1]

The public often attributes the opioid epidemic to aggressive marketing practices, misleading health claims by pharmaceutical companies, unscrupulous prescribers, and abusive opioid addicts. However, people tend to ignore the role of local pharmacies across the U.S. in this crisis. Contrary to common belief, pharmacies not only bear the responsibility to validate prescriptions but also are legally obligated to report suspicious purchases to the Drug Enforcement Agency (DEA). They are the last line of defense against opioid diversion in the supply chain. Unfortunately, some pharmacies have succumbed to profit-seeking incentives, diverting opioids for illicit use. Florida's "pill mills" are an infamous example of opioid diversion.[2]

In 2006, the DEA launched initiatives against illegitimate actors in the opioid supply chain, including prescribers, distributors, and retailers, to curtail suspicious distributions. The curtailment effort against pharmacies peaked between 2008 and 2011. We investigate the impact of the supply-side curtailment on opioid distribution, focusing on pharmacy removals and consumer reactions that ensued.[3] The effectiveness of crackdowns on rogue pharmacies faces potential setbacks as consumers can substitute for alternatives: opioid abusers may switch to other pharmacies that divert opioids or even to the black market if deprived of access to pharmacy-sold opioids; at the same time, medical users may lose their legitimate access if they had few retail outlets nearby. Without understanding consumers' substitution patterns, we cannot compre-

[1] https://wonder.cdc.gov/mcd.html. Last accessed: 04/01/24.

[2] A pill mill is an illegal facility that resembles a regular pain clinic, but regularly prescribes painkillers without a medical necessity and outside the course of normal professional practice.

[3] We begin by motivating the paper through DEA enforcement actions. However, we note that other regulatory authorities, such as state boards of pharmacy, also have the power to revoke licenses. Therefore, the observed variations in consumers' pharmacy consideration sets may also result from actions taken by these regulatory bodies.

hend the scope and severity of these unintended consequences or accurately assess the effects of direct supply-side curtailment policies.

Analyzing detailed pharmacy shipment data before and after enforcement events, we discover a noticeable decrease of 5% in total opioid shipments within a five-mile radius of a removed pharmacy, despite a small increase of about 1% in shipment volumes for the removed pharmacy's local rivals. A portion of opioid demand appears to have disappeared after a pharmacy removal. The amount of vanished opioids, in fact, tells us more than just the aggregate effect of an enforcement action. For example, in a local market where all pharmacies dispense opioids only for medical use, removing one pharmacy should minimally affect the total quantity dispensed in the local market. This is because medical users should have no difficulty switching to alternative pharmacies. However, if a substantial decrease in total quantity dispensed in the local market follows a pharmacy's closure—that is, if the quantity previously dispensed by the removed pharmacy is not offset by increases at other local pharmacies—the removed pharmacy must have catered to illicit opioid users, who cannot easily switch suppliers. Thus, the reduction in dispensed quantity in the local market around a removed pharmacy can serve as a conservative estimate of opioid diversion before its closure. This insight gives us an opportunity to answer questions about illicit demand and supply of opioids: To what extent was the removed pharmacy involved in opioid diversion? How prevalent was the local consumption of diverted opioids? After a pharmacy shutdown, where did non-medical opioid users redirect their demand, and what were the consequences of this switching?

We combine comprehensive data from ten U.S. states and a structural model of consumer choices to address the questions outlined above. Our data sources include pharmacy-level shipment data, county-level prescription data, and local market data on pain, addiction, demographic, and socioeconomic conditions in the United States from 2008 to 2010. The primary dataset used is the Automated Reports and Consolidated Orders System (ARCOS), maintained by the DEA to track all opioid shipments in the United States. We measure local pain and addiction incidence using data from the Healthcare Cost and Utilization Project (HCUP), which provides encounter-level hospital diagnosis information on conditions commonly treated with opioids or strongly correlated with opioid abuse. Additionally, we supplement our main dataset with opioid dispensing rates reported by the CDC and demographic attributes of local populations at the Zip Code Tabulation Area (ZCTA) level.

Our model combines methodologies from a spatial demand model (Ellickson, Grieco, and Khvastunov, 2020) and a limited consideration set framework (Goeree, 2008). In the utility framework for differentiated products, we distinguish between consumers' opioid consumption for medical and non-medical purposes: medical use refers to when consumers use opioids as prescribed for pain management, while non-medical use refers to when consumers exploit opioids for their psychoactive effects. Different types of opioid use are driven by consumers' respective pain or addiction conditions; consumers also perceive travel distances and store attributes differently in their utility functions. In addition, a patient's consideration set of pharmacies depends on the purpose of their opioid consumption. For medical use, a consumer can choose any pharmacy in the local market. For non-medical use, the consumer faces a limited consideration set—they can only shop at pharmacies willing to divert opioids for non-medical use. Our model includes two key non-standard features in consumer choices inspired by previous research, particularly Janssen and Zhang (2022) and Currie, Li, and Schnell (2023). First, we predict a pharmacy's probability of engaging in opioid diversion based on its past sales patterns and the competitive pressure it faces. Second, we allow the black market to enter a non-medical user's consideration set, where they obtain utility from opioid consumption subject to the risks and limited supply associated with illicit opioids in the black market.

We spatially aggregate the micro-founded consumer choices to obtain aggregate shipment volumes and prescription numbers, then estimate our model by minimizing the difference between the model-predicted quantities and observed quantities. We have three main findings in our estimates. First, there is a clear distinction between how pain, addiction, and other conditions of local populations affect opioid consumption for different purposes. Injuries and unspecified pains increase medical consumption, while previous Opioid Use Disorder (OUD), mental illness, and unspecified pains increase non-medical consumption. Both medical and non-medical users are averse to distance, but travel distance poses less of a barrier for medical users than for non-medical users. Medical users prefer chains such as CVS and Walgreens, but non-medical users prefer independent pharmacies. Second, the choice alternatives among the non-medical nest are much more dissimilar than those among the medical nest: the inclusion of the black market into the non-medical nest may be a key reason for this difference. Third, pharmacy competition incentivizes pharmacies to divert opioids for non-medical use, while prescriber competition encourages doctors to prescribe more opioids, thereby increasing the accessibility of illicit supply in the black market.

Using the estimated model, we decompose each pharmacy's opioids dispensed for medical and non-medical purposes. Approximately 8% of pharmacies across the ten states we study sell opioids for non-medical use with a probability greater than 90%—we label them as "rogue pharmacies." In Florida alone, we identify 581 rogue pharmacies, representing 14% of all Florida pharmacies. The pharmacy-diverted opioids account for 51.5% of all opioid shipments from 2008 to 2010 in these ten states. Opioid diversion is driven primarily by rogue pharmacies in Florida, Arizona, and New Jersey, which together constitute about 65% of opioid dispensation in these ten states. Averaged across states, the population of a median ZCTA has an 8.8% probability of non-medical use via pharmacies and a 2.7% probability of non-medical use via the black market. However, these numbers conceal substantial heterogeneity across ZCTAs and states. Notably, our estimated black market size can predict future opioid mortality rates in local markets, providing evidence of the external validity of our analytic framework.

We use the estimated model to evaluate potential DEA enforcement actions. We first simulate a policy that identifies and removes each county's top ten "rogue" pharmacies. This policy reduces a substantial portion of non-medical opioid supply—it reduces opioids diverted by 0.08 MGE (Morphine Gram Equivalents[4]) per capita annually, which is an over 25% reduction from the 0.29 MGE per capita average of non-medical opioid use. This reduction, however, gives rise to increased black market demand: over a third of the reduction in the probability of a consumer choosing non-medical use through pharmacies is offset by an increase in the probability of resorting to the black market. The effects of this policy also show significant variation across locations, as the incidence of medical conditions and the proximity of pharmacies vary.[5] To

[4]MGE, or Morphine Gram Equivalent, is a standardized measure that converts the dose of various opioids into an equivalent dose of morphine, allowing for comparison of opioid potency. While MME (Morphine Milligram Equivalent) is more commonly used for a single dosage, we have chosen to scale up from milligrams to grams as MGE, given that we are dealing with annual opioid consumption.

[5]In some counties, especially rural areas, this policy also risks restricting access to legitimate opioid use, as this policy could remove all pharmacies in a local area, leading to no pharmacy access for medical users.

investigate this spatial effect, we compare a cluster removal policy (i.e., removing pharmacies located close to each other) with a dispersed removal policy (i.e., removing pharmacies spread across the county) in one of the top offending counties (Miami-Dade County, FL). The cluster-based removal policy reduces the quantity of dispensed opioids more effectively than a dispersed removal approach; however, it also leads to a higher proportion of displaced non-medical users turning to the black market. While both supply-side curtailment policies appear effective at first glance, their impact diminishes if we consider the persistence of non-medical demand. Much of the reduced dispensation on the surface shifts to underground black market demand.

Related Literature In this research, we combine rich data and a structural model to understand the inner workings of the illicit opioid market. We go beyond simply evaluating the aggregate effect of direct supply-side intervention by decomposing the opioid shipment into medical and non-medical use. Substitution patterns of different types of consumers across pharmacies within a local market and between formal and informal markets serve as the transmission mechanism linking policy interventions to their final outcomes. Without understanding this mechanism, the linkage between restricted opioid accessibility, patient health outcomes, and black market activities remains non-transparent. Our micro-founded model is designed to capture these substitution patterns and predict displacement across retail outlets, distribution channels, and geographic markets. By recovering the primitive parameters in consumers' utility functions, we can measure the trade-offs of existing or proposed policies for different consumer types. We can even evaluate complex policies that elicit responses from heterogeneous decision-makers across overlapping markets, such as the cluster removal policies in Florida, which would be challenging to analyze using a reduced-form framework.

Along this direction, our work carries a message similar to that of Freylejer and Orr (2023), which shows that U.S. over-the-counter "precursor control" laws (aimed at limiting access to key inputs in methamphetamine production) between 2004 and 2006 led to substitution toward Mexican-produced methamphetamine. More broadly, we contribute a building block to a very small but burgeoning literature (Leong, Li, Rysman, and Walsh 2022, Galenianos and Gavazza 2017, Jacobi and Sovinsky 2016, Mejia and Restrepo 2016, and Galenianos, Pacula, and Persico 2012) that uses structural modeling of the demand, production and trading activities of illicit commodities to understand how illegal markets function and the effects of anti-drug policies.

Our work complements several studies (Soliman 2023, Donahoe 2022 and Meinhofer 2016) that provide the first empirical evidence on the effectiveness of enforcement actions against rogue actors in the opioid supply chain.[6] Of these existing studies, Soliman (2023) covers the longest time span and the broadest geographic scope. Soliman (2023) employs a difference-in-differences approach to examine the impact of DEA enforcement actions taken against doctors on prescription opioids, black-market prices, drug overdose, and mortality rates. While his work primarily focuses on doctors, he does observe spatial substitution when the DEA removes pharmacies. Specifically, he finds that there is little change in opioid dispensing within 100 miles of a pharmacy crackdown; at the same time, the share of pharmacies with suspicious shipment patterns in corresponding areas increases by 8%.

Methodological differences aside, we join our reduced-form predecessors in the debate about the unintended consequences of direct policy interventions aimed at curbing opioid diversion. Previous literature primarily focuses on two interventions: the 2010 reformulation of OxyContin to make the pill abuse-deterrent and the implementation of prescription drug monitoring programs (PDMPs) across states at different times.[7] In this line of research, only Janssen and Zhang (2022) examine pharmacies. They utilize the OxyContin reformulation to investigate the role of pharmacy ownership and pharmacy competition in opioid diversion. They find that independent pharmacies dispense significantly more opioids compared to chain pharmacies in the same zip code area, and half of such difference in dispensed OxyContin doses can be attributed to drug diversion.

Lastly, our research contributes to the growing interest in limited consideration sets (Moraga-González, Sándor, and Wildenbeest 2021, Honka 2014 and Goeree 2008) and spatial demand estimation (Verboven and Yontcheva 2022, Ellickson, Grieco, and Khvastunov 2020, and Holmes 2011). To the best of our knowledge, we are the first study to allow different consideration sets

[6] Meinhofer (2016) studies enforcement actions to shut down pain clinics in Florida from 2010 to 2012, and Donahoe (2022) examines the effects of enforcement actions against pharmacies and distribution centers following a 2008 enforcement workforce expansion. Neither study empirically investigates the substitution patterns among different dispensing channels.

[7] Evans, Lieber, and Power (2019), Alpert, Powell, and Pacula (2018) and Severtson et al. (2013) link the timing of OxyContin reformulation to a transition toward heroin and, subsequently, to fentanyl. In a similar vein, Mallatt (2022) and Mallatt (2018) link PDMPs to an uptick in heroin-related criminal activities and a shift in consumer preference toward heroin.

for heterogeneous sub-populations in a spatial demand model. This extends beyond the type of consumer heterogeneity typically allowed in standard demand estimation literature (Brand and Demirer 2022, Berry et al. 1995), where heterogeneous consumers all face the same consideration sets. Furthermore, typical retail data at the product level does not distinguish market shares across different groups of consumers. To overcome this challenge, we integrate a consideration set framework into the spatial demand model developed by Ellickson, Grieco, and Khvastunov (2020).[8] This methodology can be extended to other retail markets where different types of consumers face distinct consideration sets and make different choices based on their respective sets. For example, consumers on welfare vouchers can only choose stores that accept the vouchers — a notable example of this is the Women, Infants, and Children program for baby formulas.

This paper proceeds as follows. Section II introduces the opioid diversion problem and clarifies the role of pharmacies in this context. Sections III and IV describe the data we use and highlight notable facts derived from it. Section V presents a model of pharmacy choices for medical and non-medical consumers and explains how we aggregate individual consumer choices to derive pharmacy demand. Section VI reports the estimation results, and Section VII analyzes two counterfactual experiments to evaluate the welfare trade-offs of different supply-side curtailments. Section VIII offers concluding remarks. Complementary empirical facts, estimation details, and additional results are provided in the Appendix.

II. Institutional Background

This section provides the necessary background for the opioid retail market. In particular, we examine the role of pharmacies in opioid diversion and the regulation of pharmacies, with a focus on the enforcement actions taken by the DEA.

A. Opioid Diversion and the Opioid Epidemic

The opioid diversion began in the 1990s, coinciding with Purdue Pharmaceutical's aggressive marketing and promotion of its branded painkiller, OxyContin, the brand name for oxycodone.

[8] In the process, we improve the method proposed by Goeree (2008) by incorporating a self-normalizing step in the importance sampling process.

Purdue's potentially misleading claims, initially sanctioned by the Food and Drug Administration, suggested that the controlled-release formulation of OxyContin would result in reduced abuse potential.[9] This "reduced abuse" label, coupled with an assertive marketing campaign, led to a significant increase in opioid prescriptions by physicians. However, individuals seeking to exploit opioids for their euphoric effects can bypass these protective measures simply by cracking the pills. In addition, users rapidly develop tolerance to opioids and require increasingly higher doses to achieve the desired effect.[10]

In the early 2000s, the continuing ease of obtaining opioid prescriptions for pain management increased, followed by a surge in opioid overdose. The alarming rise in opioid-related mortality and widespread drug abuse prompted the U.S. Center for Disease Control and Prevention (CDC) to officially declare an opioid epidemic in 2011. Subsequently, state and federal governments have implemented policies to mitigate opioid diversion. Early policy interventions on the supply side focused on patients and prescribers of opioids. A notable initiative is the Prescription Drug Monitoring Program, allowing tracking patients' previous prescriptions and enabling doctors to make more informed decisions when prescribing opioids. Various studies, such as those by Meara et al. (2016) on opioid misuse outcomes, Grecu, Dave, and Saffer (2019) on treatment center admissions, and Dave, Deza, and Horn (2021) on crime rates, have examined the effects of this program, but the findings on its effectiveness are inconclusive. Another line of research investigates physicians' roles in this market(Schnell 2017, Schnell and Currie 2018), pointing out that the heterogeneity in opioid prescription patterns depends on physicians' awareness of the black market and their medical school training.

As a consequence of stringent supply policies and limited access to appropriate treatment, individual opioid addicts were driven to transition from prescription opioids to the black market rather than stopping opioid misuse altogether. This shift is evident in the increase in heroin-related fatalities and a notable surge in fentanyl-related deaths in 2013.[11]

[9] https://www.fda.gov/drugs/information-drug-class/timeline-selected-fda-activities-and-significant-events-addressing-substance-use-and-overdose, last accessed: January 2024.

[10] This phenomenon is observed in both medical and non-medical settings. Even in medical contexts, Buntin-Mushock et al. (2005) find that patients frequently develop a tolerance to opioids, often necessitating a more than tenfold increase in dosage for chronic pain management.

[11] Initially, opioid addicts may not have actively sought more dangerous substances like heroin or fentanyl. Nevertheless, synthetic opioids, such as fentanyl, swiftly dominated the market due to the low cost of laboratory-based production. As a result, fentanyl became a focal point in the opioid epidemic, with fentanyl recently becoming the leading cause of death

B. Pharmacy's Role in Drug Diversion

The path of opioids from manufacturers to consumers involves various intermediaries. To obtain opioids, a consumer needs a prescription from a doctor, which is subsequently filled by a pharmacy that acquires its supplies from distributors and manufacturers. Among the suspects accused of contributing to the opioid epidemic, pharmacies have been largely overlooked. Over the years, pharmacies contended that they merely fulfilled prescriptions for government-approved drugs prescribed by doctors and, therefore, bore no responsibility for opioid diversion.

The regulation of opioid distribution relies on prescribers, pharmacies, and distributors policing each other. Pharmacies and pharmacists can play a critical role in preventing opioid drug diversion. Under the Controlled Substances Act, pharmacists are responsible for ensuring that controlled substance prescriptions are issued for legitimate medical purposes. This requires pharmacists to fill prescriptions as written and evaluate whether the medication is being prescribed appropriately and for valid reasons. As clearly stated below in the Code of Federal Regulation,

> *21 § 1306.04(a) Purpose of Issue of Prescription: . . . The responsibility for properly prescribing and dispensing controlled substances is upon the prescribing practitioner, but* ***a corresponding responsibility rests with the pharmacist who fills the prescription****. 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.*

As indicated above, pharmacists should play an active role in the distribution of opioids instead of passively handing out any order to customers with prescriptions. A pharmacist can question a doctor-written prescription and not accept it if the pharmacist deems it suspicious. Pharmacies also must notify the DEA when they identify suspicious orders, such as those of unusual size or frequency, to prevent drug diversion.

among individuals aged 18 to 45, surpassing both car accidents and cardiovascular diseases.

Undoubtedly, the self-policing system was susceptible to each link's incentives to pursue higher profit — increasing sales of opioids could outweigh potential penalties. For example, Janssen and Zhang (2022) document that retail pharmacies, independently-owned ones, in particular, performed poorly in exercising discretion in dispensing opioids. To exacerbate these incentives, the DEA did not provide clear guidelines on what constitutes a legitimate medical purpose, leaving the interpretation up to individual pharmacists. Pharmacies may evade the requirement of reporting due to the lack of codified standards and the discretion extended to pharmacists to interpret whether a physician's practice is beyond the usual course of practice.

C. The DEA's Enforcement Actions Against Pharmacies

A pharmacy must obtain approval from the state's Board of Pharmacy before it starts operation. However, the pharmacy must also secure registration and approval from the DEA to distribute controlled substances. Given that opioids are classified as controlled substances, the DEA has complete records of their shipment from manufacturers to pharmacies, as mandated by the Controlled Substances Act of 1971. This extensive database offers the DEA a unique advantage over state-level regulatory agencies, especially in interstate distribution cases.

In the early stages of the opioid epidemic, the DEA focused primarily on drug trafficking rather than on the diversion of drugs from retail channels. The Diversion Control Division, the smallest division within the DEA, relied on an honor system requiring pharmacies, distributors, and manufacturers to self-report suspicious activities. This passive approach was largely ineffective, as only 8 of 1,400 manufacturers and distributors ever reported to the DEA's Suspicious Order Reporting. System.[12]

In response to the growing opioid crisis, the DEA took a more proactive approach in 2006 to target rogue actors within the supply chain. The DEA adopted two tools: Orders to Show Cause (OTSC) and Immediate Suspension Orders (ISO). An OTSC initiates legal proceedings against a DEA registrant, detailing the DEA's rationale for action. The registrant is given an opportunity to counter the allegations and present their defense. An OTSC could lead to suspending or revoking a DEA registration, thereby barring the registrant from manufacturing, distributing,

[12] Office of the Inspector General (2019)

or dispensing controlled substances. Compared to OTSC, ISO was more drastic: it immediately halts controlled substance distribution from a facility, without prior notice, if the DEA deemed the facility's practices posing an "imminent threat" to public health or safety. These two tools enabled the DEA to quickly halt suspicious shipments or opioid sales in the supply chain, from manufacturers to distributors to retailers to consumers. Compared to investigating questionable prescribing behavior one doctor at a time, these DEA's enforcement actions had more potential in curbing locally concentrated outbreaks of opioid abuse. From 2008 to 2011, the DEA ramped up using these two tools, but this effort was later halted due to internal and external pushback. We provide a more detailed description of the DEA's enforcement tools in Appendix A.A1.

The DEA monitored opioid shipment patterns and tried to identify which pharmacies warranted closer attention. In the National Prescription Opiate Litigation, initiated in 2017, a former DEA agent outlined five metrics monitored by the DEA:

- If a monthly shipment exceeds the largest monthly shipment in the past six months.
- If a monthly shipment exceeds twice the average shipment of the past 12 months.
- If a monthly shipment exceeds triple the average shipment of the past 12 months.
- If the pharmacy dispenses more than 8,000 dosage units in a month.
- If the pharmacy dispenses more than a daily ceiling.[13]

These five metrics measure the potential for opioid diversion from different angles. The first three aim to identify a consistent upward trend over time, while the latter two establish absolute limits to identify instances of excessive shipments. According to the testimony, DEA field agents employed these metrics to flag pharmacies for further investigation. Notably, these five metrics were not included in any public DEA guidelines or officially acknowledged. Public disclosure of these thresholds could enable pharmacies to evade detection. For instance, splitting a 500-dosage order across two days could avoid exceeding the maximum of 300 daily dosage units. Appendix A.A2 illustrates the distribution of violations of DEA criteria among pharmacies that dispense opioids.

[13]In the court documents, the DEA field agent did not specify a precise daily ceiling. Based on historical DEA enforcement patterns, we posit that 300 dosage units is a reasonable daily dosage ceiling. Each dosage unit contains 90MME opioid.

III. Data

We employ four primary datasets to examine consumer purchasing decisions for prescription opioids in the United States. This section highlights the key features of each dataset that are most relevant to our analysis.

ARCOS: The Automation of Reports and Consolidated Orders System (ARCOS), maintained by the Diversion Control Division of the DEA, is an automated and comprehensive drug reporting system. Reporting shipment and dispensing of controlled substances to this system is mandated under the Control Substance Act of 1971. ARCOS effectively monitors the flow of controlled substances from their point of manufacture, through commercial distribution channels, to the point of dispensing or sale (typically to hospitals and retail pharmacies). Each reported shipment includes details such as the names of drugs, their dosages, and their weight, as well as information about both the sender and receiver of the shipment. The DEA has made this opioid-related portion of dataset publicly available from 2006 to 2019.[14]

Our study focuses on the period from 2008 to 2010, during which the DEA intensified its enforcement efforts against opioid misuse and abuse. By narrowing down our analysis to this time frame, we avoid the confounding effects of the OxyContin reformulation in 2010, which led to a decline in opioid shipments starting in 2011. Following the focus of prior opioid literature, we include opioids with hydrocodone and oxycodone as major active ingredients, as these two drugs together account for 75% of total opioid shipments to pharmacies. These drugs are highly interchangeable, both in medical uses and appeal to abusers. To standardize measurement, we convert the shipment volumes of various opioids into Morphine Gram Equivalents (MGE) and aggregate these quantities annually at the pharmacy level. As we study pharmacies' behavior, we exclude dispensers integrated with hospitals, clinics, or doctor's offices where patients receive treatment under direct medical supervision.

County-level Prescriptions and Mortality We obtain county-level opioid dispensing rate data from the CDC website. As the current site only provides data from 2019 onward, we use the Wayback Machine to access historical data.[15] The dispensing rates are projected by IQVIA

[14]https://www.washingtonpost.com/health/how-an-epic-legal-battle-brought-a-secret-drug-database-to-light/2019/08/02/3bc594ce-b3d4-11e9-951e-de024209545d_story.html (Accessed April 1, 2020)

[15]We accessed the archived version of the CDC website through the Wayback Machine:

Xponent, which covers approximately 49,900 retail (non-hospital) pharmacies and account for nearly 92% of all retail prescriptions dispensed in the United States. The opioid dispensing rate is the annual number of filled opioid prescriptions per capita. To obtain the total filled prescriptions at the county level, we multiply the county population from the American Community Survey by the dispensing rates.[16]

We also obtain opioid-related mortality data from the restricted National Vital Statistics System for the years 2013 to 2016. This dataset provides granular details on the date and location (down to the county level) of all deaths in the United States, along with their causes. Consistent with standard practices in opioid research, we use multiple cause-of-death codes to identify fatal drug overdoses involving opioids, specifically T40, X42, X62, and Y12.

HCUP: We obtain hospital discharge data from 2008 to 2010 for ten U.S. states from the Healthcare Cost and Utilization Project (HCUP), a national and state healthcare database developed by a partnership among the federal government, states, and industry and sponsored by the Agency for Healthcare Research and Quality. Opioids are often prescribed for patients for short-term pain relief from specified and unspecified pain. Our analysis focuses on two medical diagnoses often treated with opioids (musculoskeletal injuries and unspecified pain), and two addiction diagnoses highly correlated with opioid abuse (OUD and mental illnesses) (Webster 2017). We aggregate diagnoses to the patient's residence ZCTA to obtain the count of each type of diagnosis. Details on the construction of these variables are provided in Appendix A.A3.

ZCTA-level Demographics: We obtain population characteristics at the Zip Code Tabulation Area (ZCTA) level from the American Community Survey (5-year ZCTA group estimates). We select demographics and socioeconomic variables, including median age, gender, race, income, educational attainment, poverty, and unemployment rate. We report the attributes of the local population in Table A1.

Additional Data Sources: We manually match grocery stores that sell prescription drugs with their respective chains, using information from Wikipedia's List of Supermarket Chains

https://web.archive.org/web/20210801165454/https://www.cdc.gov/drugoverdose/rxrate-maps/index.html.

[16]The CDC opioid prescriptions data include a range of opioids, such as hydrocodone, oxycodone, buprenorphine, codeine, and fentanyl, without distinguishing them. We only use major types of opioids (oxycodone and hydrocodone) from the ARCOS data. Despite this inconsistency, the CDC county-level prescription data serve as strong predictors of county-level shipments in a regression model with time-varying county attributes and year- and county-level fixed effects.

in the United States.[17] Table A2 illustrates the competitive landscape of pharmacies. The pharmacy industry is extremely competitive — the average number of pharmacies within a 5-mile radius of a focal pharmacy exceeded 30, and within a 10-mile radius was approximately 90 to 95. Chain pharmacies (CVS, Walgreens, Walmart, Albertson's, or regional chains) dominated the market, comprising nearly nearly 60% of all pharmacies in our sample periods. Moreover, nearly 30% of the pharmacies that sold prescription opioids in our sample also sold groceries.

Lastly, we measure the number of doctors operating within 10 to 20 miles of a ZCTA using the Data Axle historical business directory, which allows us to track doctors' historical locations. In this directory, doctors are categorized as "Offices and Clinics of Medical Doctors." We incorporate this data to account for factors that may influence the diversion of opioids to the black market across a broader area surrounding the focal ZCTA.

IV. Stylized Facts

In this section, we begin with a case study analyzing market-level shipments before and after the shutdown of a particular pharmacy following a DEA enforcement action. Building on the rationale from this case, we then examine the average displacement effect of pharmacy removals.

A. Immediate Suspension Order on Bob's Pharmacy and Diabetic Supplies

On August 15, 2008, the DEA revoked the registration of an independent pharmacy *Bob's Pharmacy and Diabetic Supplies*, located in Winter Haven, Florida, for alleged "knowingly engaging in a scheme to distribute controlled substances ... for other than legitimate medical purpose." Michele M. Leonhart, Deputy Administrator at the DEA at the time, issued the following notice:

> *... between April 25 and December 28, 2007, Respondent [Bob's Pharmacy and Diabetic Supplies] had purchased 2.3 million dosage units of drugs containing hydrocodone, or approximately 287,000 dosage units per month. By way of contrast, I have previously found that the national average purchase of combination hydrocodone drugs by retail pharmacies is approximately 6,000 dosage units.*

[17] https://en.wikipedia.org/wiki/List_of_supermarket_chains_in_the_United_States. (Accessed April 2020)

As discussed in the previous section, the DEA relied on ARCOS for its initial investigation and often used excessive volumes as evidence in allegations, as noted by the above excerpt. Figure A3 (In the Appendix) illustrates how the shipment pattern of *Bob's Pharmacy and Diabetic Supplies* appeared suspicious to the DEA. This pharmacy surpassed the monthly ceiling for most months from April 2007 to August 2008, and exceeded the trailing 6-month maximum in June and July of 2008.

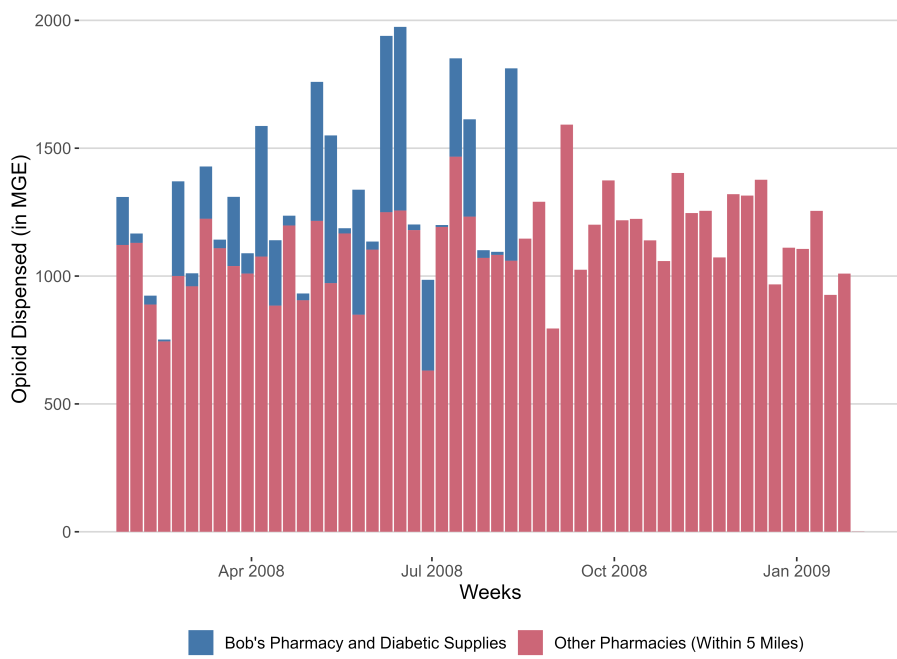


Figure 1. Bob's Pharmacy's and Nearby Pharmacies' Weekly Volume of Opioids Dispensed

Note: This figure displays the weekly volume of opioids sold by Bob's pharmacy (in blue) and the sum of all pharmacies other than Bob's (in red). We use MGE to standardize the potency of opioids to morphine in order to aggregate over different types of opioids.

We analyze the monthly opioid shipments within a five-mile radius of *Bob's Pharmacy*, distinguishing between shipments to Bob's Pharmacy and those to nearby pharmacies. Figure 1 highlights two key observations after the DEA shut down *Bob's Pharmacy*. First, the overall local opioid supply decreased following the pharmacy's closure. Second, while the supply from other pharmacies slightly increased, it did not fully offset the gap left by the closure. This finding raises questions about the demand initially served by Bob's Pharmacy. The minimal increase in the supply from neighboring pharmacies indicates that Bob's Pharmacy customers did not simply switch to nearby options despite their availability. This suggests that the lost opioid supply may have been primarily purchased by non-medical users, who could not seamlessly transfer their (suspicious) prescriptions to competing local pharmacies.

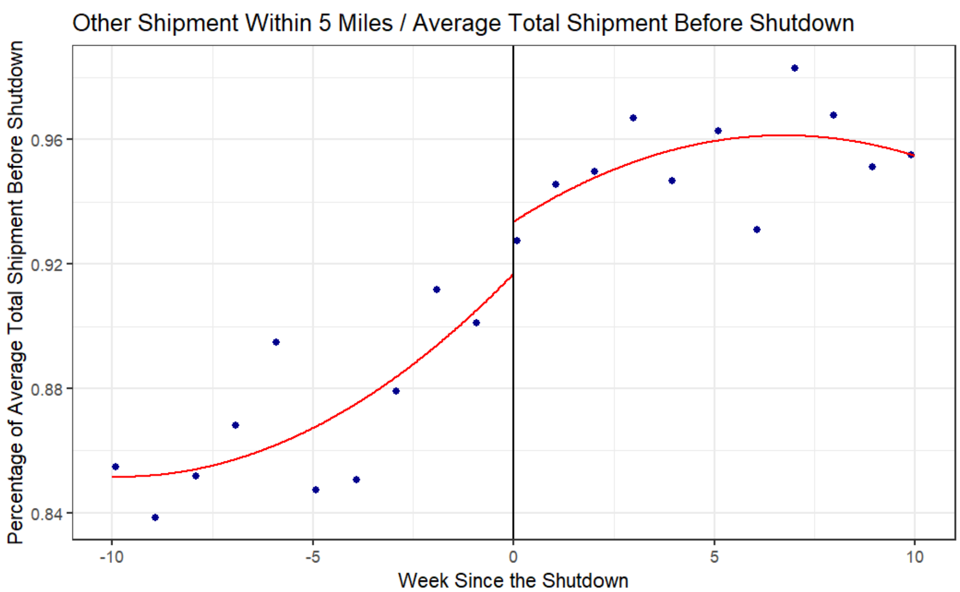
B. Regression Discontinuity on Local Opioid Supply

To generalize from the above case study, we conduct a Regression Discontinuity in Time analysis based on the timing of pharmacy closures, following Hausman and Rapson (2018). We classify pharmacies as DEA-removed if they disappeared from ARCOS and experienced at least a 20% increase in prescription opioid sales in the year prior to removal. These pharmacies were thriving in opioid sales and were unlikely to have exited the market due to unprofitability. Using this definition, we identified about 800 "removed-by-brute-force" pharmacies out of 3,000 that discontinued shipments from 2006 to 2010.[18]

We use the removal dates as the discontinuity point and compare shipment volumes within a 5-mile radius of the removed pharmacy—both including and excluding the removed pharmacy—before and after the removal event. Panel (a), Figure 2 shows an approximate 5% in the total shipment volume to the market following a pharmacy's removal. Panel (b) reveals a minor, statistically insignificant increase of about 1% in pharmacy shipment volumes (excluding the removed pharmacy) within a 5-mile radius, hinting at some degree of consumer substitution. Comparing these figures highlights a significant gap between the reduction in opioid shipments due to a pharmacy's removal and the slight increase at other nearby pharmacies, consistent with our findings from the *Bob's Pharmacy* case study. A similar pattern emerges when using a 10-mile radius instead of 5 miles. The minimal compensatory increase in shipments to other pharmacies after a pharmacy shutdown incident suggests the existence of non-medical opioid users who could not easily switch to nearby retailers. The disappeared opioids likely represent the supply that had previously served non-medical users.

[18]This selection may be an overstatement of the total shutdowns by the DEA, as Donahoe (2022) and Soliman (2023) report fewer closures during this period. Nevertheless, our list may include shutdowns initiated by state agencies.

(a) Total Shipment within 5 Miles



(b) Total Shipment (excluding the Removed Pharmacy) within 5 Miles

Figure 2. Effects of Pharmacy Removal

Note: The figures shows the average effect of a pharmacy shutdown on the amount of opioids shipment within a five-mile radius of the shutdown pharmacy. Shipment quantities were divided by the average shipment of ten weeks prior to the shutdown.

V. Model

Would non-medical opioid users immediately cease their habit after losing access to opioids from the pharmacy channel? How far would they be willing to travel to seek out distant pharmacies? Or would they turn to the black market to obtain diverted opioids? While the descriptive analyses above provide some insights, they lack the structure about consumer behaviors to address these questions.

In this section, we formulate a structural model of consumers' opioid demand and pharmacy choices. Consumers derive utility from opioid consumption for medical or non-medical purposes based on their medical history (including prior substance use disorders) and personal attributes. They also consider pharmacy location and pharmacy characteristics. In particular, we model the different accessibility situations for medical and non-medical opioid users. Medical consumers have access to all nearby pharmacies, but non-medical users face limited options as some pharmacies refuse to sell non-medical use opioids. For non-medical purposes, a consumers' consideration sets include only pharmacies that may sell non-medical use opioids, as well as the black market. We use the estimated model to understand the incidence of opioid diversion in different local markets. Furthermore, we investigate the effects of hypothetical policy interventions, as the model parameters dictate how consumers substitute across pharmacies (or alternative channels) of different attributes and different distances away.[19]

Our framework builds on the spatial competition model proposed by Ellickson, Grieco, and Khvastunov (2020), integrating two new elements that enhance its applicability to the opioid market context. First, we introduce a prediction mechanism identifying pharmacies likely to engage in non-medical use opioid sales, thereby refining the set of potential choices for these consumers, akin to Goeree (2008)'s consideration set setup. Second, we incorporate the black market as an outside option within the non-medical nest, providing an additional substitute for non-medical users.

[19]DEA removals sometimes occur in clusters as part of specialized operations, which differs significantly from removing a single pharmacy in an isolated market. A structural model that considers the spatial distribution of pharmacies can predict consumers' substitution patterns and the displacement effects in response to these large-scale enforcement actions.

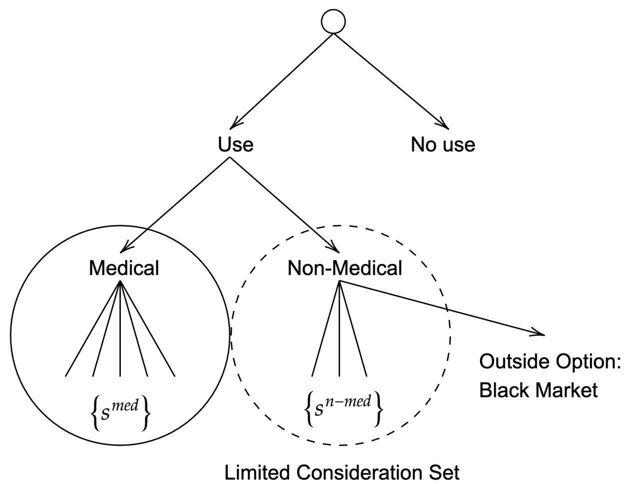


Figure 3. Three-Level Nested Logit with Limited Consideration Set

A. *Utility Formulation*

Figure 3 illustrates the nested structure of our demand model. A representative consumer i in a local market at year t decides on whether or not to consume opioids. If consumer i chooses to use opioids, the next decision is whether to use them for medical or non-medical purposes. Next, a medical consumer can choose any pharmacy within a 10-mile radius, while a non-medical consumer can shop only at a pharmacy that sells non-medical use opioids or resort to the black market. We use s^{med} to represent the option for purchasing opioids for medical purposes at pharmacy s, and s^{n-med} for non-medical purposes at the same pharmacy s. Both options share common pharmacy characteristics. We assume that whether a pharmacy sells opioids to non-medical consumers is known to consumers. We do not model addiction or historical consumption patterns; each period is treated as separate and independent.

The utility derived by the consumer from purchasing opioids at a pharmacy is composed of two distinct elements: consumption utility and shopping utility. The consumption utility represents the direct benefit derived from using opioids to address the individual's pain or addiction conditions. The shopping utility reflects the consumer's satisfaction or convenience derived from the characteristics and location of the pharmacy. Specifically, the following equations express the utility for consumer i visiting pharmacy s in year t for medical or non-medical purposes:

$$u_{ist}^{med} = PC_{it}\alpha^{med} + Z_{it}\beta^{med} + \tau^{med}d_{is} + X_s\gamma^{med} + \epsilon_{ist}^{med} \tag{1}$$

$$u_{ist}^{n-med} = \underbrace{AC_{it}\alpha^{n-med} + Z_{it}\beta^{n-med}}_{consumption} + \underbrace{\tau^{n-med}d_{is} + X_s\gamma^{n-med}}_{shopping} + \epsilon_{ist}^{n-med} \tag{2}$$

In Equation (1), a consumer's consumption utility for medical purposes depends on the individual's pain conditions, denoted as PC_{it}, and personal attributes Z_{it}. The shopping utility depends on this consumer's distance to pharmacy d_{is} and pharmacy characteristics X_s, a vector of dummy variables indicating a pharmacy's chain affiliation.[20] Equation (2) is structured similarly, with AC_{it} denoting addiction conditions, which affects a user's utility from opioid consumption for non-medical purposes.

In the above formulation, PC_{it} and AC_{it} are the only characteristics that are different between u_{ist}^{med} and u_{ist}^{n-med}, however, we do allow all coefficients to differ across these two utility formulations. Specifically, we allow health condition coefficients α, demographic coefficients β, distance preference coefficients τ, and pharmacy attribute coefficients γ to be nest-specific to incorporate observed heterogeneity in consumer preferences. These nest-specific parameters allow consumers to receive different shopping utilities from medical and non-medical use opioids even with the same attributes.

Within the non-medical use nest, there exists an outside option, "black market," with the following specification,

$$u_{i0t}^{blk} = AC_{it}\alpha^{n-med} + Z_{it}\beta^{n-med} + \delta_0 + M_{st}\delta + \epsilon_{i0t}^{blk} \tag{3}$$

The consumption component of the utility is the same as in Equation (2), which is the non-medical user's utility function. We replace the shopping utility with δ_0 and $M_s\delta$. The constant δ_0 represents consumers' aversion towards engaging in transactions on the black market. This aver-

[20]Including pharmacy's chain affiliation also controls for a potential channel of unobserved price. The pharmacy's chain affiliation indicates the firm's broader pricing strategy. Previous studies, such as those by DellaVigna and Gentzkow (2019) and Hitsch et al. (2019), suggest that price variation is more pronounced between chains than within a single chain.

sion is twofold: first, the black market could have been inundated with counterfeit prescription opioids, posing increased health risks; second, consumers are naturally disinclined to participate in illicit transactions due to the associated legal and ethical implications. The vector M_{st} is a proxy for the search cost associated with the black market. We include population density, as the salience of the black market is likely to vary geographically, being less prominent in rural areas than in the urban centers of large cities. We also include the census region interaction with a linear year trend, which indicates the black market's evolution over time by region.

Most importantly, we include the influence of prescribers' behavior on black market opioid supply. During the studied periods, heroin and fentanyl had not yet become dominant, making the black market primarily a secondary market for prescription opioids. Currie, Li, and Schnell (2023) find competition increases opioids prescribed by general-practice physicians. Building on this insight, we use the number of general-practice physicians from the previous year as a measure of lagged prescriber capacity,[21] which also proxies for prescriber competition. To address the chicken-and-egg endogeneity issue, we construct a "donut" measure of lagged prescribing capacity. This measure captures prescribing activity within a 10- to 20-mile radius of a focal ZCTA. We assume that drug dealers source opioids from outside the 10-mile radius while consumers obtain them within this range. Consequently, the lagged prescribing capacity in this "donut" area may have contributed to the flow of prescription opioids into the black market of the focal ZCTA, thereby increasing consumer utility from black market purchases due to the expanded supply.

Lastly, we normalize the outside option's utility to zero:

$$u_{i0t} = \epsilon_{i0t} \tag{4}$$

As specified in Equation (1) to Equation (4), we allow every choice decision to be influenced by an idiosyncratic preference shock, denoted as ϵ_{ist}^{med}, ϵ_{ist}^{n-med}, ϵ_{i0t}^{blk}, and ϵ_{i0t}. These shocks are *i.i.d.* distributed with Type I Extreme Value distribution within a three-level nesting structure. This

[21] We impose a one-period lag to allow a delay between when opioids were dispensed by pharmacies and when they were circulated in the black market. Without this delay, we risk "double counting," as the pharmacy-dispensed opioids appear again in the black market instantaneously for illicit consumption.

structure allows for correlation between the medical and non-medical categories, captured by a dissimilarity parameter σ. If σ equals zero, then medical and non-medical categories are perfect substitutes. Moreover, correlation within each specific-use category is also allowed and captured by the dissimilarity parameter μ^{med} and μ^{n-med}. If μ equals zero, all pharmacies within each category are perfect substitutes.[22]

B. Limited Consideration Sets Faced by Non-medical Users

In our model, non-medical users face a restricted consideration set because a law-abiding pharmacy would uphold standards and exercise discretion when dispensing opioids. A non-medical user's consideration set only consists of opioid-diverting pharmacies. We, as econometricians, do not directly observe the identities of these pharmacies, but we can predict which ones are more likely to be offenders. Specifically, we use suspicious shipment patterns that would trigger DEA investigation (details described in Section II.C). In addition, in this prediction, we borrow the insight of Janssen and Zhang (2022), which finds that independent pharmacies are more likely to sell opioids to non-medical users, especially when they face greater competition.

To formalize this intuition, we use ϕ_{st} to denote the probability that a pharmacy s sells opioids to non-medical users in year t.

$$\phi_{st}(\lambda) = \frac{\exp(\lambda_0 + DEA\_Criteria_{st}\lambda_D + W_{st}\lambda_W)}{1 + \exp(\lambda_0 + DEA\_Criteria_{st}\lambda_D + W_{st}\lambda_W)} \tag{5}$$

In the above specification, the probability of a pharmacy selling opioids to non-medical users is a nonlinear(logit) function of $DEA\_Criteria_{st}$ (a pharmacy's suspicious sales patterns according to the DEA criteria) and W_{st} (factors incentivizing opioid diversion). Five metrics, outlined in the DEA agent's testimony, comprise the DEA watch list. The first three are about growth patterns within a year: the percentage of months exceeding the maximum quantity from the trailing 6 months, exceeding twice the trailing average quantity from the preceding 12 months, and exceeding treble the trailing average quantity from the preceding 12 months. The next two are threshold-crossing patterns, including the percentage of monthly shipments exceeding 720

[22]Note that this model does not allow correlation between medical and non-medical uses within the same pharmacy.

MGE (8,000 dosage times 0.09 MGE) and the percentage of months that had a daily shipment exceeding 27 MGE (300 dosage times 0.09 MGE). As these five metrics can be highly co-linear, we perform dimension reductions using the principal component analysis, detailed in Appendix B. We include Principle Components 1 and 2 into $DEA\_Criteria_{st}$, as these two components capture 70% of the variation of the five metrics of shipping patterns in the DEA watch list. Principle Component 1 captures the overall violation index weighted by the correlation between the original variables and the principal component. Principle Component 2 captures the balance between the growth and the threshold-cross metrics: if positive, there are more growth-type violations than threshold-cross-type violations.

For variables in W_{st}, we use an indicator function for independent (as opposed to chain) pharmacies, the distance (in miles) between the focal pharmacy and its closest competitor, and the log number of competing pharmacies within one mile of the focal pharmacy. The last variables are proxies for local competition intensity, which helps to identify the ϕ_{st} function because the local competitive landscape of pharmacies only affects consumer choices through the channel of affecting consumers' consideration sets.

With the ϕ_{st} function specified, we now construct a non-medical user's consideration set of pharmacies. Let $\mathcal{S}_{it} = S_{it} \cup 0^{blk}$ denote all pharmacies within a 10-mile radius $S_{it} = \{s \text{ exists in year t} \cap d_{is} \leq 10 \text{ miles}\}$ and the black market option, and $\mathcal{P}(\mathcal{S}_{it})$ denote the power set of $\mathcal{S}_{it}$. The set of consideration sets that contain a specific pharmacy s, denoted as $\mathbb{P}_{it}(s)$, is defined as follows:

$$\mathbb{P}_{it}(s) = \{C_{it} : \{0^{blk}, s\} \subseteq C_{it} \in \mathcal{P}(\mathcal{S}_{it})\} \tag{6}$$

where C_{it} is an element of $\mathcal{P}(\mathcal{S}_{it})$. The probability that a set of pharmacies, C_{it}, is considered, given each pharmacy's probability of selling opioids to non-medical users is independent, can be written as:

$$\pi_{C_{it}} = \prod_{s \in C_{it}} \phi_{st}(\lambda) \prod_{s' \notin C_{it}} (1 - \phi_{s't}(\lambda)) \tag{7}$$

C. *Choice Probabilities for Medical and Non-medical Purposes*

With the definition of consideration sets, we can now write down the probability of a representative consumer i visiting a pharmacy s in a year t in this three-level nested logit demand model. A deviation from standard practices is that we have two probabilities for the same pharmacy - the probability that a consumer would visit for medical purposes and the probability that they would visit for non-medical purposes.

The probability for a representative consumer i visits pharmacy s for medical use opioids in year t is given by,

$$P_{it}(s^{med}) = \sum_{C_{it} \in \mathbb{P}_{it}(s)} \pi_{C_{it}} p(use|C_{it}) p(med|use, C_{it}) p(s^{med}|use, med) \tag{8}$$

Similarly, the probability for a representative consumer i visits pharmacy s for non-medical use opioids in year t is given by,

$$P_{it}(s^{n-med}) = \sum_{C_{it} \in \mathbb{P}_{it}(s)} \pi_{C_{it}} p(use|C_{it}) p(n-med|use, C_{it}) p(s^{n-med}|use, n-med, C_{it}) \tag{9}$$

In Equations (8) and (9), we can break down the probability of choosing a pharmacy into three sets of probabilities, following a three-level nested logit construction. Note in the probability decomposition for Equation (8), a non-medical consideration set C_{it} also enters a medical user's probability of choosing the medical nest and choosing the "use" nest because medical users do have the option to choose the non-medical nest. Appendix C spells out each component of these probabilities step by step.

In the above calculation, we face a computational challenge: summing over $2^{|s|}$ possible consideration sets in each iteration step of our estimation. With the number of pharmacies within 10 miles averaged to about 90 in our data, the curse of dimensionality renders brute-force computation and estimation infeasible. To alleviate this problem, we use an importance sampling technique (as used by Goeree (2008)) with a new self-normalizing step to improve accuracy, which is explained in Appendix D. Intuitively, we simulate draws of consideration sets rather than assessing all potential consideration sets. This simulation process approximates the objective function at various points by reweighting these simulated draws through the importance weight. Importance weight, in this context, is defined as the ratio of the probability of a given consideration set and the probability of the initial consideration set. However, this approach encounters limitations when the size of the consideration set is large. In such cases, the probability of any consideration set is considered tends to be extremely small, as it results from a series of multiplications involving numbers less than one. Consequently, dividing a small number by another small number can cause the objective function to become unstable, leading to a very flat and large objective value. This flatness can make it difficult for optimization algorithms to find any minimum. To mitigate this issue, we employ a self-normalization technique. This approach involves adjusting the weights such that their sum equals one, effectively bounding the possible range of outcomes between 0 and 1. This is commonly used in statistics literature (Neddermeyer 2009, Cappé et al. 2004, Kong 1992). This normalization would stabilize the value and ensure a more robust and reliable approximation of the objective function.

D. Aggregation

To link the model-predicted pharmacy choice probabilities to the observed pharmacy-level shipment and county-level prescription data, we assume that a market's volume of opioid consumption, provided by pharmacy s at year t, is proportional to the local population n_{it} — the population size of ZCTA i in year t. We use η to denote the average dosage of opioids per prescription and ι to denote the average number of prescriptions per consumer per year. The product $\eta\iota$ thus reflects the annual opioid consumption for a representative consumer. Lacking information about the dosage differences for medical and non-medical use, we assume the same η and ι for different consumption purposes, with the understanding of the limitation in interpreting this η and ι.[23]

The total volume of pharmacy-dispensed opioids by pharmacy s to ZCTA i at year t, denoted by R_{ist}, is set to be equal to the sum of the demand for medical and non-medical purposes for

[23] In reality, each consumer's opioid consumption volume depends on the severity of her pain and addiction conditions. As we focus on the extensive margin of opioid use instead of on the intensive margin, we make this simplification assumption for a reasonable approximation.

this pharmacy:

$$R_{ist} = \eta \iota n_{it}[P_{it}(s^{med}) + P_{it}(s^{n-med})] \tag{10}$$

Similarly, we link the model-predicted pharmacy choice probabilities to observed county-level prescription data. Assuming the same proportionality as in Equation (10), the total number of filled prescriptions by pharmacy s to ZCTA i at year t, denoted by Q_{ist}, is,

$$Q_{ist} = \iota n_{it}[P_{it}(s^{med}) + P_{it}(s^{n-med})] \tag{11}$$

By our assumption of a 10-mile shopping radius, Pharmacy s fulfills opioid orders from all markets within 10 miles. Therefore, the total annual shipment of pharmacy s is the sum of each R_{ist} within a 10-mile radius for this pharmacy,[24]

$$R_{st} = \sum_{\{i:d_{is} \leq 10miles\}} R_{ist} \tag{12}$$

Similarly, the total number of prescriptions filled within a county, $Q_{county,t}$, is the sum of prescriptions from all pharmacies within the county, accounting for the 10-mile radius aggregation as in Equation 12:

$$Q_{county,t} = \sum_{\{s:s \in county\}} \sum_{\{i:d_{is} \leq 10miles\}} Q_{ist} \tag{13}$$

E. Estimation

To account for measurement errors in the observed pharmacy shipment and county prescription data, we assume that the observed quantities $\tilde{R}_{st}$ and $\tilde{Q}_{county,t}$ (counterparts to model predictions R_{st} and $Q_{county,t}$) are perturbed by multiplicative shocks, which are *i.i.d.* across pharmacies (or counties) and over time.

[24] One notable aspect of this spatial aggregation approach is that it does not impose arbitrary geographic market boundaries. Instead, each pharmacy is located at the center of a 10-mile radius, and pharmacies located near each other can have overlapping markets.

To estimate the model parameters, we minimize the weighted total of the squared error loss between our predicted and observed pharmacy shipments and that between predicted and observed county-level prescriptions. We estimate the parameters $\theta = \{\alpha^l, \beta^l, \tau^l, \gamma^l, \delta, \lambda, \sigma, \mu^l, \eta, \iota\}$, where $l \in \{med, n-med\}$ using nonlinear least squares, with weights w_s and w_{county}:

$$\arg\min \sum_s w_s(\log(\tilde{R}_{st}) - \log(R_{st}))^2 + \sum_{county} w_{county}(\log(\tilde{Q}_{county,t}) - \log(Q_{county,t}))^2 \tag{14}$$

This provides a sketch of our estimation approach. We define weights used in the minimization procedure and describe the detailed estimate procedure, step by step, in Appendix D.

F. Identification of Structural Parameters

The identification of the structural parameters comes from two sources. First, enforcement actions generate exogenous variations in consumers' consideration sets. Second, we impose exclusion restrictions on how attributes impact consideration or utility: 1) a pharmacy's past shipment history and local pharmacies' competitive landscape only affect the consideration set, and 2) the excluded variables in the utility functions for opioid consumption via different dispensing channels only affect consumer utility.[25]

Identification of Parameters within ϕ: The identification of the parameters within ϕ relies on cross-market and over-time variations in consumers' consideration sets, which have exogenous variations due to supply-side curtailment policies. We observe consumers' substitution patterns in response to a pharmacy closure. If a "normal" pharmacy exits the local market, the total opioid dispensed should remain relatively stable over time because consumers can easily switch to other pharmacies. In contrast, if an opioid-diverting pharmacy exits the market, the total opioid supply should decrease because non-medical consumers would find it difficult to switch to an alternative dispenser. This difference pins down λ_0 in the ϕ function. Furthermore, correlating such substitution patterns with a pharmacy's shipment history and geographic variations on competition forces identifies the rest of the λ parameters. For example, if we see

[25]The identification of many parameters in our model, including parameters in the nesting structure, is standard, based on the differentiated demand estimation literature following Berry, Levinsohn, and Pakes (1995). We omit this discussion to focus on the non-standard parameters in our models.

more “disappeared opioids” if a closed pharmacy has a shorter distance to closest competitors, then being closer to the competition increases the likelihood of this pharmacy selling opioids for non-medical purposes. The variations we explore here do not directly enter consumers’ utility functions; they only enter the determination of their consideration sets.

Our approach to predicting the ϕ_{st} function leverages supply-side factors to identify demand. Rather than modeling pharmacies’ decisions regarding opioid diversion, we focus on consumer choices, using supply-side constraints to define the consideration sets consumers face. As long as the DEA’s enforcement actions do not immediately change pharmacies’ opioid dispensing practices, we can use this framework to evaluate the short-term effects of these enforcement actions on consumer choices.

Identification of Parameters within Utility Formulation: In our model, local markets’ attributes affect the utility of opioid consumption via different dispensing channels differently. Pain conditions only enter the consumption utility of opioids for medical purposes, while addition conditions only enter the non-medical use utility. Similar to the previous example, if we see more “disappeared opioids” associated with pharmacy closure in a market with more addiction conditions, then addiction conditions are positively correlated with the consumption utility of opioids for non-medical purposes.

Identification of the Black Market: The identification of the consumption utility via the black market is more challenging. This is because, with the “disappeared” opioids, we do not know whether consumers quit consuming opioids or resort to the black market for previously diverted opioids. The structures of our model help to identify these parameters. First, in our model, as the consumption utility and shopping utility are additively separable, we can assume that the consumption utility is the same within the non-medical category, regardless of whether opioids are obtained from a pharmacy or the black market. An interpretation of this assumption is that the consumption utility within the non-medical use opioid category represents an “average” utility derived from consuming non-medical use opioids, regardless of the dispensing channel. Second, we assume that the accessibility of the black market depends on loose prescriber behaviors in the last period from a broader geographic region. We carefully choose factors to be used in the black market shopping utility, which affect the black market accessibility but do not directly affect the utility of medical or non-medical users via the pharmacy channel (discussed in Section V.A). Third and most importantly, we place the "real" outside option and the "black market" option at different levels of the nesting structure in our model: the non-medical users have the same access to the black market option, but the medical users do not. The "disappeared opioids" due to a normal pharmacy closure mostly go to the outside option, and those due to an opioid-diverting pharmacy closure go to both the outside option and the black market. The difference between these two quantities identifies the constant term in the black market utility function and the magnitudes of the black market. Finally, we acknowledge the limitations of our identification strategy for the black market, as we lack direct measures of black market consumption.

VI. Estimation Results

In this section, we first report the estimated parameters of our model. We then convert these estimates to the model-predicted incidence of opioid diversion, including the number of rogue pharmacies,[26] the volume of opioids dispensed for non-medical purposes, the population distribution of opioid use via different dispensing channels and more. Lastly, we relate the model-predicted population consuming opioids via different channels to opioid-related mortality at the county level to check the external validity of our estimated model.

A. Estimated Parameters

Table 1 displays the estimates of the pharmacy-level opioid-diverting probability (the ϕ function), along with the utility functions and the nesting structure, organized in the top, middle, and bottom panels, respectively. Three notable patterns emerges for the parameters in the ϕ function. First, a pharmacy's past shipment history, especially the metrics that the DEA monitors is a strong predictor of opioid diversion. We performed dimension reductions on the shipment history using the Principal Component Analysis to focus on two components: principal component 1 is about the overall violation index, while principal component 2 captures the balance between sales growth and threshold crossing in the pharmacy's monthly shipments.

[26]From this section on, we define rogue pharmacies as pharmacies with a higher than 90% probability of selling opioids for non-medical purposes.

Our results report a significantly positive coefficient for principal component 1, meaning that a pharmacy with a higher overall violation index is more likely to engage in opioid diversion. At the same time, a significantly negative coefficient for principal component 2 means that the pharmacy is also more likely to divert opioids when its shipment history shows more threshold-crossing violations than growth violations. Second, similar to Janssen and Zhang (2022), we find that independent pharmacies are more likely to divert opioids. Third, more intense competition seems to push pharmacies toward unethical practices: both a reduction of the distance from its closest competitor and an increase in the number of competing pharmacies within one mile increases a pharmacy's opioid-diverting probability. For a typical independent pharmacy with a mean distance of 0.96 miles to the closest pharmacy and average values for the two principal components (PC1 and PC2 both at zero), the predicted probability of selling opioids for non-medical use is 15.7%. The low average likelihood, however, masks significant heterogeneity in the ϕ function — our estimates reveal a bimodal distribution, with one peak around 0% and the other around 100%(see Figure E1 in Appendix E.E1 for this distribution). This suggests that a pharmacy is unlikely to be "halfway" illegal: they either sell or not sell opioids for non-medical purposes.

In terms of utility functions, we see clear distinctions in how pain/addiction conditions and the socioeconomic status of local populations affect opioid consumption for different purposes. Injuries and unspecified pains drive up medical consumption, while previous Opioid Use Disorder, mental illness, and unspecified pains drive up non-medical conditions. Socioeconomic attributes of consumers typically affect both types of opioid use, but the directions and the magnitudes of these effects are quite different across usage purposes. For example, higher education, lower average income, and higher poverty rates are strongly positively correlated with the medical use utility. In contrast, the correlation between these attributes and the non-medical use utility is the opposite. In addition, travel distance is less of a barrier for medical users than non-medical users. Non-medical users show an aversion to chain stores, which is exactly the opposite of medical users.

We now turn to non-medical use utility through the black market. As we discussed in our utility formulation, we assume that non-medical users receive the same consumption utility

Table 1— Estimated Parameters

Panel a: ϕ Probability of Selling for Non-medical Purposes

Intercept	-1.708	(0.002)
Principle Component 1 Violation Index	1.301	(7e-4)
Principle Component 2 Balance Index	-1.704	(0.001)
Independent Pharmacy	0.052	(0.002)
Distance to the Closest Competitor	-0.069	(0.002)
log(Competitors within 1 Mile)	0.033	(3e-4)

Panel b: Utility Functions

Medical			Non-medical			Black Market		
Consumption Utility								
Injury	0.032	(3e-4)	Lag OUD	0.022	(4e-4)			
Pain	0.048	(3e-4)	Mental	0.011	(0.001)			
			Pain	0.031	(0.002)			
Age	0.120	(2e-5)	Age	0.100	(3e-5)			
Female	0.491	(0.576)	Female	-3.586	(1.636)			
White	3.194	(0.029)	White	1.412	(0.053)			
Above HS	6.595	(0.261)	Above HS	-7.991	(0.714)			
log(Income)	-1.660	(0.005)	log(Income)	0.091	(0.009)			
Poverty	4.669	(0.134)	Poverty	-0.291	(0.559)			
Unemployment	0.571	(0.432)	Unemployment	7.074	(1.759)			
Shopping Utility								
Distance	-0.005	(1e-5)	Distance	-0.029	(1e-4)	Intercept	-10.994	(0.339)
Grocery	0.109	(2e-4)	Grocery	-0.248	(0.003)	Lag Capacity	0.125	(7e-4)
CVS	0.401	(8e-4)	CVS	-0.148	(0.003)	log(Pop Density)	1.571	(0.008)
Walgreen	0.401	(7e-4)	Walgreen	-0.067	(0.014)	NE × Year Trend	-4.715	(5.865)
Walmart	0.080	(4e-4)	Walmart	-0.068	(0.010)	West × Year Trend	-0.346	(0.002)
Albertsons	0.029	(9e-4)	Albertsons	-0.049	(0.019)	South × Year Trend	-0.016	(6e-4)
Regional	0.101	(2e-4)	Regional	-0.408	(0.003)			

Panel c: Nesting and Other Parameters

σ: top nest	0.988	(0.003)
μ^{med}: medical nest	0.309	(7e-4)
μ^{n-med}: non-medical nest	0.640	(9e-4)
η: MGE consumed per Prescription	0.409	(2e-4)
ι: Number of Prescription	5.070	(0.084)
R^2	0.532	
N (Pharmacy-Year)	35,538	
N (ZCTA-Year)	10,653	

Note: Table 1 reports the estimated model parameters. The top panel reports estimates for the coefficients in the ϕ function; the middle panel, going from left to right, reports estimates for the coefficients in the utility functions for medical, non-medical via pharmacy, and non-medical via black market uses, respectively; and the bottom panel reports estimates for nesting and other parameters. R^2 is calculated using the formula, $1-\sum(R_{st}-\hat{R_{st}})^2/\sum(R_{st}-\bar{R}_{st})^2$.

regardless of drug sources, but their shopping utility can be different across dispensing channels. In this shopping utility, the estimated negative intercept can be interpreted as the disutility of deviating from legal means, as accessing the black market inherently carries risks of encountering counterfeit pills, strong stigma, and closer contact with crime-prone populations. A positive coefficient for higher population density suggests easier access to the black market in urban centers. Furthermore, the "Lag Capacity" variable (the number of doctors within 10 to 20 miles of a focal ZCTA in the previous year), which captures black market accessibility, significantly increases black market utility. We suspect that doctor capacity and competition pushed them to over-prescribe opioids, as found by Currie, Li, and Schnell (2023), which increased diverted opioids flowing into the local market and made it easier for non-medical users to obtain opioids.[27]

Lastly, we discuss the remaining parameters. The parameter σ is estimated to be close to 1, indicating that choosing medical and non-medical nests is highly uncorrelated. The parameter μ^{med} is low, indicating that pharmacy choices within the medical nest are highly substitutable. In contrast, μ^{n-med} is much higher, meaning that alternatives within the non-medical nest are not as correlated as those within the medical nest. One of the major contributors to this dissimilarity is the existence of the "black market" among the alternatives, as the black market channel is vastly different from pharmacies that sell non-medical use opioids. Additionally, we find that the parameter η is 0.409, indicating that, on average, a pharmacy prescribes 0.409 MGE of opioids to each consumer per year. Each consumer is estimated to receive approximately five prescriptions annually. Therefore, the average annual consumption volume per consumer is about 2.07 MGE, calculated by multiplying the dosage by the frequency of prescriptions per year. This translates to approximately 46 30mg OxyContin pills per year.[28]

[27] It is noteworthy that the black market has become less attractive for all three regions over the years. This trend is the smallest in the South (Kentucky, Florida, and North Carolina), likely because the most intensive enforcement actions were implemented in Florida, leading consumers to prefer the black market more in the Southern region as accessing non-medical use opioids via pharmacy becomes harder over time in this region

[28] According to the CDC guideline Dowell (2022), a dosage of 0.3 to 1.2 MGE per day, which translates to 20mg to 80mg of OxyContin is considered a medium dosage for chronic pain management (treatment lasting more than 90 days). A prescription of 46 30mg OxyContin tablets would provide a medium dosage for a duration ranging from 17.25 to 69 days, depending on the individual patient's daily dosage. It is important to note that each patient's dosage is determined by multiple factors, including the severity of their condition and the duration of their treatment.

B. *Decomposition: Medical vs. Non-medical Dispensation*

To translate the above estimates into meaningful quantities, we decompose the volume of opioid shipments into use for different purposes. Columns (1) and (2) of Table 2 report model-predicted shipment and prescription numbers for each state, listed in alphabetical order. Columns (3) and (4) show a sharp contrast between the medical use and non-medical use opioids per capita. The medical use opioids per capita per year have much less variations across states, with most hovering around 0.3 MGE. In contrast, non-medical use opioids per capita vary considerably, from 0.053 MGE in Vermont to 0.436 MGE in Arizona. This comparison suggests that the substantial interstate differences in opioid dispensation primarily result from opioid diversion.

Columns (5) and (6) report the incidence of pharmacy-level opioid diversion. Column (5) reports the number of model-predicted rogue pharmacies (those with a higher-than-90% probability of selling opioids for non-medical use). Column (6) reports the proportion of rogue pharmacies within each state by dividing the number of rogue pharmacies reported in Column (5) by the total number of pharmacies in that state. Across these ten states, 8% (952/11,915) pharmacies can be called "rogue." Despite the low percentage, these pharmacies are the culprits for the opioid diversion pattern we see in the data.

Remarkably, column (7) reports that 51.5% of opioid shipments are diverted to non-medical use. However, this extremely high incidence of opioid diversion is driven by three states — Arizona, Florida, and New Jersey (emphasized in light gray in Table 2). These three states, especially Florida, stand out in total shipment, the number of prescriptions per capita, the non-medical use opioids per capita, and the proportion of rogue pharmacies. Florida alone takes up 43% of total shipments and houses 60% of rogue pharmacies in these ten states.

Our model can predict the displacement effects of each DEA enforcement action. Appendix E.E2 illustrates how the removal of a rogue pharmacy would impact the shipment patterns of other pharmacies and how consumers would substitute in response to the shutdown using our model. In Table E1, we report the displacement effects across pharmacies following the simulated removal of Bob's Pharmacy and Diabetic Supplies in 2008 using the pre-removal data. We can see that the top five pharmacies experiencing changes in opioid shipment for

Table 2— State-level Shipment Decomposition and Pharmacy Categorization

State	(1) Total Shipment Predicted(MGE)	(2) # Prescriptions per Capita	(3) Med Opioid per Capita	(4) NM Opioid per Capita	(5) # Rogue Pharmacies	(6) % Rogue Pharmacies	(7) % Opioid Diverted
AZ	4,292,716	1.814	0.306	0.436	246	0.236	0.587
CO	1,599,288	0.830	0.241	0.098	10	0.013	0.290
FL	12,687,714	1.682	0.317	0.371	581	0.141	0.539
KY	1,862,765	1.480	0.392	0.213	17	0.019	0.352
NC	3,184,095	0.914	0.213	0.161	20	0.015	0.432
NJ	2,379,060	1.622	0.267	0.397	46	0.042	0.598
RI	134,822	1.407	0.342	0.234	4	0.032	0.406
UT	841,145	0.785	0.209	0.113	15	0.031	0.351
VT	206,660	1.111	0.402	0.053	0	0.000	0.116
WA	2,409,081	1.011	0.295	0.119	14	0.012	0.287
Total	29,597,352	1.359	0.269	0.286	952	0.080	0.515

Note: The reported numbers in this table are based on the estimated model using results in Table (1). We predict each pharmacy's total shipment, decompose it into medical and non-medical purposes, and then aggregate these volumes to their state. For columns (4) and (5), we divide the shipment quantities by state populations. Columns (5) and (6) report the predicted number and percentage of pharmacies with an estimated probability of selling opioids for non-medical purposes greater than 0.9 ($\phi > 0.9$).

non-medical purposes are either full-blown rogue pharmacies or those in close distance.

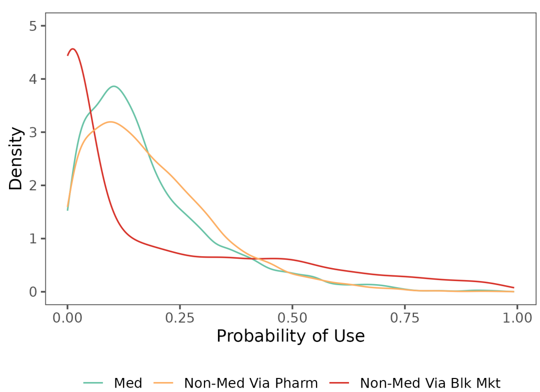
C. The Dissection of Different Dispensing Channels

In the previous subsection, we analyze the quantities of opioids dispensed and diverted; in this subsection, we focus on the estimated probability of consumers obtaining opioids from three dispensing channels: medical use via pharmacy, non-medical use via pharmacy, and non-medical use via the black market.

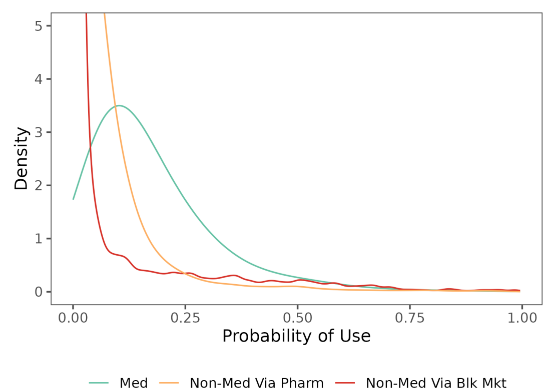
Figure 4 presents the distribution of these probabilities across ZCTAs in two groups of states. Figure 4a lumps Arizona, Florida, and New Jersey together as they are the "heavy offender" states, as shown in Table 2. Figure 4b combines the rest of the seven states. The side-by-side comparison shows a sharp contrast between the heavy offending states and the rest. While the probability distributions of medical use are comparable — roughly a log Normal distribution with a peak around 0.15 — the probability distributions of the non-medical use look vastly different. On the right, the yellow curve (non-medical use via pharmacy) and the red curve (non-medical use via the black market) exhibit sharp spikes at the lower end and a thin right tail. In contrast, the distributions for non-medical use show more mass at higher probabilities.

The long right tails of all three curves in both graphs reveal the substantial heterogeneity in opioid use across local markets, suggesting finding a "typical" local market would be difficult within any of these states.

We provide Table 3, which reports the across-ZCTA median probability of each dispensing channel state by state to illustrate the huge differences across states. Even among the heavy offenders, there are distinct differences. For example, Florida had a remarkably large black market, while New Jersey had a negligible one. Washington had the most significant black market presence among the "rest seven" group, despite its overall non-medical use probabilities lagging behind Rhode Island, Kentucky, and Colorado. The incidence of opioid use is on the higher side compared to previous studies, but still falls in the reasonable range of CDC reports.[29]



(a) Arizona, Florida, and New Jersey



(b) The Rest Seven States

Figure 4. Distribution of Probability of Opioid Use by Channels

Note: The figure describes the distribution, over ZCTAs, of the probability of consumers using opioids for different purposes and via different channels, which include medical use, non-medical use through pharmacies, and non-medical use through black markets.

[29]The CDC reports that, between 2008 and 2010, the across-county average number of opioid prescriptions per capita was 0.836, with a median of 0.905. If an opioid user receives five prescriptions a year (as estimated by our model), then about 16% to 18% of the county population uses opioids.

Table 3— Opioid Use Probabilities, State by State

	(1)	(2)	(3)
	Medical Use (%)	Non-Medical Pharmacy Use (%)	Non-Medical Black Market Use (%)
AZ	13.89	18.09	3.85
CO	14.08	2.69	0.50
FL	15.01	15.36	13.70
KY	19.07	6.94	0.38
NC	9.27	4.96	0.74
NJ	14.14	18.92	0.01
RI	16.13	8.82	0.003
UT	11.71	1.66	0.19
VT	23.58	1.12	0.00
WA	15.33	3.73	1.47
State Average	15.62	8.83	2.68

Note: The table reports the across-ZCTA median of the percentage of consumers using opioids through three dispensing channels: medical use, non-medical use via pharmacy, and non-medical use via the black market.

D. *Does the Predicted Black Market Use Predict Mortality?*

Can we trust our estimate of the black market size? After all, we do not have direct data on the size of the black market. Our identification rests on the comparisons of "disappeared opioids" between a rogue pharmacy shutdown and a normal pharmacy exit. To answer this question and, more importantly, to assess our model's external validity, we investigate whether our estimated black market size correlates with future opioid-related mortality.

We collected data on opioid-related mortality at the county-year level from the CDC from 2013 to 2015, roughly five years after the intense DEA enforcement effort captured by the 2008-2010 period. We allow a five-year time lag for a reasonable incubation period of the black market development.[30] For each year, we aggregate the predicted ZCTA populations of opioid use via three channels to a county and normalize them by dividing them by county populations. We then regress the opioid-related mortality rate five years later against the three (relative) market sizes, as well as (time-varying) county attributes and fixed effects at the year and county level.

[30]Notably, 2013 marks a turning point in the opioid epidemic. For the first time, synthetic opioid-related mortality increased while prescription opioid-related deaths declined, indicating that many individuals switched from prescription opioids to fentanyl in the black market.

Table 4 reports the regression results, with additional controls introduced incrementally across columns. Column (4) reports results for our preferred model — adding county-level fixed effects increases the model fit substantially as the R-squared increased from 0.05 to 0.94 from column (3) to column (4). Notably, the black market size is the only variable that remains significant when controlling for county-level fixed effects. Column (4) suggests that a one percentage increase in black market size results in a 1.7% (calculated as $0.01 \times 0.416/0.244$) increase in opioid-related mortality five years later. If the black market were to double in size, which is highly plausible given the rapid rise of opioid use in the late 2000s, the increase in mortality would be substantial. If we double the black market size by adding 0.042 to the share of black market use, this would result in a 7.1% increase in mortality, calculated as $0.042 \times 0.416/0.244$. The projected impact of our estimated black market size confirms the CDC-reported sharp increase of opioid-related mortality after 2013,[31] especially the rise in overdose deaths attributed to synthetic opioids, which were typically manufactured and distributed in the black market.

Table 4— Black Market Use Predicts Opioid-Related Mortality

	Opioid Mortality/County Pop. * 1000			
	(1)	(2)	(3)	(4)
% County Population Medical Use	-0.211	0.906	0.951	-0.228
	(0.213)	(0.855)	(0.893)	(0.490)
Mean: 0.173				
% County Population NM Pharmacy Use	1.082**	1.133**	1.155**	0.376
	(0.513)	(0.533)	(0.552)	(0.612)
Mean: 0.088				
% County Population NM Black Market Use	-0.523*	-0.0921*	-0.950*	0.416*
	(0.269)	(0.489)	(0.517)	(0.219)
Mean: 0.042				
Demographics		✓	✓	✓
Year Fixed-Effects			✓	✓
County Fixed-Effects				✓
Mean	0.244			
# obs (county-year)	1,320			
R^2	0.018	0.050	0.050	0.940

Note: Each observation is a county-year combination from 2008 to 2010. Opioid mortality data, covering the years 2013 to 2015, is sourced from the NVSS-restricted county-level mortality dataset. Standard errors are adjusted for clustering within counties and are provided in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

[31]In 2010, the national opioid-related mortality rate was 7.9 per 100,000, rising by 14% to 9.0 per 100,000 by 2013. By 2016, the rate had doubled to 14.5 per 100,000.

VII. Evaluating Counterfactual Policies

The DEA enforcement actions were halted due to political pressures.[32] In this section, we perform simulations using our estimated model to investigate what would happen if the DEA were able to carry out consistent, stringent enforcement actions against opioid-diverting pharmacies. Our first counterfactual policy implements consistent enforcement actions across ten states in our data, and our second counterfactual policy compares a cluster removal policy with a dispersed removal policy in Florida, the worst offending state by many metrics of measuring opioid diversion. In both counterfactual simulations, the opioid dispensation would mechanically decrease, but the effectiveness of such policies relies on quantity decomposition: Which markets are affected, to what extent, and how much will consumers substitute to the black market? This calculation depends on consumers' substitution patterns estimated in our model and the spatial distribution of pharmacies within and across local markets.

A. *Removing Heavy Offenders Across States*

In this counterfactual experiment, we remove the top offenders in each county among the ten states in our data. We round up all pharmacies within a county with an above 90% probability of selling opioids for non-medical purposes and rank them, from highest to lowest, by their total annual shipment for non-medical use.[33] We remove the top ten based on this rank; if a county has less than ten pharmacies on this list, we remove all of them. This is a very aggressive policy, removing 427 pharmacies across 117 counties.

Figure 5 illustrates the effectiveness of this policy across 117 counties: the red bars report the change in opioids dispensed for non-medical purposes, and the blue bars for medical purposes. This policy can be effective: Overall, we find a decrease of 0.08 MGE per person in non-medical use opioids dispensed, which is over 25% of 0.286 MGE per capita per year (the average amount for non-medical use across these ten states). However, there is significant heterogeneity in this effect across counties. About 9% of counties removed more non-medical shipments than 0.286

[32] https://www.washingtonpost.com/investigations/the-dea-slowed-enforcement-while-the-opioid-epidemic-grew-out-of-control/2016/10/22/aea2bf8e-7f71-11e6-8d13-d7c704ef9fd9_story.html. Article Accessed: 04/01/2024.

[33] We also add a qualifier that pharmacies on this list need to dispense at least 50 MGE of non-medical use opioids in the year.

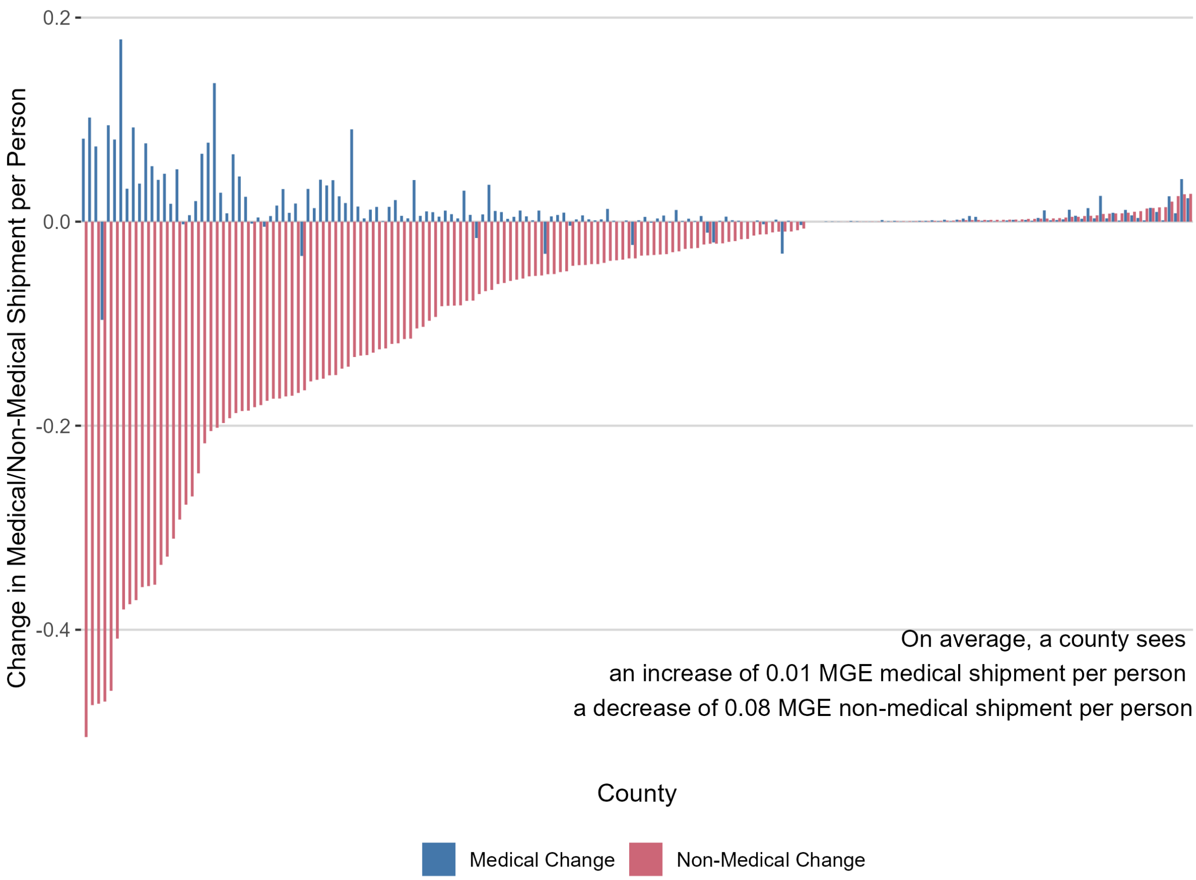


Figure 5. County-Level Shipment Change Per Capita

Note: In this counterfactual experiment, we remove the top ten pharmacies within a county with the probability of selling opioids for non-medical purposes over 0.9 ($\phi > 0.9$). This removes 424 pharmacies in 117 counties across ten states. We report the change in opioids dispensing for medical (in blue, at the top) and non-medial purposes (in red, at the bottom) county by county, going from the county with the highest reduction in opioids dispensed for non-medical purpose to the one with the lowest from left from right.

MGE. In the middle to far-right sections of the figure, the reduction in non-medical opioid use is minimal or nonexistent.[34] Some counties even see a reduction in opioids dispensed for medical purposes, driven by the removal of the sole pharmacy in a consumer's consideration set. For example, in rural America, a pharmacy involved in non-medical opioid sales may also be the only provider of medical-use opioids within a reasonable distance.

Figure 5 is inadequate to show the real danger of this policy: non-medical use does not simply disappear. As long as the root cause (addiction conditions) exists, demand for illicit supply exists. Table 5 shows the substitution patterns after the crackdowns. For each state, we report the changes in the numbers of consumers after the leading rogue pharmacies are removed. Directly comparing policy effectiveness across states is challenging, as states like Florida or Arizona may see more pharmacy removals than others, such as Washington. In each state, the reduction in non-medical pharmacy use is offset by a significant increase in the black market population. Of the 1.4 million consumers who leave the rogue pharmacy channel, nearly half a million (34%) switch to the black market.

Looking across columns, this unintended consequence due to the existence of the black market varies by state. In some states, including Arizona, Kentucky, North Carolina, New Jersey, Rhode Island, and Vermont, this policy leads to more "no use" than a "black market" increase. This variation can be attributed to the incidence and distribution of pain and addiction conditions as well as the pre-existing spatial distributions of pharmacies.[35]

B. Cluster Removals

As enforcement actions' effectiveness depends on offenders' geographic distributions, we perform counterfactual experiments to compare dispersed and cluster removals. This comparison is motivated by the DEA's special raids in areas deemed as particularly problematic for opioid abuse. Examples of these raids include Operation Oxy Alley, Operation Pill Nation, Operation Snake Oil, and Operation Juice Doctor 2 in Florida in 2010 and 2011. The DEA's operations

[34] Some counties even experienced increases in opioids dispensed for non-medical purposes — this is mostly likely due to the removal of pharmacies in neighboring counties.

[35] We observe that this policy often results in a slight increase in opioid dispensing for medical use. This suggests that some non-medical users may return to doctors for legitimate prescriptions to address their medical conditions. This shift can be seen as a harm reduction angle, as these individuals now receive care under doctors' supervision.

Table 5— Consumer Reactions to Top Ten Rogue Pharmacy Shutdown, State by State

	(1)	(2)	(3)	(4)	(5)
State	# Removed Pharmacies	Non-medical Pharmacy Use	No Use	Medical Use	Non-medical Black Market Use
AZ	72	−156,849	92,084	8,675	56,090
% Change		−2.71	+1.59	−0.15	+0.97
CO	7	−28,015	15,529	3,131	9,355
% Change		−0.59	+0.33	+0.07	+1.93
FL	232	−850,584	332,547	161,744	356,292
% Change		−4.62	+1.80	+0.88	+1.93
KY	18	−42,677	29,026	8,133	5,517
% Change		−1.39	+0.94	+0.26	+0.18
NC	21	−88,796	66,173	9,855	12,767
% Change		−1.04	+0.78	+0.12	+0.15
NJ	45	−149,156	115,079	33,140	936
% Change		−4.16	+3.21	+0.92	+0.03
RI	4	−7,216	6,289	872	54
% Change		−3.09	+2.69	+0.37	+0.02
UT	16	−47,774	25,734	2,308	19,732
% Change		−1.82	+0.98	+0.09	+0.75
WA	12	−37,214	16,717	3,416	17,081
% Change		−0.64	+0.29	+0.06	+0.29
Total	427	−1,408,283	699,179	231,278	477,827
% Change		−2.65	+1.31	+0.43	+0.90

Note: We aggregate the ZCTA-level population in each use to the state level. For each state, we first report the change in the number of opioid consumers across four different channels after removing the top pharmacy offenders. We then calculate the percentage change in these numbers. Vermont is not reported in the table, as no pharmacies in the state meet the removal criteria.

often focused on Florida because 90 of the nation's top 100 oxycodone-prescribing doctors and 49 of the country's top 50 oxycodone-dispensing clinics in 2010 were in Florida. Consider Operation Pill Nation,[36] a comprehensive operation aimed at closing down opioids-diverting pain clinics in South Florida. This operation led to the closure of 40 closely-clustered pain clinics within a year. Such cluster removals present challenges for us employing a reduced-form approach to evaluate the impact of these interventions. We cannot clearly define treatment and control groups because removals often occur simultaneously in a region rather than sequentially.

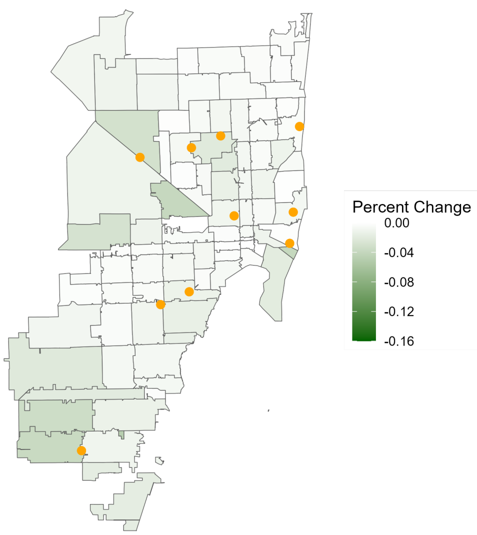
We choose Miami-Dade County, FL, where a total of 20 rogue pharmacies operated during our study period, to run two counterfactual experiments. In the "Dispersed Removal" policy, we remove ten pharmacies with relatively dispersed locations in this county in 2009, a year before the aforementioned special raid operations in Florida. In the "Cluster Removal" policy, we remove ten closely located rogue pharmacies in the center of the county in the same year. Figure 6 displays the locations of removed pharmacies as orange dots. Both the top and bottom rows follow a similar structure: the left graphs (Figure 6a and Figure 6c) use color shading to illustrate changes in consumer choice probabilities for non-medical use via the pharmacy channel. The right graphs (Figure 6b and Figure 6d) depict such changes via the black market channel. Darker colors indicate greater changes resulting from the policy.

Comparing the top and bottom panels, the cluster removal policy is more effective in reducing the incidence of non-medical consumption. The color is much darker in sub-markets affected, with many ZCTAs experiencing above 10% decrease in the probability of non-medical use via pharmacies. The impression is confirmed by Tables E2 and E3 (in Appendix E.E3): the dispersed removal policy, on average across ZCTAs, reduces the probability of non-medical use through pharmacies by 0.09 percentage point, while the cluster removal policy achieves 1.5 percentage point reduction. In total, the dispersed removal policy removed 0.015 MGE non-medical use opioids per capita in the county in 2009, while the cluster removal policy removed 0.021 MGE per capita.

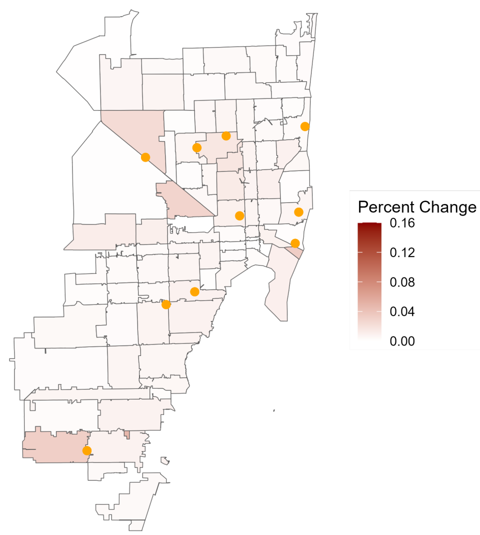
The unintended consequences of removing rogue pharmacies are evident in the analysis. In the dispersed removal scenario, 21,907 people stop using non-medical pharmacies, with 16,985

[36]https://www.dea.gov/press-releases/2011/02/24/dea-led-operation-pill-nation-targets-rogue-pain-clinics-south-florida

Dispersed Removal

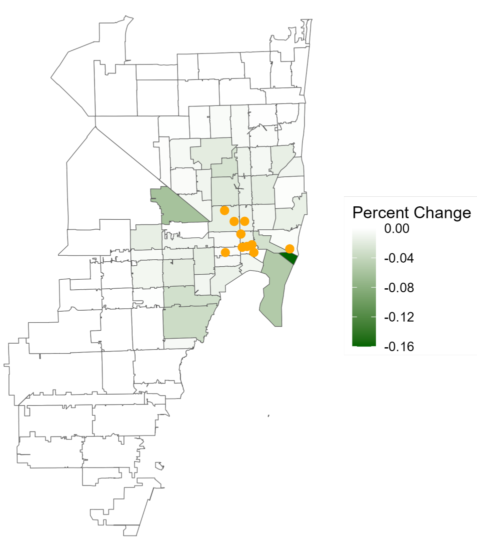


(a) Non-Medical Use - Pharmacy Channel

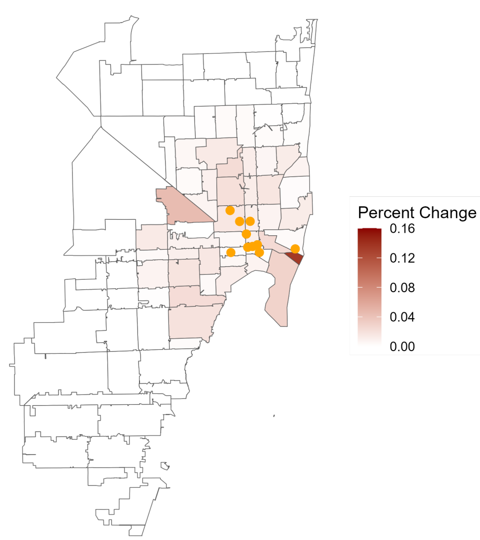


(b) Non-Medical Use - Black Market

Cluster Removal



(c) Non-Medical Use - Pharmacy Channel



(d) Non-Medical Use - Black Market

Figure 6. Consumer Response to Different Enforcement Actions

Note: The orange dots represent the locations of pharmacies removed in Miami-Dade County in our counterfactual scenarios. In different shades, the blocks at the ZCTA level show the change of the probability for non-medical use (via pharmacy or black market) in response to two types of enforcement actions: dispersed removals or clustered removals.

(77.5%) shifting to black market use. In the cluster removal scenario, 16,933 people leave non-medical pharmacies, and 14,618 (86.3%) switch to the black market. The cluster market policy eliminates all accessible rogue pharmacies around Miami, FL, leaving non-medical users with no alternative but the black market. This makes evaluating the effectiveness of these two policies more complex — the reduction in non-medical use via pharmacy is offset by the surge in the black market use, more so for the cluster removal policy.

VIII. Conclusion

The U.S. opioid crisis over the past three decades calls for a critical evaluation of its contributing factors, which can inform the development of forward-looking policies that address the root causes. We examine the role of pharmacies, the gatekeepers in opioid distribution. We modify the existing demand estimation methodology to account for heterogeneous consumers with varying consideration sets. In particular, we allow the inclusion of the black market as a choice alternative. A deep understanding of consumers' substitution across licit and illicit dispensing channels brings us closer to correctly predicting the impact of supply-side curtailment policies.

We show that pharmacy suspensions displace a substantial share of non-medical users into other pharmacies or the black market rather than stop using opioids altogether. Simply restricting access to opioid supply could push users towards riskier, unregulated sources, worsening the epidemic. The DEA enforcement actions need to be combined with demand-side policies (for example, providing opioid treatment programs to alleviate addiction conditions in the local population) to address the root cause of the opioid epidemic.

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Online Appendix

A) Additional Stylized Facts

A1. The DEA Toolbox

The OTSC/ISO tools allowed the DEA to curb opioid diversion swiftly. Despite their effectiveness, the DEA used these tools sparingly, with enforcement actions peaking at just 124 (59 ISOs and 65 OTSCs in 2011), as shown in Figure A1. The reasons for this underutilization remain unclear. However, various sources have suggested that the influence of drug companies was behind the scenes. According to The Washington Post,[37] former DEA and Justice Department officials hired by drug companies began advocating for a softer approach in 2012. Consequently, officials at DEA headquarters delayed or blocked enforcement actions, and the number of cases dropped significantly after 2012. The Office of Inspector General also cited an example in which a U.S. District Court Judge in Washington, D.C., issued a temporary restraining order that prevented the DEA from enforcing an ISO against Cardinal Health, Inc. in 2012.

A2. DEA Criteria Variation

Figure A2 shows the distribution of the number of months in the given year a pharmacy violated one of the five DEA criteria over the three-year span from 2008 to 2010. This figure reveals a clear dichotomy: most pharmacies did not violate any DEA criteria, while a small subset of pharmacies repeatedly violated the DEA criteria for multiple months within a year. The DEA considered this latter group as suspects of selling opioids without a legitimate medical purpose.

A3. Pain Conditions, Consumer Characteristics, and Pharmacy Competition

We use the HCUP data to construct major diagnosis groups based on conditions that, according to medical literature, are likely to be treated with opioids for pain management. Specifically, we use the International Classification of Diseases, Ninth Revision (ICD-9), to categorize whether

[37]See https://www.justice.gov/archive/usao/fls/PressReleases/2011/110901-01.html, last accessed in April 2024.

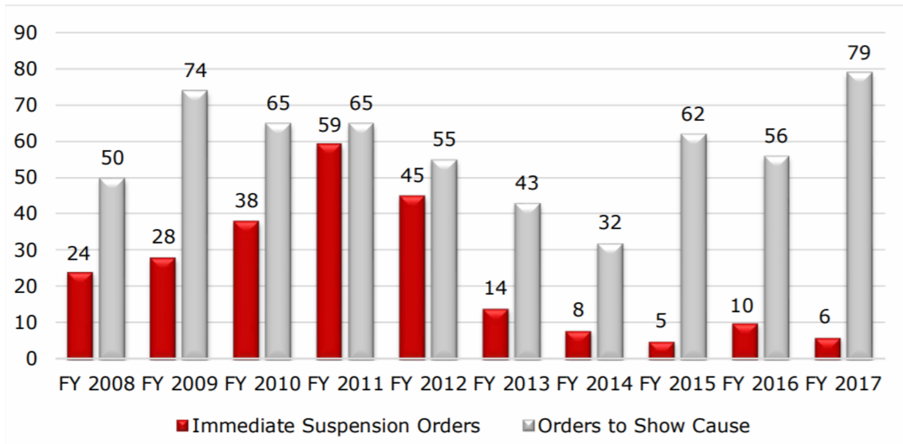

Figure A1. ISOs and OTSCs Issued by DEA, FYs 2008 - 2017

Note: This figure shows the total number of ISOs (Immediate Suspension Orders) and OTSCs (Orders to Show Cause) issued by the DEA on prescribers, pharmacies, distributors, and manufacturers, as reported by the Office of Inspector General's review of the DEA's response to the opioid epidemic. We obtained this figure from https://oig.justice.gov/reports/2019/e1905.pdf.

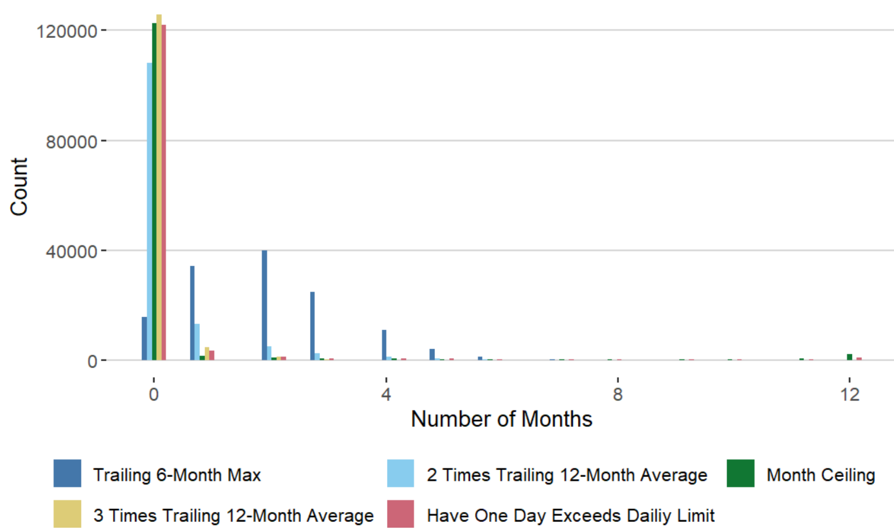

Figure A2. DEA Criteria Variations From 2008 to 2010

Note: This figure displays the distribution of the number of months in a given year a pharmacy violated one of the DEA criteria for suspicious shipments. From 2008 to 2010, each pharmacy is treated as three separate observations, one for each pharmacy-year pair.

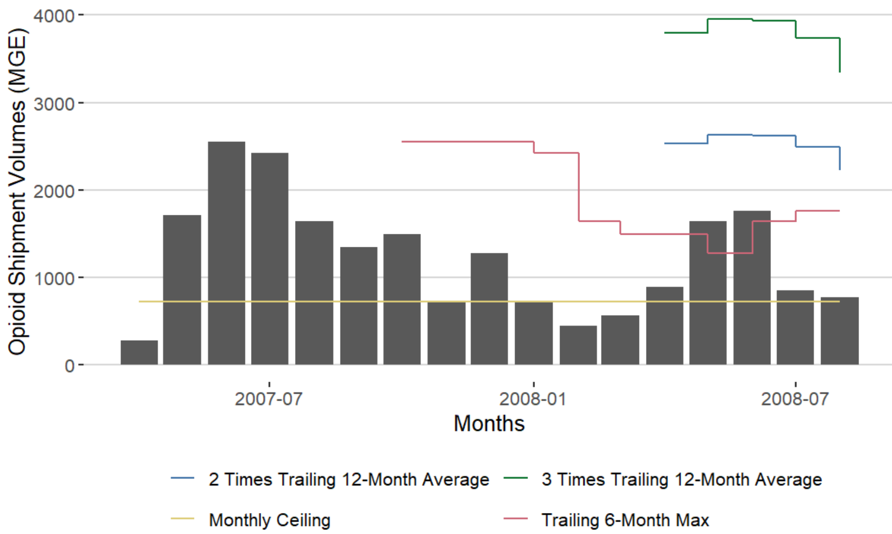

Figure A3. DEA Criteria Project on Bob's Pharmacy and Diabetics Supplies

Note: This figure displays the monthly volumes of opioids dispensed (in MGE) by Bob's pharmacy based on ARCOS data, before its shutdown on August 15, 2008. Four DEA criteria maps on the monthly volume of opioids by Bob's pharmacy.

an encounter is classified as injury, unspecified pain, opioid user disorder, or mental illness and then add up the occurrences of these medical conditions for each ZCTA. We count each code separately if an encounter is associated with multiple ICD-9 codes.

- For injuries, we use ICD-9 codes starting with 800-839 (fractures and dislocations), 870-894(open wounds), 920-949(superficial injuries, contusions, and crushing injuries), and 950-957(nerve and spinal cord injuries). These codes roughly cover injuries that likely use opioids to treat. We select codes that correspond to severe physical injuries that likely require opioid treatment, for example, burns of the face, head, and neck(code 942). We ignore minor injuries that are unlikely to be treated with opioids, for example, sprains of the ankle and foot (code 845).

- For unspecified pain, we use ICD-9 codes 338.4, 338.29, 338.19, 338.0, which cover conditions that an injury might not directly cause. These are often standalone conditions (not co-occurring with other conditions) in the HCUP data, such as chronic pain syndrome (code 338.4) and other chronic pain (code 338.29).

- For OUD, we first select two main categories: dependence (codes beginning with 304) and abuse(codes beginning with 305), which are about all substance abuse. We then select only opioid-related conditions within these categories. In addition, we include cases of poisoning by opium/opioids such as ICD-9 code 965.00. The ICD-9 codes we use to classify OUD include 304.00, 304.01, 304.02, 304.03, 304.70, 304.71, 304.72, 304.73, 305.50, 305.51, 305.52, 305.53, 965.00, 965.01, 965.02, 965.09, 970.01.

- For mental illnesses, we include various mental health conditions, such as anxiety (code 300) and manic-depressive psychosis (code 296). These conditions are often treated with benzodiazepines, which are depressants that produce sedation and hypnosis, relieve anxiety and muscle spasms, and reduce seizures. Notably, benzodiazepines are the most commonly co-used drugs among opioid addicts. The ICD-9 codes we use to classify mental illnesses include 296.23, 296.33, 311, 300.0, 300.4, 300.11, 296.20, 296.34, 296.24, 296.30, 296.32, 300.12, 296.31, 309.81, 296.22, 296.25, 300.21, 300.14, 309.89, 296.21, 300.19, 300.15, 296.35, 300.23, 300.16, 300.29, 296.36, 296.26, 300.22, 300.20, 300.10, 309.83, 309.82, 300.13.

B) Principle Component Analysis

Principal Component Analysis (PCA) is a technique used to transform the original data, in this case, pharmacies' shipment patterns, into a new coordinate system. This transformation allows us to identify the principal components, which are a set of orthogonal unit vectors that capture the directions of maximum variance in the dataset.

Intuitively, the first principal component can be considered as a best-fit line, minimizing the average squared orthogonal distance from the data points to the line. The second principal component is another line orthogonal to the first one and minimizes the average squared orthogonal distance again. This process continues iteratively, with each subsequent principal component being orthogonal to all the previous ones and capturing the remaining variance in the data. We proceed to the fifth iteration to explain all data variations, obtaining five principal components (PC1 to PC5).

Table A1— Consumer Medical Conditions and Population Characteristics at the ZCTA Level

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max	Mean	St. Dev.
Panel a. Medical condition								
Injury	10,653	0.000	0.004	0.466	0.715	9.284	0.480	0.491
Pain	10,653	0.000	0.000	0.137	0.290	6.028	0.212	0.331
Lagged OUD	10,653	0.000	0.000	0.066	0.148	7.829	0.125	0.261
Mental	10,653	0.000	0.004	0.694	1.126	13.274	0.762	0.833
Panel b. Demographics								
Age	10,653	9.800	35.500	40.000	44.600	81.200	40.521	8.197
Female	10,653	0.000	0.489	0.507	0.523	0.871	0.502	0.048
White	10,653	0.000	0.769	0.885	0.952	1.000	0.832	0.170
Above HS	10,653	0.000	0.794	0.874	0.931	1.000	0.851	0.107
log(Income)	10,653	6.084	9.857	10.081	10.361	11.839	10.110	0.410
Unemployment	10,653	0.000	0.065	0.091	0.123	1.000	0.099	0.060
Poverty	10,653	0.000	0.078	0.134	0.204	1.000	0.154	0.108
Population	10,653	200	2,514	9,851	24,266	92,586	14,994	14,838
Pop. Density	10,653	0.57	63.78	274.77	1,643.25	35,901.23	1,277.72	2,201.75
Panel c. Doctor Competition								
Lag Capacity	10,653	0	39	140	565	9199	426.7	647.677

Note: This table presents the summary statistics of ZCTA-year-level variables used in this paper. “Injury,” “Pain,” “Lagged OUD”, and “Mental” (mental illness) represent the number of diagnoses per 100 people at the ZCTA level, sourced from the HCUP database. The remaining variables—age, female, white, above HS (percentage of high school graduates), log income, poverty, and population—are from the 5-Year American Community Survey reported at the ZCTA-year level. The “lag capacity” variable is the number of doctors within 10 to 20 miles of a ZCTA.

Table A2— Pharmacy Competition

	2008	2009	2010
Market Share:			
CVS	11.5%	11.4%	11.55%
Walgreens	13.7%	14.5%	14.8%
Walmart	7.12%	7.21%	7.21%
Albertson	2.16%	1.65%	1.21%
Regional Chain	25.4%	24.8%	24.5%
Chain	59.8%	59.56%	59.22%
Grocery	28.0%	27.5%	27.0%
Mean # of Pharmacies within 1 Mile	2.95	3.00	3.06
Mean # of Pharmacies within 5 Mile	32.1	32.7	33.4
Mean # of Pharmacies within 10 Mile	91.7	93.2	95.6
Number of Pharmacies	11,609	11,901	12,028

Note: This table reports various measurements of competition year by year from 2008 to 2010. The top of the table reports the fraction of each pharmacy type among all pharmacies in the ten states we study. A type can be CVS, Walgreens, Walmart, Albertson's, a regional chain, a chain or a grocery store. A regional chain is defined as any chain that is not among the four largest national chains (CVS, Walgreens, Walmart, and Albertson's). The grocery category is defined as pharmacies that carry fresh produce (e.g. Walmart). The bottom of the table shows the mean number of pharmacies within a specified radius (X miles) to measure competition intensity in the local market.

Table B1 shows the variance explained by each principal component. As intuition suggests, the first component explains the most variation in the data. Table B2 presents the coefficients (loadings) within the rotation matrix, revealing how much the original variables influence each component. PC1 is a linear combination of the original variables, with the scale specified in the first column of Table B2.

Based on the information provided in Tables B1 and B2, we choose to use PC1 and PC2 due to their ability to explain a significant portion of the data's variance and their interpretability. Table B1 shows that PC1 and PC2 collectively represent approximately 71.38% of the total variance in the data. In principle, we can include PC3. However, this only adds 17% of variance and does not have a nice interpretation as PC1 and PC2.

The loading coefficients can be used for interpretation. For instance, PC1 can be interpreted as the overall violation index, with the second and third pharmacy shipping patterns contributing the most to this index. On the other hand, PC2 illustrates the balance between the first three metrics (concerning the shipment growth patterns) and the next two metrics (concerning whether the shipment has exceeded a certain threshold).

Table B1— Principal Component Analysis Rotation

	PC1	**PC2**	**PC3**	**PC4**	**PC5**
Standard deviation	1.4288	1.2361	0.9121	0.54901	0.54526
Proportion of Variance	0.4083	0.3056	0.1664	0.06028	0.05946
Cumulative Proportion	0.4083	0.7138	0.8803	0.94054	1.00000

Note: The standard deviation values represent the square roots of the eigenvalues associated with each principal component. The proportion of variance represents the percentage of the total variance in the data explained by each principal component. The cumulative proportion indicates the total proportion of variance explained by the current principal component and all preceding principal components.

Table B2— Principal Component Analysis Rotation

	PC1	**PC2**	**PC3**	**PC4**	**PC5**
$>$ 6M Max	0.358	0.196	0.899	-0.053	-0.150
$>$ 2× 12M Average	0.539	0.382	-0.172	0.080	0.726
$>$ 3× 12M Average	0.495	0.394	-0.397	-0.060	-0.662
$>$ 8,000 Monthly	0.413	-0.572	-0.013	0.703	-0.086
$>$ 5,000 Daily	0.406	-0.578	-0.066	-0.702	0.064

Note: The table presents the rotation matrix obtained from the Principal Component Analysis. Each row corresponds to a variable, and the columns represent the principal components (PC1 to PC5). The values in the table are the loadings or coefficients of the variables on each principal component, rounded to the first three digits.

C) Probability decomposition

For a fixed C_{it}, we can decompose each element of Equation 8 and 9 as follows:

1) Bottom level choice probabilities:

(C1)
$$p_{it}(s^{med}|med, use) = \frac{\exp(u_{ist}^{med}/\mu^{med})}{\sum_{k\in S}\exp(u_{ikt}^{med}/\mu^{med})}$$
$$p_{it}(s^{n-med}|n-med, use, C_{it}) = \frac{\exp(u_{ist}^{n-med}/\mu^{n-med})}{\sum_{k\in C_{it}}\exp(u_{ikt}^{n-med}/\mu^{n-med}) + \exp(u_{i0t}^{blk}/\mu^{n-med})}$$

The bottom nest inclusive value is defined as:

(C2)
$$IV(med|use) = \log\sum_{k\in S}\exp(u_{ikt}^{med}/\mu^{med})$$

(C3)
$$IV(n-med|use, C_{it}) = \log(\sum_{k\in C_{it}}\exp(u_{ikt}^{n-med}/\mu^{n-med}) + \exp(u_{i0t}^{blk}/\mu^{n-med}))$$

2) Middle-level probabilities:

(C4)
$$p_{it}(med|use, C_{it}) = \frac{\exp(\mu^{med}/\sigma IV(med|use))}{\exp(\mu^{med}/\sigma IV(med|use)) + \exp(\mu^{n-med}/\sigma IV(n-med|use, C_{it}))}$$

(C5)
$$p_{it}(n-med|use, C_{it}) = \frac{\exp(\mu^{n-med}/\sigma IV(n-med|use, C_{it}))}{\exp(\mu^{med}/\sigma IV(med|use)) + \exp(\mu^{n-med}/\sigma IV(n-med|use, C_{it}))}$$

The inclusive value of the middle nest is defined as:

(C6)
$$IV(use|C_{it}) = \log(\exp(\mu^{med}/\sigma IV(med|use)) + \exp(\mu^{n-med}/\sigma IV(n-med|use, C_{it})))$$

3) Top-level probabilities:

$$p_{it}(use|C_{it}) = \frac{\exp(\sigma IV(use|C_{it}))}{1 + \exp(\sigma IV(use|C_{it}))} \tag{C7}$$

The above probabilities feature the nesting parameters μ^l and σ, with μ^l denoting the dissimilarity parameters within nests and σ denoting the dissimilarity parameters between the nests. A lower value of μ^l implies a higher correlation within the nest l, while a higher value of σ indicates less correlation between the "medical" and "non-medical" nests. We expect σ to be higher than μ^l, as medical and non-medical users cannot easily substitute across nests.

D) Estimation Steps

Here we describe a general outline for the estimation process, omitting the time subscript for clarity. For the most part, calculations are conducted at the pharmacy-ZCTA pair level for each year. In the final step, we aggregate ZCTA quantities to the pharmacy and county level.

1) For each simulation, $k = 1, \ldots, K$, we draw a random number, denoted by u_{sk}, from a uniform distribution between 0 and 1 for each pharmacy s. Once drawn, this value remains constant throughout the estimation process.

2) Choose an initial value of the parameters θ_0.

3) Calculate ϕ_s,

$$\phi_s(\lambda) = \frac{\exp(\lambda_0 + DEA\_Criteria_s \lambda_D + W_{st}\lambda_W)}{1 + \exp(\lambda_0 + DEA\_Criteria_s \lambda_D + W_{st}\lambda_W)} \tag{D1}$$

4) For each ZCTA, construct the initial non-medical consideration set $C_i^{k0} = \{s : \phi_s(\lambda^0) > u_{sk}\}$ for each simulation k.

5) Calculate $P_i(s^{n-med}|C_i^{k0})$ and $P_i(s^{med}|C_i^{k0})$ for each simulated initial consideration set C_i^{k0}, using the steps described in Appendix C.

6) For each simulation k, calculate:

(D2) $$R_{is}^{k} = n_i \eta \iota [(P_i(s^{med}|C_i^{k0}) + P_i(s^{n-med}|C_i^{k0}))]$$

7) Using the importance sampling technique as in Goeree (2008), calculate the importance weight:

(D3) $$W_k = \frac{\pi_{C_i^{k0}}(\lambda)}{\pi_{C_i^{k0}}(\lambda^0)}$$

where the denominator $\pi_{C_i^{k0}}(\lambda^0)$ is the probability of the initial consideration set C_i^{k0} is considered at the initial parameters λ^0,

(D4) $$\pi_{C_i^{k0}}(\lambda^0) = \prod_{s \in C_i^{k0}} \phi_s(\lambda^0) \prod_{s \notin C_i^{k0}} (1 - \phi_s(\lambda^0))$$

and the numerator $\pi_{C_i^{k0}}(\lambda)$ is the probability of the initial consideration set C_i^{k0} is considered at the parameters λ,

(D5) $$\pi_{C_i^{k0}}(\lambda) = \prod_{s \in C_i^{k0}} \phi_s(\lambda) \prod_{s \notin C_i^{k0}} (1 - \phi_s(\lambda))$$

Throughout the estimation, $\pi_{C_i^{k0}}(\lambda^0)$ stays the same. Note that the importance weight, constructed in Equation (D3), is calculated at the initial generated consideration set.[38]

8) Calculate the predicted shipment at each pharmacy-ZCTA pair,

(D6) $$R_{is} = \sum_k \frac{W_k}{\tilde{W}} R_{is}^{k}$$

[38] Equation (D5), if we follow Goeree (2008) exactly, would be different. The consideration set in Equation (D5), according to Goeree (2008), would be $C_i^k = \{s : \phi_s(\lambda) > u_{sk}\}$ rather than the initial simulated consideration set C_i^{k0}. This means that throughout the estimation process, the simulated consideration set would have to change (through updating λ in each iteration), which is inconsistent with the intended framework. After discussing with other researchers in the search literature, we suspect that the original paper contained a typo and we corrected it to be our Equation (D5).

where $\tilde{W} = \sum_k W_k$.

We differ from Goeree (2008) in Equation (D6), as Goeree (2008) uses the following formula in this importance sampling step:

$$R_{is} = \frac{1}{K}\sum_k W_k R_{is}^k \tag{D7}$$

It is likely that Equation (D7) will be inaccurate if the true λ is far from λ^0. This is because π is likely to be a very small number, which contains a series of multiplication of numerical values under 1. Consequently, dividing a small number by another small number can cause the objective function to become unstable, leading to a very flat and large objective value. This flatness can make it difficult for optimization algorithms to find any minimum. To mitigate this issue, we employ a self-normalization technique. This approach involves adjusting the weights such that their sum equals one, effectively bounding the possible range of outcomes between 0 and 1. This is commonly used in statistics literature (Neddermeyer 2009, Cappé et al. 2004, Kong 1992). This normalization would stabilize the value and also ensure a more robust and reliable approximation of the objective function.

9) Aggregate R_{is} to the pharmacy level to obtain R_s:

$$R_s = \sum_{\{i:d_{is}\leq 10miles\}} R_{is}$$

10) Construct the county-level prescription quantity, Q_{county}, using a process analogous to that outlined in Equation (D2). To do this, we begin by calculating Q_{is}^k, defined as: $Q_{is}^k = n_i\eta\iota[(P_i(s^{med}|C_i^{k0}) + P_i(s^{n-med}|C_i^{k0}))]$. Following the same steps as in Steps 6 to 8 and applying the importance sampling weight W_k for each simulation k, we obtain the county-level prescription quantity:

$$Q_{county} = \sum_{\{s\in county\}}\sum_{\{i:d_{is}\leq 10miles\}} Q_{is}$$

11) Next, we stack the two-moment conditions that match the predicted shipment at the pharmacy level and the predicted prescription number at the county level to their observed counterparts. Define a vector:

$$y(\theta) = (R_s(\theta), Q_{county}(\theta)) \tag{D8}$$

We solve the following minimization problem using a two-stage weighted nonlinear least squares method:

$$\min_{\theta} \sum_{h} (w_h[\log(\tilde{y}_h) - \log(y_h)])^2 \tag{D9}$$

In Equation (D9), we use h to denote either pharmacy or county, and $\tilde{y}_h$ to denote the observed shipment or prescription number. In the first stage, we set $w_h = 1$ and obtain estimate $\hat{\theta}_{1st}$. In the iteration process in this minimization step, we update the importance weight using new λ in each iteration.

12) In the second stage, we update the weights to $w_h = \frac{1}{\hat{u}_h^2}$, where:

$$\hat{u}_h = \log(y_h(\hat{\theta}_{1st})) - \log(y_h) \tag{D10}$$

We then minimize Equation (D9) again to obtain more efficient estimate $\hat{\theta}$.

E) Additional Results

E1. Graphical Presentation of the Estimated Model

Figure E1 is a histogram of the predicted values for estimated ϕ, using Equation 5. We can see that ϕ is highly bimodal, with two peaks on either end of the support.

E2. Remove Bob's Pharmacy and Diabetics Supplies

To further illustrate how our model works, we conduct a counterfactual analysis by simulating the removal of *Bob's Pharmacy and Diabetic Supplies*. This pharmacy is selected based on the

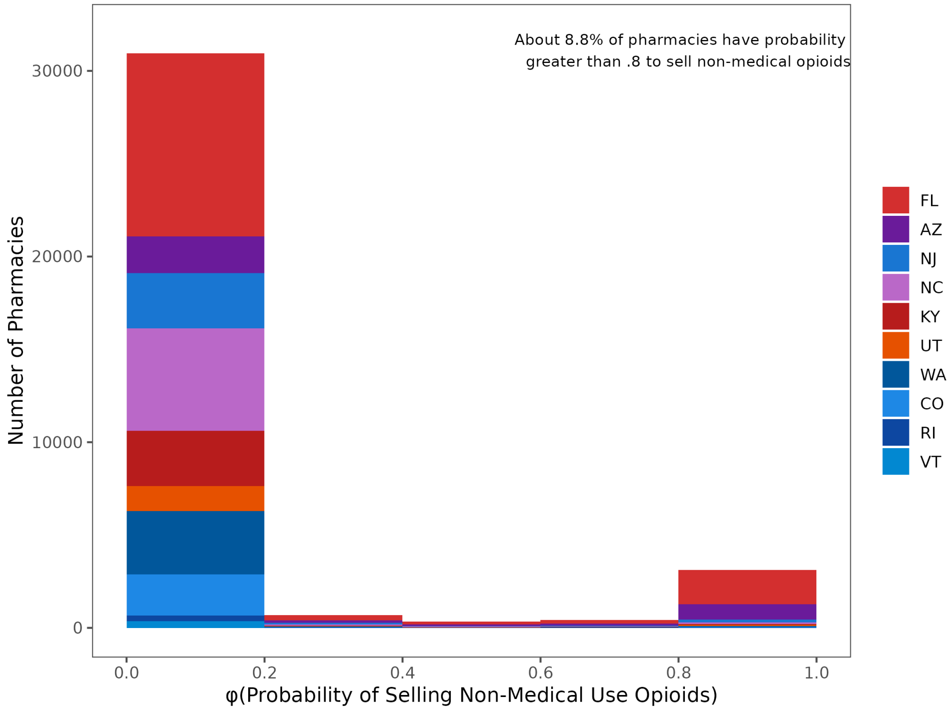

Figure E1. Distribution of Predicted ϕ

Note: This figure presents a histogram of the predicted values for estimated ϕ, using Equation 5.

descriptive evidence reported in Section IV. Table E1 reports the model-predicted pharmacy-level shipment changes resulting from Bob's Pharmacy's removal using pre-removal data.

The first row under the header shows that Bob's Pharmacy had limited sales of medical opioids before its removal. The next two rows show that the most displacements happened to a nearby pharmacy, a Walgreens, despite it having a moderate probability of being rogue. Row 3 shows that another pharmacy benefiting from the shutdown, though located 18 miles away, had an almost 100% probability of being rogue. Rows 4 and 5 follow a similar pattern. Row 6 lists another pharmacy within a 4-mile radius, while Rows 7 to 11 show pharmacies experiencing negligible effects.

There are two clear messages from these displacement effects. First, consumers cared about travel distances in pharmacy choices; second, rogue pharmacies competed with rogue ones in our spatial demand model, even if they are more than 10 miles away. For example, *Careplus*

Table E1— Pharmacies' Shipment Responses to Shutting Down Bob's Pharmacy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pharmacy	**Distance**	ϕ	**Before**		**After**		**Change**	
			Medical	**Non-Medical**	**Medical**	**Non-Medical**	**Medical**	**Non-Medical**
Bob's Pharmacy	0.00	1.00	788	23,308	-	-	-	-
WALGREEN CO.	4.32	0.33	2,888	6,942	3,050	7,962	162	1,020
CAREPLUS PHARMACY	17.74	0.99	613	17,584	622	18,346	9	761
HOLIDAY CVS	2.95	0.24	2,885	3,530	3,047	4,063	163	534
SUN & LAKE PHARM	21.53	1.00	717	19,221	721	19,565	5	344
VOLEL PRFSNL	3.33	0.08	788	2,075	833	2,370	44	295
HOLIDAY CVS	10.87	0.07	3,677	1,611	3,808	1,826	131	216
MERCY COMMUNITY	3.05	0.08	789	1,566	833	1,758	44	193
HOLIDAY CVS	12.00	0.07	2,032	1,031	2,141	1,188	109	157
ALBERTSONS	1.96	0.07	1,235	973	1,304	1,125	70	152
HOLIDAY CVS	12.90	0.07	2,662	1,077	2,794	1,227	132	151
⋮								
Total Affected (N = 74)			141,912	135,667	144,656	119,481	2,743	-16,185

Note: This table reports the top ten pharmacies that would experience shipment changes after the shutdown of Bob's Pharmacy and Diabetic Supplies, ranked by the quantity change of opioids dispensed for non-medical purposes. Column(1) is the distance between each reported pharmacy and Bob's Pharmacy. Column (2) reports each pharmacy's predicted probability of selling opioids for non-medical purposes. Columns (3) to (8) report simulated decomposition of opioid shipment for medical and non-medical purposes.

Pharmacy, 18 miles away from Bob's Pharmacy (outside our pre-imposed distance of 10 miles for a consumer's consideration set), took a significant chunk of switched consumers. This occurred because consumers located between *Careplus Pharmacy* and *Bob's Pharmacy* included both in their consideration sets.

After removing *Bob's Pharmacy*, the total opioid shipment of all pharmacies affected by this shutdown decreased by about 4.8%((2,743-16,185)/(141,912+135,667), and the non-medical shipment decreased by 11.9% (16,185/135,667). Opioid shipments did not fully recover to the pre-removal level, as non-medical users either switched to no use or the black market. However, we also note that the medical shipment increased by 1.9% (2,743/141,912). This is because, in our model, the non-medical nest is a viable substitute with the medical nest. Non-medical users may be returning to see doctors and getting valid prescriptions to treat their medical conditions — after all, many opioid addicts were initially introduced to opioids for medical purposes, such as treating injuries sustained in car accidents. This can be viewed as a harm reduction angle:

these patients were placed under the care of their physicians.

E3. Cluster Removals vs. Dispersed Removals in Miami-Dade County, FL

Tables E2 and E3 report the effects of removing ten dispersed rogue pharmacies versus ten closely-located rogue pharmacies, respectively.

Table E2— Effects of Dispersed Removals

	(1)	(2)	(3)	(4)	(5)	(6)
	N	Mean	St. Dev.	Per Capita Change	Population Change	Substitute to Black Market
NM Use Opioids (MGE)	110 pharmacies	−441	1732	-0.015		
NM Pharmacy Prob.	89 ZCTAs	−0.009	0.010		-21,907	
NM Black Market Prob.	89 ZCTAs	0.007	0.008		16,985	77.5%

Note: This table reports the effects of a dispensed removal policy that shuts down ten scattered pharmacies in Miami-Dade County, FL. The first row reports the changes in pharmacy shipments for non-medical use (in MGE) for 110 pharmacies affected. The second and third rows report the changes in consumer choice probabilities for 89 ZCTAs affected. Columns (2) and (3) report the mean and standard deviation of row quantities. Column (4) aggregates the total change in shipments from all affected pharmacies and divides it by the county population. Column (5) reports the change in the affected population, which is the difference between the population consuming opioids for non-medical purposes after the removals and that before the removals. Column (6) reports the percentage of the population switching from non-medical use via pharmacy to non-medical use via the black market.

Table E3— Effects of Cluster Removals

	(1)	(2)	(3)	(4)	(5)	(6)
	N	Mean	St. Dev.	Per Capita Change	Population Change	Subsitute to Black Market
NM Use Opioids (MGE)	64 pharmacies	−578	1,507	-0.021		
NM Pharmacy Prob.	52 ZCTAs	−0.015	0.020		-16,933	
NM Black Market Prob.	52 ZCTAs	0.012	0.016		14,618	86.3%

Note: This table is structured the same as Table E2, reporting the effects of a cluster removal policy that shuts down ten closely located pharmacies in Miami-Dade County, FL.