Retail Pharmacies and Drug Diversion during the Opioid Epidemic*

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Abstract

This study investigates the role of retail pharmacy ownership in the opioid epidemic in the United States by comparing independently owned pharmacies' and chain pharmacies' prescription opioid dispensing practices. Using data of prescription opioid orders at the pharmacy level between 2006 and 2012, we find that compared to chain pharmacies within the same ZIP code area, independent pharmacies on average dispense 40.9% more opioids and 61.7% more OxyContin. We further confirm that after being acquired by a chain, a previously independent pharmacy reduces dispensing of opioids by 31.7% and OxyContin by 43%. Using the OxyContin reformulation in 2010, which reduced the demand for diversion for illegal recreational use but not the demand for medical use, we show that half of the difference in dispensed OxyContin doses between independent and chain pharmacies can be attributed to drug diversion. In addition, we find that independent pharmacies' OxyContin dispensing is higher in areas with greater competition. Furthermore, a larger county-level recreational demand is correlated with a larger difference between independent and chain pharmacies' prescription opioid dispensing. We discuss two reasons that may explain why independent pharmacies are more likely to be linked to drug diversion. First, they have stronger financial incentives due to lower expected costs of misdoing. Second, they may have less information on patients' prescription drug use history. Prescription drug monitoring programs help to reduce the information gap between independent and chain pharmacies to some extent, but monitoring of small independent pharmacies needs to be strengthened.

Keywords: pharmacy, ownership, prescription opioids, drug diversion
JEL codes: I11, I18, L22

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1 Introduction

In 2017, 11.4 million Americans misused opioids, including 11.1 million who misused prescription drugs (NSDUH 2018). In 2017, on average 130 Americans died every day from an opioid overdose (CDC 2019*a*). Prescription opioid analgesics are at the root of the current opioid epidemic (Dart et al. 2015; Okie 2010; Substance Abuse and Mental Health Services Administration 2013; Schnell 2019; Schnell and Currie 2018), and thus it is important to analyze the roles played by different actors related to the dispensing of prescription opioids (Maclean et al. 2020).[1] While prescribers have fueled the market with prescriptions (Schnell 2017), insurers provide generous coverage of prescription opioids (Pacula and Powell 2018), and manufacturers have spent enormous resources in advertising prescription opioids (Alpert et al. 2019; Hadland et al. 2019; Nguyen et al. 2019), the role of dispensing pharmacies is not well understood.

Drug diversion, defined as when prescription medicines are obtained or used illegally (CDC 2019*b*), is an important source for opioid drug abuse. In particular, pharmacies are a main stakeholder involved in nearly 80% of all prescription drug diversion. Police and regulatory agencies perceive that about 39.4% of drug diversion involves doctor shopping, 35% involves prescription theft or forgery, 2% involves insurance fraud, and 1.5% involves pharmacy thefts and robberies (Inciardi et al. 2007).[2] As gatekeepers or the last line of defense ensuring that prescriptions are filled and drugs dispensed only for legitimate medical use, pharmacies play an important role in all four of these diversion channels. In fact, surveys show that compared with physicians, pharmacists have better knowledge of whether patients abuse drugs (Cicero et al. 2011), and pharmacists perceived a larger percentage of patients (41%) abusing opioid pain relievers than their prescribing colleagues perceived (17%) (Hagemeier et al. 2013). By law, pharmacists have obligations to inspect prescriptions for validity and ensure that controlled substances are dispensed legally (Drug Enforcement Administration 2005). However, empirically, we know little about how pharmacies use their discretion and what factors may affect pharmacies' discretion in dispensing prescription opioids.

This paper analyzes whether pharmacy ownership affects prescription opioid dispensing and rates of drug diversion. As a starting point, we directly compare independent and chain pharmacies across the country in their opioid dispensing. We find consistent evidence that independent pharmacies on average dispense more opioids than their chain counterparts. We consider all prescription opioids and OxyContin specifically. Since OxyContin is especially prone to abuse and therefore diversion (Alpert et al. 2018; Cicero et al. 2011), we expect a stronger impact of owner-

[1] Substance Abuse and Mental Health Services Administration (2013) reports that among heroin users between 2002 and 2011, almost 80% reported previous prescription opioid usage (Schnell, 2019).

[2] The rest of the sources are residential burglary (5.9%), physician "pill mills" (3.4%), internet (3%), smuggling (1.5%), in-transit losses (1%), theft of institutional drug supplies (2%), and others (5.4%).

ship status on OxyContin dispensing. Using variation within a ZIP code, we show that independent pharmacies, compared with chain pharmacies, dispense on average 136.2 (40.9%) more Morphine Equivalent Doses (MED, in grams) of all opioids and 16.8 (61.7%) more MED of OxyContin.

Although the direct comparison on a granular local level shows consistently that independent pharmacies on average dispense more opioids, various differences between pharmacies can explain the differences in dispensing. For example, independent pharmacies may dispense more opioids if their location is more convenient for patients or if they face less competition. Therefore, we investigate acquisitions to examine whether the corresponding ownership change from an independent to a chain pharmacy affects the dispensing. Following the identification strategy of Eliason et al. (2019), we show that the same facility switching from an independent to a chain pharmacy dispenses 105.4 less MED of all opioids (31.7%) and 11.7 less MED of OxyContin (43%) after an acquisition. The results show that neither location nor other store-specific characteristics such as store size or the number of surrounding pharmacies, but only the ownership of a specific facility, drives differences in prescription opioid dispensing.

The acquisition analysis reduces the rationale for differences in dispensing to the ownership alone. However, two types of prescription opioid users are grouped together in the acquisition analysis. The first are patients who use opioids in a medically necessary and appropriate way with valid prescriptions. The second group uses opioids for recreational purposes, diverting the drugs from their intended medical use. These users may obtain opioids by doctor shopping, pharmacy shopping, forging prescriptions, stealing, or purchasing from drug dealers. A pharmacy has the responsibility to detect and prevent diversion by title 21 of the Code of Federal Regulations (Drug Enforcement Administration 2005). However, pharmacies may have other considerations or limitations that prevent them from fulfilling this responsibility. Specifically, we suspect that independent and chain pharmacies may have different incentives and capabilities with regard to containing drug diversion.

To show that diversion drives (part of) the difference in dispensing between independent and chain pharmacies, we exploit the quasi-experiment arising from the reformulation of OxyContin into an abuse-deterrent formula in mid-2010. The OxyContin reformulation did not change its therapeutic benefit (Mastropietro and Omidian 2015), nor did it affect prices (Coplan et al. 2016; Evans et al. 2019). Therefore, it mainly reduced the diversion demand for OxyContin.[3] By comparing the dispensing of OxyContin before and after the reformulation between independent and chain pharmacies, we find the difference greatly narrowed after the reformulation, mainly driven by the reduction among independent pharmacies. The difference in dispensing of OxyContin shrank by

[3]Previous research shows that the reformulation of OxyContin reduced demand for diversion and led recreational users to substitute to other drugs. For discussion, see, for example, Alpert et al. (2018), Evans et al. (2019), Severtson et al. (2013), Butler et al. (2013), Sessler et al. (2014), Havens et al. (2014), Dart et al. (2015), Larochelle et al. (2015), Coplan et al. (2016), and Chilcoat et al. (2016).

approximately 6 MED. Given that the reduction in OxyContin dispensing is almost entirely driven by independent pharmacies, this implies that part of the overall difference between independent and chain pharmacies (estimated from the acquisition analysis) can be attributed to different responses to diversion demand. We conclude that 50% of the higher dispensing in independent pharmacies is due to drug diversion.[4]

We further analyze the effect of competition and areas of high diversion on dispensed opioids. Creating a spatial measure of the number of competing pharmacies in a radius and using variation within counties, we show that an additional competing pharmacy is associated with more dispensing of OxyContin. When allowing for heterogeneous responses by independent and chain pharmacies, we find that the effect is mostly due to the behavior of independent pharmacies and only before the OxyContin reformulation. In addition, we show that differences in dispensing between independent and chain pharmacies are larger in counties with higher drug abuse rates.

As more than half of the difference in dispensing between independent and chain pharmacies resulted from diversion, we identify and examine two mechanisms behind why independent pharmacies are more likely to be involved in drug diversion. First, independent pharmacies may have stronger financial incentives due to squeezed profit and lower expected costs of being caught in misdoing due to a smaller firm size. Although we do not have direct evidence on the former, we compare the general revenue growth trends of independent and chain pharmacies and show that independent pharmacies are at a disadvantage. For the latter, we compare smaller chains, independent pharmacies, and major chain pharmacies, and we find that smaller chains behave more similarly to independent pharmacies, which suggests that firm size matters; that is, the smaller the firm size, the more likely it is to misbehave. Second, compared with chains, independent pharmacies may lack sufficient data to track customers' drug use history. To test this, we exploit the implementation of must-access prescription drug monitoring programs (PDMPs) for dispensers in four states between 2006 and 2012. We find that the implementation of a must-access PDMP narrowed the gap between independent and chain pharmacies in OxyContin dispensing by about 15%.[5]

Our analysis suggests that stricter monitoring and regulation of small chains and independent pharmacies are important, as these can increase their expected costs of committing a crime. Although each independent pharmacy might be negligible, together they account for 47% of all pharmacies between 2006 and 2012 and dispensed 45% of all prescription opioids and 49% of all

[4]Column (2) in Table 4 indicates that on average independent pharmacies dispense 11.74 more MED than chain pharmacies, and column (4) shows that after the reformulation of OxyContin in a abuse-deterrent formula, the differences decrease by 5.97 MED, a 52.2% ($-5.97/-11.43$) reduction.

[5]In addition, pharmacists in independent pharmacies may have lower human capital or outdated knowledge on painkillers. However, pharmacists in independent pharmacies generally have higher ratings of their on-the-job training (Schommer 2013; Schommer et al. 2007).

OxyContin during that period. In addition, in line with the positive impact found in other studies of the effect of must-access PDMPs on prescriptions, we also find a small positive impact of must-access PDMPs for dispensers on drug dispensing by pharmacies.

Our study adds to the literature on the supply side's role in the opioid epidemic. Our study provides, to our knowledge, the first evidence on how pharmacies contribute to the opioid crisis. The existing literature on the supply of prescription opioids focuses on the roles played by physicians, pain clinics, manufacturers, and the government (Alpert et al. 2019; Meinhofer 2016; Powell et al. 2015; Schnell 2017), but pharmacies are often overlooked (Simeone 2017). Although we may think pharmacies are innocent and just fill prescriptions from prescribers, our analysis reveals that pharmacies can significantly influence the dispensing of prescription opioids. In particular, independent pharmacies, compared with independent pharmacies, dispensed 50% more OxyContin to meet the diversion demand, and competition exacerbates their diversion incentives.

Our paper also contributes to the literature of asymmetric competition between large and small firms by comparing the behavior of chain and independent retail pharmacies. Large chain pharmacies have increased their market share since 2000 (Zhu et al. 2015). Similar to other industries such as physicians (Capps et al. 2017), consolidation of pharmacies into chains has taken place and is continuing.[6] We show that besides economic efficiency, higher opportunity costs of misbehavior may cause larger chain pharmacies to behave closer to the social optimum. As we also investigate the effect of acquisitions on pharmacy behavior, we add to the growing literature on mergers and acquisitions in the health care market. A body of literature considers hospital mergers and finds that mergers result in price increases for insurers (Dafny 2009; Dafny et al. 2019; Gowrisankaran et al. 2015). Closely related to our analysis of chain acquisitions, Eliason et al. (2019) show that independent dialysis facilities acquired by large chains behave more similarly to the chains by replacing nurses with less-skilled technicians and wait-listing fewer patients for kidney transplants. These changes reduce health outcomes of patients. In our analysis, we find a similar effect that after being acquired by chains, independent pharmacies behave more like chains, with less dispensing of abusive opioids.

In addition, we add new empirical evidence on the effect of competition on illegal/unethical behavior. Under standard assumptions, competition is important as it lowers prices and increases quality. However, in markets with excessive demand over the social optimum, competing for "higher quality" may lead to lower standards and social loss. A stream of oligopoly theory literature specifies such a mechanism in theory.[7] Empirically, there is limited evidence on the relation

[6] See, for example, the discussion in Eliason et al. (2019) about consolidation through acquisitions. However, in the pharmacy sector, the majority of acquisitions by chain pharmacies are acquisitions of other, smaller chain pharmacies.

[7] For example, Shleifer (2004) argues that an increase in competition may not necessarily discipline markets. Instead, the increasing competitive pressure can lead to a divergence from the socially optimal behavior. The pharmacy market works in a similar fashion. Branco and Villas-Boas (2015) argue that higher competition results in lower costs

between competition and illegal behavior.[8] Existing studies have examined the areas of vehicle inspection services in New York (Bennett et al. 2013) and Sweden (Habte et al. 2017), corporate tax avoidance (Cai and Liu 2009), and the liver transplant market (Snyder 2010); these studies show that fiercer competition raises the incentive to be lax in upholding standards. The main mechanism of all these studies is that competitive pressure increases the incentive to please certain customers while diverging from a socially optimal level, which is defined by a regulator. We add to the literature by presenting additional evidence of the positive relationship between competition and leniency in the market of opioid-dispensing pharmacies. Leniency results in higher drug dispensing and drug diversion, deviating from the social optimum and resulting in negative health effects.

2 A Stylized Model of the Opioid Market

To exemplify the key idea of our article, we turn to a stylized model of pharmacy ownership. The setup intends to show our key approaches rather than reproduce the details of the retail pharmacy market. Consider the retail market for OxyContin with an independent and a chain pharmacy denoted as $i \in \{I,C\}$. The market is divided into two sub-markets, $j \in \{M,A\}$ where M is the market for medically appropriate and necessary usage and A is the market for recreational and abusive use. While the market for medically necessary usage is solely based on legitimate prescriptions, the market for abusive use is based on drug diversion, which includes illicit prescriptions from patients that engage in doctor/pharmacy shopping or steal/forge prescriptions. In each market j the demand is defined by a function $D_i^j(p_i,u^j)$, where p_i is a price of an opioid in pharmacy i and u^j a factor displaying the general size of the market. In the case of the medically necessary market, the size is determined by legitimate prescriptions, while for abusive markets the factor is based on diversion incentives, such as the potential for abuse of the drug, the number of users, and black market value. The demand for both markets may be correlated, $Corr(D_i^M,D_i^A) > 0$, as medically necessary usage is potentially correlated with abusive behavior.

In equilibrium, we observe dispensing q_i, which includes both markets, that is, $q_i = q_i^M + q_i^A$. In the first part of the article we show that $q_I > q_C$. In detail, we start by comparing variation

of illegal behavior. Dewatripont and Tirole (2019) show that competition may promote unethical behavior when firms are profit maximizing. The authors show that the replacement excuse (the possibility of being replaced in case of sticking to an ethical behavior) lead to divergence between private and social values. Hermalin (1992) theorizes that competition may lead to shirking by executives. Considering competition between bureaucrats, Drugov (2010) finds that competition may lead to corrupt behavior, and Bolton et al. (2012) present a model where competition between credit rating agencies leads to inflated ratings. The prediction from these theories diverges from the standard view that competition is beneficial, everything else being equal.

[8] Some experimental literature confirms that market competition decreases moral values of individuals (Falk and Szech 2013).

in q_i within counties to show that independent pharmacies dispense more prescription opioids. Using acquisitions we further control for a number of factors that could drive the difference in dispensing, such as specific geographical locations. We show that the effect of $q_I > q_C$ is driven by the ownership.

However, higher dispensing by independent pharmacies itself does not imply more drug diversion, because the market for abusive use is not the only factor that may drive the effect. Independent pharmacies may offer lower prices and better service, and thus attract more patients from both segments M and A. In the second part of our identification strategy, we use the OxyContin reformulation to show that the difference in dispensing between independent and chain pharmacies is at least partly due to the market segment of abusive use. The number of legitimate prescriptions in M, u^M, is not affected by the reformulation to an abuse-deterrent formula that did not affect its medical use. The abuse-deterrent formula reduces demand in market A, so D_i^A $\forall i$ decreases due to a lower u^A. Furthermore, we assume that prices p_i $\forall i$ are unaffected by the reformulation, as documented by existing studies (Coplan et al. 2016; Evans et al. 2019). Following the reformulation, we are able to evaluate which market drives the result of $q_I > q_C$ as only the demand for recreational use D^A decreased. If pharmacies fill only legitimate medically appropriate prescriptions, the reformulation should have no effect on the overall differences, whereas we expect to observe a decline in OxyContin dispensing if there was dispensing to the abusive market before the reformulation.

3 Institutional Background

3.1 The Retail Pharmacy Market

Over 85,000 retail pharmacies existed in the United States between 2006 and 2012. Pharmacies filled 3.6 billion prescriptions, and nearly all Americans (93%) lived within a 5-mile radius of a pharmacy (Fein 2011*a*). Retail pharmacies include independent and chain pharmacies. Independent pharmacies are defined as pharmacies with no more than three stores under a corporate umbrella. During our study period, approximately 53% of pharmacies are chain pharmacies. Since 1980, large national chains such as Walgreens, CVS, and Rite Aid have increased their market shares drastically, while the number of independent pharmacies has declined (Appold 2019). Additionally, the industry has been characterized by frequent acquisitions and mergers (Pharmacy Times 2018).

Independent pharmacies face challenges in competition with chain pharmacies. Most importantly, independent pharmacies have less power in bargaining for reimbursements with pharmacy benefit managers (PBMs) and other third-party managers of prescription drug programs for health plans (Appold 2019). Often, independent pharmacies get paid less than larger chains for the medicines they dispense. In addition, independent pharmacies' bargaining power with distributors is limited (Chaffee 2019). Therefore, prices (copayments and coinsurance) in independent pharmacies are often higher (Gellad et al. 2009; Luo et al. 2019). Nevertheless, some consumers prefer independent pharmacies because of their better service. According to consumer polls, independent pharmacies have higher ratings due to their better knowledge about drugs, helpfulness, courtesy, and personalized service (Cohen 2011).

During the period of our study, between 2006 and 2012, the number of pharmacies increased by almost 10%. Thus, competition between pharmacies increased. In addition to the negative effect of competition on drug prices (Chen 2019), it is possible that competition also has an effect on the service or general behavior of pharmacies.

3.2 Prescription Opioids and Their Distribution

The opioid epidemic in the United States dates back to the late 1990s. While opioids have been long known, and oxycodone specifically has been in clinical use since 1917 (Kalso 2005), the entry of OxyContin, an extended-release formulation of oxycodone, by Purdue Pharma changed the medical landscape (Evans et al. 2019). About 100 million Americans suffered from chronic pain in 2010 (Simon 2012), and pain is the most common reason for doctor visits (Watkins et al. 2008). Starting as postsurgery and pain-management medications, opioids became commonly prescribed. In 2012, US health care providers issued more than 259 million opioid prescriptions (Paulozzi et al. 2014), 0.8 prescriptions of opioids per capita. OxyContin specifically became one of the most successful pharmaceuticals, with worldwide sales of 35 billion (Evans et al. 2019). The foremost reason for the large number of prescriptions is that it became common to prescribe opioids for patients with chronic pain after medical guidelines were changed (Berry and Dahl 2000). In addition, recommendations from medical boards increased the number of prescriptions (Soffin et al. 2017). Finally, the literature shows that Medicare Part D and promotional activities by the pharmaceutical industry boosted prescriptions (Alpert et al. 2015; Hadland et al. 2019; Haffajee and Mello 2017; Quinones 2015; Van Zee 2009).

The increase in prescribing went hand in hand with more drug abuse. Opioids started to be diverted from their original therapeutic use (Alexander et al. 2012). The National Survey on Drug Use and Health (NSDUH) defines opioid misuse as taking a prescription opioid that was "not prescribed for you or only for the experience or feeling it caused." The NSDUH showed that 51.3% of people who misused pain relievers in the 2017 survey obtained their most recent pain reliever from a friend or relative (NSDUH 2018). Drug diversion, in detail, can happen in several ways. First, patients may engage in doctor shopping, meaning that they visit numerous health care providers to receive multiple prescriptions (Peirce et al. 2012; Simeone 2017). Second, patients forge prescriptions or fill prescriptions at multiple pharmacies (Peirce et al. 2012; Yang et al. 2015). Finally, opioid theft is also a source of diversion.

Pharmacists are legally required to ensure that controlled substances are prescribed for a medical purpose and are not diverted (Bach and Hartung 2019; Drug Enforcement Administration and others 2010). Therefore, pharmacists should screen for prescriptions and behavior that suggest diversion (Bach and Hartung 2019). Nevertheless, pharmacists may face a conflict of interest, as their profit depends on filling prescriptions. Furthermore, qualitative research suggests that some pharmacists are uncertain in the role of screening prescriptions (Hartung et al. 2018).

The OxyContin Reformulation

During our study period, the abuse-deterrent reformulation of OxyContin took place, and we use it to investigate how independent and chain pharmacies respond when diversion demand plummets. Purdue Pharma, the producer of OxyContin, once the world's top-selling opioid analgesic, pleaded guilty to a felony charge of "misbranding" on May 10, 2007, meaning that the firm falsely advertised the safety of this painkiller (Alpert et al. 2018, 2019). On April 5, 2010, a reformulated abuse-deterrent OxyContin was approved by the Food and Drug Administration (FDA). Before 2010, OxyContin's main ingredient, oxycodone, was slowly released over the course of twelve hours. Drug abusers crushed or liquefied OxyContin pills to gain full and immediate access to the oxycodone content. Purdue Pharma marketed reformulated pills starting in August 2010 and ceased shipment of the old OxyContin (Butler et al. 2013; Evans et al. 2019). The new formulation could not be crushed and thus could not be abused.

Prescription Drug Monitoring Programs

Multiple tools have been implemented to reduce diversion: quantitative prescription limits, patient identification requirements, doctor-shopping restrictions, pain clinic shutdowns, and state-run PDMPs (Doleac et al. 2018). Meara et al. (2016) show that the majority of tools did not have an effect between 2006 and 2012. However, research shows that recently implemented PDMPs decreased diversion. PDMPs suggest or require that prescribers and pharmacists access a within-state electronic database that tracks patients' prescription histories (Doleac et al. 2018). There are two types of PDMPs: voluntary and must-access PDMPs. The difference is that doctors and pharmacists can voluntarily access or must access the system before prescribing or dispensing controlled substances. Most states have implemented PDMPs, and the majority started in the late 2000s. Buchmueller and Carey (2018) show that only the must-access PDMPs are successful, and they decrease doctor shopping by 8% and pharmacy shopping by 15%. The results are confirmed by other studies (Ayres and Jalal 2018; Meinhofer 2018). Four states had implemented must-access laws for dispensers (including pharmacists) during our study period (2006–2012): Arizona in July 2011, Delaware in January 2012, New Mexico in August 2012, and Ohio in August 2011.[9]

4 Data and Summary Statistics

We use the 2006–2012 data from the Automation of Reports and Consolidated Orders System (ARCOS), maintained by the Diversion Control Division of the US Drug Enforcement Administration (DEA). Manufacturers and distributors are legally required to report their controlled substance transactions to the DEA. We observe quantities (in grams) of every controlled prescription opioid dispensed in the United States.[10] We aggregate the data at the pharmacy level by each month and convert the dosage into Morphine Equivalent Doses (MED) so that dosages of different opioids are comparable. We consider only retail pharmacies and exclude pharmacies that are integrated into hospitals, clinics, or doctor's offices.[11] We connect the data set with the geographical information of pharmacies offered by the *Washington Post* (Rich et al. 2019).

Table 1 provides basic summary statistics of our sample. We observe 85,417 pharmacies during 2006 and 2012. Of these, 45,275 are chain pharmacies while the remaining ones are independent pharmacies. Compared with chain pharmacies, independent pharmacies face more competition nearby. We observe 14,845 entries and 10,175 exits over these six years. Among these entries, 6,484 (44%) were chain pharmacies, and 8,461 (56%) were independent pharmacies. However, exits among independent pharmacies (7,301) were more than double those among chain pharmacies (2,874).[12] As a result, the relative number of chains increased between 2006 and 2012. We also observe 4,681 acquisitions. We define an acquisition as an ownership change of an existing pharmacy. The majority of the acquisitions are within the same pharmacy type, that is, chain pharmacies acquired by another chain or independent pharmacies that changed ownership but remained independent. However, we observe 223 cases of chain pharmacies that become independent and 371 independent pharmacies that were acquired by chains. Panel C of Table 1 describes the dispensing. On average, pharmacies dispense 333 MED of all opioids and 27 MED of OxyContin each month. An independent pharmacy dispenses on average more MED, and the relative difference is higher for OxyContin. For pharmacies that started as independent and were acquired by a chain, the comparison between the last two rows and the first two rows in Panel C shows that prior

[9] Data come from the Prescription Drug Monitoring Program Training and Technical Assistance Center: https://www.pdmpassist.org/State.

[10] We assume that all the deliveries from manufacturers/distributors to pharmacies are finally dispensed by pharmacies (or via other channels such as theft or robbery) to customers.

[11] Our retail pharmacy market captures over 81% of the dispensing of prescription opioids. Note that this exclusion also excludes the pill mills that prescribed and dispensed opioids within one facility.

[12] In Appendix A we analyze the role of exiting pharmacies. We observe decreasing opioid dispensing by those pharmacies before the date of exit.

to their acquisition, they did not differ in dispensing from other independent pharmacies that did not get acquired.

Table 1: Summary Statistics

	All	Chain	Independent
	A: Pharmacies		
Number of pharmacies	85,417	45,275	40,142
Competitors within 1-mile radius	4.5	3.73	5.62
	(9.11)	(7.17)	(11.26)
Competitors within 5-mile radius	53.08	43.7	66.72
	(114.51)	(87.08)	(11.26)
Competitors within 15-mile radius	259.17	220.7	315.07
	(487.74)	(380.31)	(606.73)
	B: Entries, Exits, and Acquisitions		
Entries	14,845	6,484	8,361
Exits	10,175	2,874	7,301
Acquisitions	4,681	-	-
Chain to chain	1,435	-	-
Chain to independent	223	-	-
Independent to independent	2,652	-	-
Independent to chain	371	-	-
	C: Opioid Dispensing		
Monthly MED dispensing, all opioids	332.54	308.97	366.17
	(1,195.38)	(355.24)	(1,812.75)
Monthly MED dispensing, OxyContin	27.25	23.64	32.4
	(196.71)	(51.01)	(300.25)
Monthly MED, all opioids, independent acquired by chain			358.91
			(446.68)
Monthly MED OxyContin, independent acquired by chain			31.79
			(61.09)

Notes: Panel A describes the number of pharmacies as well as the number of competing pharmacies in different radii. Panel B shows the number of entries, exits, and acquisitions. Note that entries and exits are defined by the presence of a new owner. We divide acquisitions into different types of ownership changes. Panel C describes opioid dispensing. We divide dispensations into dispensing of all opioids and of OxyContin only. The last two rows describe dispensing by independent pharmacies acquired by chains prioir to acquisition. Standard deviations are in parentheses.

5 Empirical Strategy

We now turn to investigate whether the ownership of pharmacies is an important determinant of opioid dispensing. That is, do chain and independent pharmacies behave differently when dispensing opioids?

Following our stylized model in Section 2, we conduct three analyses to investigate how independent and chain pharmacies differ in their dispensing behavior and disentangle the difference driven by the two types of demand: legal medical demand and illegal diversion demand. First, we document the difference between independent and chain pharmacies directly. Second, we examine how the ownership change from independent to chain pharmacy via acquisition affects dispensing. Finally, we use the OxyContin reformulation as a quasi-experiment, which decreased the abuse potential and therefore diversion demand exogenously.

Direct Comparison of Independent and Chain Pharmacies

Our first empirical strategy is simple and straightforward, as we directly compare independent pharmacies with chain pharmacies as shown below:

$$Y_{it} = \beta Indep_i + \mu_t + \gamma_{FE} + \varepsilon_{it}, \tag{1}$$

where Y_{it} represents the amount of prescription opioids dispensed. Specifically, we consider the dispensed MED of all types of prescription opioids at a pharmacy i in month t as well as the dispensed MED of OxyContin.[13] $Indep_i$ is a dummy that takes the value 1 if a pharmacy is independent, μ_t are year-month fixed effects, and γ_{FE} represents different geographic fixed effects. We add county as well as ZIP fixed effects successively to control for unobserved area-specific characteristics and thus to eliminate the potential bias due to possible correlation between the pharmacy ownership and area-specific factors.

A positive $\hat{\beta}$ with county/ZIP fixed effects indicates that an independent pharmacy, in a given county/ZIP code, on average dispenses $\hat{\beta}$ more MED of opioids compared with a chain pharmacy. Considering OxyContin only, we evaluate whether the divergence between chain and independent pharmacies is larger for this drug that is prone to diversion, as we expect that higher diversion incentives would result in more lax dispensing and, therefore, a larger $\hat{\beta}$.

Pharmacy Acquisitions

Independent and chain pharmacies could differ in numerous dimensions. Estimates obtained from equation (1) are not able to capture the exact difference between independent and chain pharma-

[13] As a robustness check, we show estimates using the dispensed MED per capita by each pharmacy i in month t as an outcome variable for equation (1) and the other regressions in Appendix B. We use the ZIP code-level population from the 2010 census of pharmacy i's location to calculate the per-capita dispensed MED of all prescription opioids and OxyContin. In addition, although our main analysis is at the month level, we conduct robustness checks with quarterly analysis in Appendix C. In addition, we also show unconditional quantile regression results in Appendix D to examine the impact of pharmacy ownership on prescription opioids dispensing at different quantiles.

cies' dispensing behavior, because even within the same ZIP code, these two types of pharmacies may have other differences. Therefore, we employ an identification strategy which shows that ownership rather than store-specific factors drives differences in dispensing. Specifically, we are interested in pharmacies that initially were independent and then were acquired by a chain. In those cases, the geographic location and the surrounding environment are constant, and solely the ownership changes. Therefore, we can attribute almost all of the difference before and after the acquisition to the ownership change. We identify 4,681 acquisitions.[14] Among them, the majority are independent pharmacies acquiring other independent pharmacies or chains acquiring other chains. We are interested in ownership changes from independent to chain, which account for 371 of the acquisitions.[15]

Following the difference-in-differences approach of Eliason et al. (2019), we show effects of the acquisition of an independent pharmacy by a chain pharmacy on dispensing of all opioids and OxyContin by comparing independent pharmacies acquired by chains to those that were never acquired. The identification assumption is that the change in ownership is uncorrelated with characteristics of the independent pharmacy. We use the following model:

$$Y_{it} = \beta_0 D_{it}^{PRE} + \beta_1 D_{it}^{POST} + \beta_C D_{it}^{CHAIN} + \alpha_i + \mu_t + \varepsilon_{it}, \tag{2}$$

where Y_{it} are the dispensed dosages of all opioids and OxyContin. We compare the sample of pharmacies that were chains during the entire period and the sample of pharmacies that changed from independent to chain pharmacies. The baseline is those pharmacies that were always independent. D_{it}^{PRE} is an indicator that takes the value 1 for pharmacies before acquisition. Similarly, D_{it}^{POST} takes the value 1 if a pharmacy has been acquired. D_{it}^{CHAIN} takes the value 1 if a pharmacy has always been owned by a chain. We include ZIP and pharmacy fixed effects (α_i). Note that we drop D_{it}^{PRE} and D_{it}^{CHAIN} when including α_i due to multicollinearity. μ_t are time fixed effects.

If acquired independent pharmacies dispense similarly to nonacquired independent pharmacies, we expect that $\hat{\beta}_0$ would not be different from zero. Therefore the identification assumption also requires an insignificant $\hat{\beta}_0$ estimate. Further, we expect that independent pharmacies that are acquired by chain pharmacies reduce their dispensing of opioids. Thus $\hat{\beta}_1$ is expected to be negative.

The OxyContin Reformulation

Our third empirical strategy uses the OxyContin reformulation as a quasi-experiment to test whether chain and independent pharmacies respond differently when diversion demand declines. As the

[14] In these instances, we observe a change of the DEA number and name for the same location.

[15] We evaluate acquisitions of chains by independent pharmacies in Appendix E.

OxyContin reformulation reduced only the demand for diversion but did not change the price or medical use (Coplan et al. 2016; Evans et al. 2019; Mastropietro and Omidian 2015), it creates a neat setting to separate the demand from the legal medical market and the demand from the illegal diversion market. As a result, an reduction in OxyContin dispensing after the reformulation implies that pharmacies reduce their dispensing of OxyContin to the diversion market. As we believe chain pharmacies have stricter rules on dispensing controlled substances and thus are less likely to be involved in diversion, we expect to see a larger decline in OxyContin dispensing among independent pharmacies than among chain pharmacies after the reformulation.

We use the following model to test our hypothesis:

$$Y_{it} = \beta Indep_i \cdot PostReform_t + \alpha_i + \mu_t + \varepsilon_{it}, \tag{3}$$

where Y_{it} represents OxyContin dispensing at pharmacy i in month t. $PostReform_t$ takes the value 1 for all months after August 2010, when the new OxyContin formulation entered the market and shipment of the old OxyContin ceased. $Indep_i$ indicates whether a pharmacy is an independent pharmacy, μ_t are year-month fixed effects, and α_i are pharmacy fixed effects. A negative $\hat{\beta}$ would suggest that independent pharmacies are more susceptible to the diversion demand.

6 Results

Direct Comparison of Independent and Chain Pharmacies

Table 2 presents results from regression (1). Columns (1)–(4) evaluate the relation between pharmacy ownership and all opioids dispensing, and columns (5)–(8) examine OxyContin specifically. The effects are robust to different geographic fixed effects. When we add ZIP/county fixed effects to compare pharmacies within a county/ZIP code, the effects become stronger, supporting our hypothesis that pharmacy ownership plays a role in determining the amount of opioids dispensed. Column (4) indicates that independent pharmacies on average dispense 136 (41%) more MED of all opioids. Moreover, if independent and chain pharmacies respond differently to diversion, the type of pharmacy that is more susceptible to it would dispense disproportionately more OxyContin, one of the most popular drugs in street markets. We find that independent pharmacies on average dispense 17 (62%) more MED of OxyContin per month, as shown in column (8). This demonstrates that independent pharmacies on average dispense more prescription opioids, especially of the type prone to diversion.

Table 2: Regression, Direct Comparison

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	57.660***	58.575***	115.339***	136.174***	8.810***	9.017***	14.848***	16.840***
	(4.495)	(4.499)	(5.472)	(5.453)	(0.551)	(0.551)	(0.694)	(0.731)
Constant	309.344***				23.676***			
	(1.573)				(0.209)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	333.09	333.09	333.09	333.09	27.3	27.3	27.3	27.3
Mean effect in percent	17.31	17.59	34.63	40.88	32.27	33.02	54.38	61.68
Observations	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419
R-squared	0.001	0.002	0.019	0.048	0.0005	0.003	0.010	0.025

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

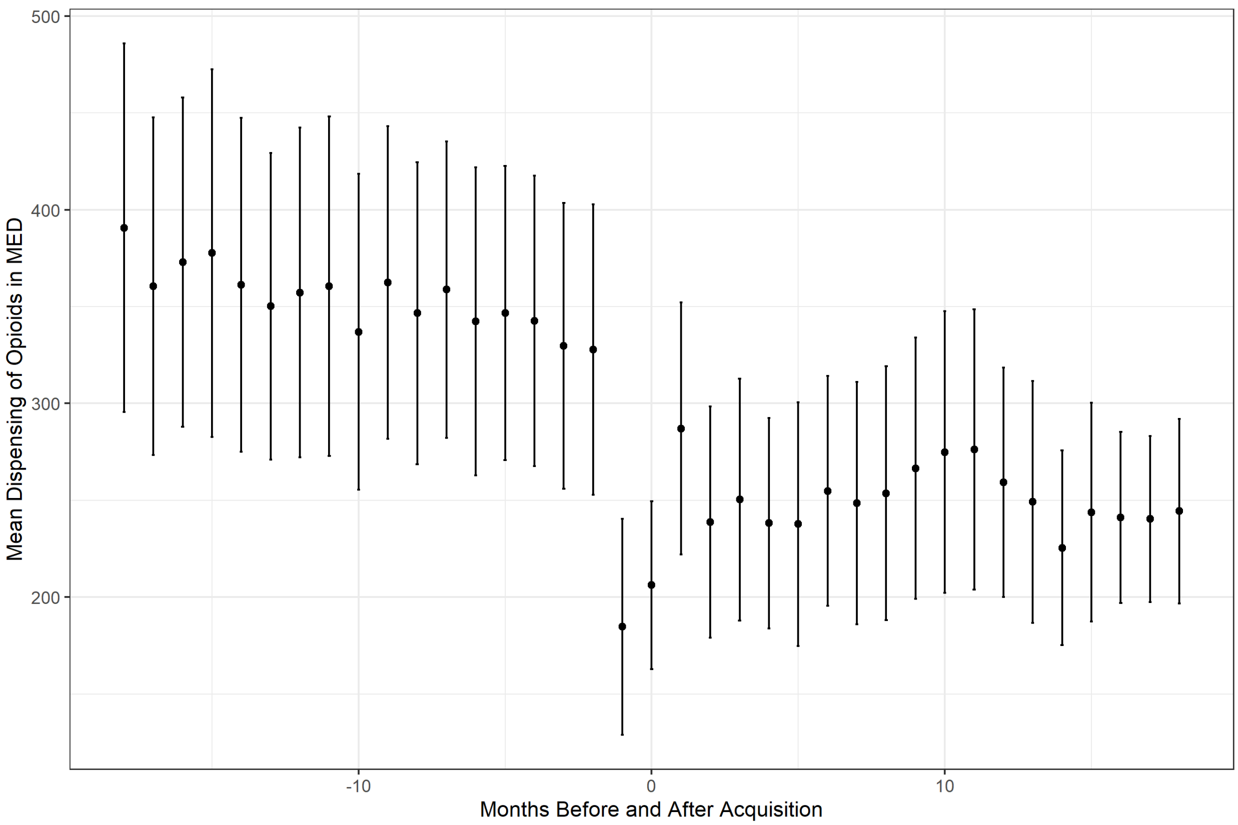
Notes: Results of the direct comparison between independent and chain pharmacies, presented in equation (1). One observation corresponds to a pharmacy within a month. In model specifications (1) to (4), the outcome is monthly dispensed opioids in MED. In models (5) to (8) we consider monthly dispensed OxyContin in MED as an outcome. *Independent* displays the coefficient β. Year-month FE, county FE, and ZIP FE indicate the use of fixed effects. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

Acquisitions: Independent Pharmacies Acquired by Chains

This section shows results of our acquisition analysis considering independent pharmacies that were acquired by a chain pharmacy. We plot the monthly average dosage of opioids dispensed by pharmacies before and after an acquisition in Figure 1. It shows a clear reduction in opioid dispensing after ownership change. In addition, the almost flat pre-trend indicates that the acquisitions are not correlated with unobserved systematic changes among independent pharmacies before being acquired. Surrounding the date of an acquisition, we observe two patterns. First, an acquired independent pharmacy decreases its dispensing during the two months prior to the acquisition. As we measure dispensing through orders shipped to pharmacies, the two-month dip can be explained by a stock reduction and the forthcoming acquisition. Second, during the first month after an acquisition, the chain pharmacy temporarily increases its dispensing. Again, a filling up of the stock of the newly acquired facility can explain the single-month increase.

Table 3 further demonstrates that a pharmacy's ownership affects its dispensing behavior, as after independent pharmacies were acquired by chains, they decreased their opioid dispensing. Columns (1) to (4) show the impact on dispensing of all opioids, while columns (5) to (8) solely evaluate OxyContin. As shown in columns (1) to (3), we observe nonsignificant coefficients of the $Before$ regressor, meaning that before the acquisition, those pharmacies that started as an in-

Figure 1: Dispensing of Monthly Opioids Before and After Acquisition



Notes: The figure represents monthly mean dispensing of all opioids in MED for independent pharmacies 18 months before and after being acquired by a chain. The error bars correspond to the 95% confidence interval.

dependent pharmacy and then were acquired by a chain are not significantly different from the all-time independent pharmacies. However, after the acquisition, formerly independent pharmacies decreased their dispensing. Using ZIP code and year-month specific effects, specification (3) shows that they dispense 154 (46%) less MED per month than their nonacquired independent counterparts. Including pharmacy fixed effects in column (4) gives us a slightly smaller but still significant estimate that independent pharmacies dispense 105 (32%) less MED of all opioids per month after being acquired by a chain.

Similarly to the findings for all opioids, independent pharmacies that have been acquired do not differ before acquisition from their nonacquired peers in terms of OxyContin dispensing, as shown in column (5) to (7). However, after acquisition, the acquired independent pharmacies reduce their OxyContin dispensing by 12 (43%) MED per month, as shown in column (8).

Thus, we show that the differences are due to the ownership rather than facility-specific factors such as geography. In Appendix E, we evaluate cases of chain pharmacies that become independent and show that results do not contradict our main hypothesis, that independent pharmacies dispense more opioids.[16]

Table 3: Acquisitions: Independent by Chain

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before	−2.835	29.054	−6.135		−0.054	3.916	0.755	
	(39.457)	(39.101)	(37.821)		(4.949)	(4.882)	(4.883)	
After	−104.520***	−135.679***	−153.749***	−105.407***	−9.044***	−13.023***	−16.127***	−11.740***
	(23.046)	(22.809)	(25.904)	(19.192)	(2.049)	(2.058)	(2.588)	(2.236)
Chain	−55.389***	−56.050***	−132.428***		−8.512***	−8.685***	−16.380***	
	(4.468)	(4.471)	(5.055)		(0.547)	(0.547)	(0.728)	
Constant	365.393***				32.261***			
	(4.189)				(0.506)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	333.09	333.09	333.09	333.09	27.3	27.3	27.3	27.3
Mean effect in percent	−31.38	−40.73	−46.16	−31.65	−33.12	−47.69	−59.06	−43
Observations	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419
R-squared	0.001	0.002	0.048	0.148	0.0005	0.003	0.025	0.091

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the acquisition regression analysis in equation (2). One observation corresponds to a pharmacy within a month. In model specifications (1) to (4), the outcome is monthly dispensed opioids in MED. In models (5) to (8), we consider monthly dispensed OxyContin in MED as an outcome. *Pre* displays the coefficient β_0, the effect of independent pharmacies before acquisition. *Post* displays the coefficient β_1, the effect of chain pharmacies that were independent before acquisition. *Chain* displays the coefficient β_C, the effect of chain pharmacies that did not change ownership. The baseline effect is independent pharmacies that did not change ownership. Year-month FE, ZIP FE, and pharmacy FE indicate the use of fixed effects. When using pharmacy fixed effects, only the variation of changing ownership can be used. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta_1}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

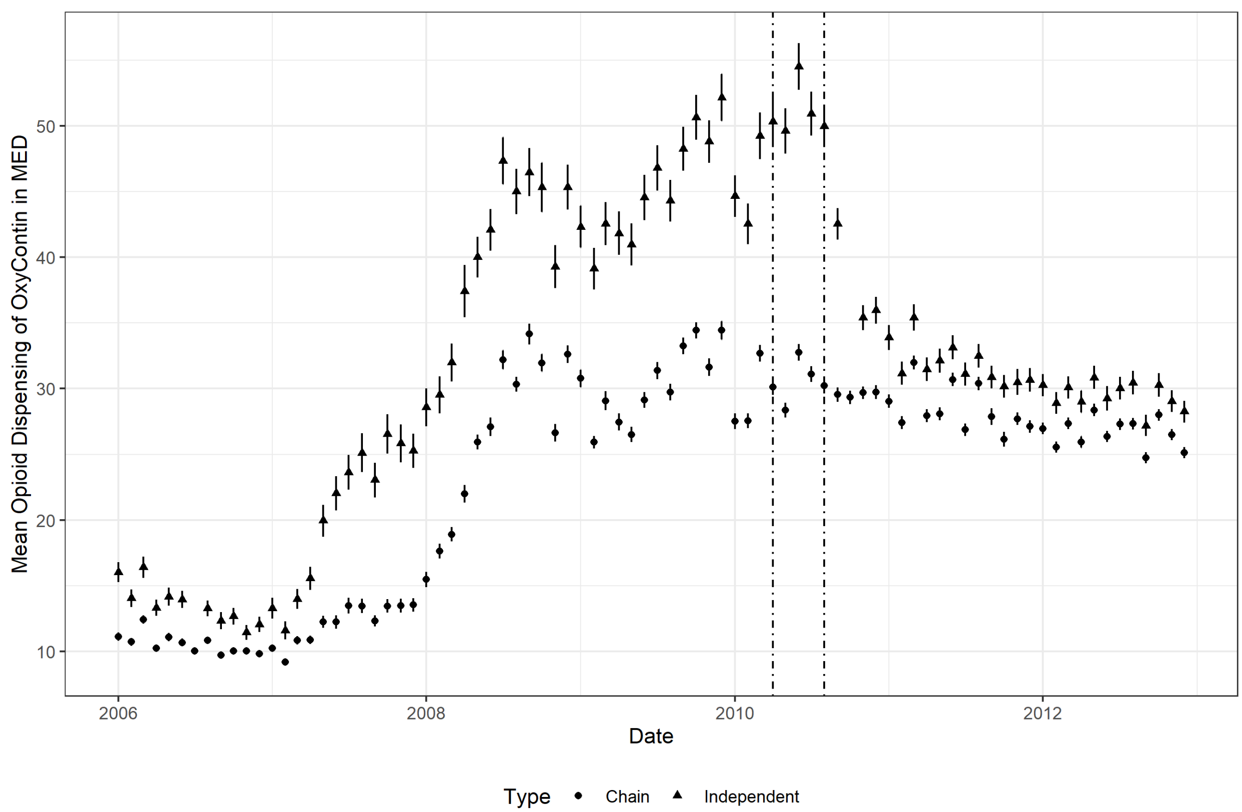
The OxyContin Reformulation

We now turn to the analysis that uses the OxyContin reformulation as a quasi-experimental setting. Figure 2 depicts the average dispensing of OxyContin before and after the reformulation by independent and chain pharmacies. In 2006, OxyContin dispensing by both independent and chain pharmacies remained at a similar level. We then observe an increase in OxyContin dispensing by both independent and chain pharmacies from 2007. However, the increase among independent pharmacies started almost one year earlier than that of chain pharmacies. From 2008 to 2010,

[16] We believe that the analysis of chain pharmacies that become independent is not optimal for analyzing the effect of ownership. Whereas independent pharmacies that get acquired by chains do not differ from their nonacquired independent counterparts, we show that chain pharmacies that become independent dispense less opioids before acquisition, compared with nonacquired chains.

the rate of increase is similar among independent and chain pharmacies, and thus the gap remains similar, with independent pharmacies dispensing on average 15 MED more OxyContin. During the interval between the FDA approval of the new OxyContin formulation in April 2010 and its market entry in August 2010, independent pharmacies further increased their dispensing, although slightly, whereas chain pharmacies slightly decreased their dispensing. Therefore, the gap increased slightly. However, after the new formula replaced the old formula in August 2010, we see a sharp reduction in OxyContin dispensing by independent pharmacies but only a slight decline among chain pharmacies.

Figure 2: OxyContin Dispensing, Chain vs. Independent Pharmacies



Notes: The figure shows average dispensing of OxyContin in MED for chain and independent pharmacies between 2006 and 2012. The first vertical line corresponds to April 2010, when the new OxyContin was approved by the FDA. The second vertical line corresponds to August 2010, when the new formula was delivered to pharmacies. The error bars correspond to the 95% confidence interval.

Table 4 shows the regression results. Columns (1)–(4) show the results using the whole sample. Our key interest is the coefficient of the interaction term $Independent * Post$. Column (1) provides the baseline estimate, and adding year-month fixed effects and ZIP code fixed effects in columns (2) and (3) generate similar estimates. In our preferred specification in column (4), we find that after the OxyContin reformulation, independent pharmacies on average reduced their dispensing of OxyContin by about 6 MED (21.9%) per month. In addition, as we notice that the pre-reformulation parallel trends in Figure 2 are more evident since 2008 between independent and chain pharmacies, we also limit the sample to 2008–2012 only and show the estimates in columns (5)–(8). The estimated effects are about 50% larger than that in the whole sample.[17]

Table 4: Regression, OxyContin Reformulation

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-6.740^{***}	-7.031^{***}	-7.456^{***}	-5.973^{***}	-10.854^{***}	-10.892^{***}	-11.112^{***}	-9.385^{***}
	(0.564)	(0.562)	(0.577)	(0.557)	(0.609)	(0.609)	(0.617)	(0.531)
Independent	11.137^{***}	11.433^{***}	19.471^{***}		15.251^{***}	15.294^{***}	24.455^{***}	
	(0.672)	(0.672)	(0.863)		(0.806)	(0.806)	(0.923)	
Post	6.584^{***}				-0.806^{***}			
	(0.139)				(0.158)			
Constant	21.316^{***}				28.706^{***}			
	(0.221)				(0.282)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	27.25	27.25	27.25	27.25	27.25	27.25	27.25	27.25
Mean effect in percent	−24.73	−25.80	−27.36	−21.92	−39.83	−39.97	−40.78	−34.44
Observations	5,104,770	5,104,770	5,079,419	5,103,585	3,679,675	3,679,675	3,661,471	3,678,562
R-squared	0.001	0.003	0.025	0.106	0.006	0.008	0.169	0.704

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

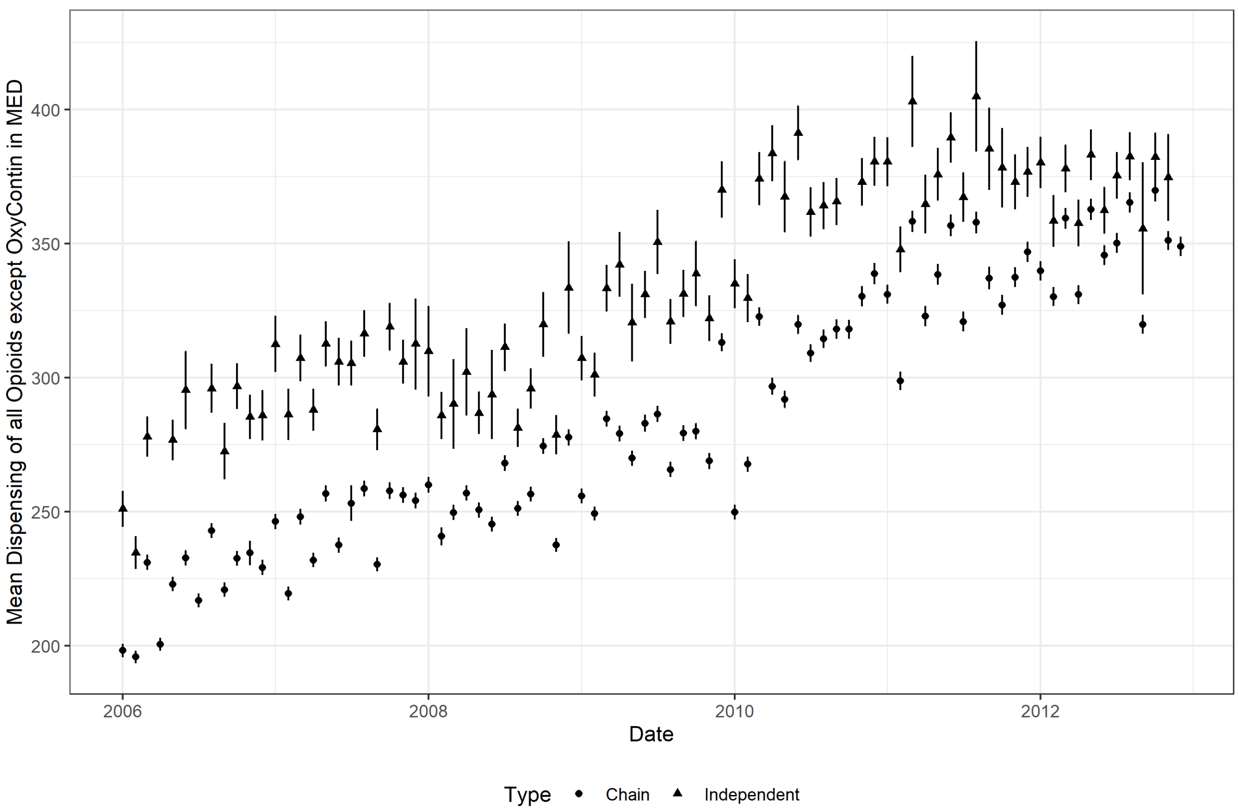
Notes: Results of the OxyContin reformulation regression analysis in equation (3). The outcome variable is OxyContin dispensing in MED per month at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation. *Independent* displays the effect of independent pharmacies. *Post* is an indicator showing months after the reformulation of OxyContin. We show the mean of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\hat{\beta}}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

We argue that only the reformulation affects the OxyContin dispensing. Specifically, the reformulation into the new abuse-deterrent formula reduced the possibility of abuse and therefore the demand for diversion. We have two assumptions here. First, we assume that the reformulation

[17] Since it is possible that the results are driven by a small proportion of misbehaving pharmacies, we conduct robustness checks in Appendix F by excluding Florida (which experienced many shut downs of pill mills around 2010) and pharmacies whose dispensing is in the top percentiles. The estimates are still negative and significant, though with smaller magnitudes. In addition, we also add ZIP-month fixed effects to control for possible neighborhood-specific time-varying characteristics that may affect pharmacies' dispensing as another robustness check in Appendix F. The estimated treatment effect is -6.3, slightly larger than our main estimate (6.0).

is uncorrelated with other concurrent factors that affect prescription opioid dispensing around the time of the reformulation. Second, we assume that the reformulation of OxyContin affects only the demand for diversion but not medical demand. Although we cannot test these assumptions directly, relevant evidence suggests they are well suited. First, we observe a structural break in dispensing for OxyContin only. Figure 3 shows the dispensing trends for all prescription opioids except OxyContin. In contrast to the OxyContin dispensing, we do not observe a break in dispensing of other opioid analgesics among both independent and chain pharmacies, which suggests that there is no confounding event that affects prescription opioid dispensing in general simultaneously with the OxyContin reformulation. Second, medical demand for OxyContin remained unaffected by the reformulation, because the reformulation did not change the medical applicability (Mastropietro and Omidian 2015). Further, prices of OxyContin did not change either (Coplan et al. 2016; Evans et al. 2019).

Figure 3: Opioid Dispensing except OxyContin, Chain vs. Independent Pharmacies



Notes: The figure shows average dispensing of all opioids except OxyContin in MED for chain and independent pharmacies between 2006 and 2012. The error bars correspond to the 95% confidence interval.

7 Additional Analysis

7.1 Competition

We investigate how competition affects pharmacies' dispensing behavior. Our hypothesis is that when facing stronger competition, pharmacies are more likely to dispense more opioids, especially OxyContin, because competition may increase unethical behavior (Bennett et al. 2013). We evaluate the effect of competition in the following model:

$$Y_{it} = \beta_1 Comp_{it} + \beta_2 Comp_{it} \cdot Indep_i + \alpha_i + \mu_t + \varepsilon_{it}, \tag{4}$$

where Y_{it} is again the MED of OxyContin dispensed by pharmacy i in month t. We focus on OxyContin since the OxyContin reformulation can help us distinguish the response to the medical demand in the period after reformulation and the response to the aggregate demand (both the medical and the diversion demand) in the period before reformulation. $Comp_{it}$ is the number of other pharmacies within a radius. We use different distances with the baseline level of a 1-mile radius. $Comp_{it} \cdot Indep_i$ is the interaction between competition and the independent pharmacy indicator, to test if independent pharmacies respond differently from chain pharmacies to the competition. μ_t are year-month fixed effects, and α_i are pharmacy fixed effects.

We conduct the analysis both without and with pharmacy fixed effects. Without pharmacy fixed effects, we use variation within a ZIP code. With pharmacy fixed effects, we evaluate the effect of increased competition on a pharmacy's opioid dispensing over time. Using variation over time results in two effects. On the one hand, it simply reflects the mechanical change of lower dispensed quantity as prescriptions are divided by a larger number of pharmacies (competition effect). On the other hand, an increase in spatial competition may result in a behavioral change by pharmacies; that is, pharmacies may be more lax in dispensing opioids in response to tougher competition to compensate for their loss from the medical market (compensation effect). The regression with pharmacy fixed effects cannot differentiate the two effects, either.

Therefore, we evaluate pharmacies' response in OxyContin dispensing before and after the OxyContin reformulation. The post-reformulation dispensing reflects more of the pure competition effect, as the diversion demand hugely declined. By comparing pharmacies' responses before and after the reformulation, we can infer whether there were compensation effects before the reformulation, when pharmacies faced tougher competition.

Table 5 shows estimates from our first competition analysis model, as shown in equation (4). Columns (1)–(4) show the effects on OxyContin dispensing considering the full sample. Columns (5) and (6) evaluate the months before the OxyContin reformulation in 2010, while columns (7) and (8) show effects after the reformulation. Odd-numbered columns show the average effect of competition on OxyContin dispensing, while even-numbered columns include the heterogeneous effects on different types of pharmacies. We expect to see a positive coefficient on the interaction term since we presume that independent pharmacies are more likely than chain pharmacies to compensate for their loss in the medical market by dispensing more OxyContin to the diversion market.

When comparing results without pharmacy fixed effects, we find that higher density of pharmacies is associated with more OxyContin dispensed by independent pharmacies. This evidence supports our hypothesis that independent pharmacies tend to be more lenient in dispensing more abusive opioids under greater competition pressure, as competition leads to more unethical behavior. Nevertheless, the effect of competition is limited. For example, from column (2) in Table 5 we infer that an additional competitor within a 1-mile radius increases dispensing of OxyContin by 0.167 MED on average among independent pharmacies. Columns (3) and (4) add pharmacy fixed effects, which estimate the effects of increased competition on each specific pharmacy's OxyContin dispensing. Conceptually, when a pharmacy faces one more new competitor, it is likely to have decreased demand, as some of the market will be seized by this newcomer. Even though pharmacies may become more lenient to cater to drug dealers or other people who are more prone to drug diversion/abuse, the increase would hardly compensate for the decrease due to the decline in demand. Therefore, it is not surprising to find entirely negative effects from competition when pharmacy fixed effects are included. Although we expect that independent pharmacies may compensate for their loss from the medical market by being more lenient to the diversion needs than their chain counterparts, we do not find a positive coefficient on the interaction term during the entire period.

The OxyContin reformulation substantially decreased the diversion demand for OxyContin. Therefore, we expect to see little compensation impact after reformulation but larger compensation impact before reformulation among independent pharmacies. Columns (6) and (8) support our hypothesis. Before the reformulation, independent pharmacies suffer less from competition. However, after the reformulation, the negative impact of competition was borne by independent pharmacies only.

In Figure 4, we evaluate the effect of competition for independent pharmacies ($\hat{\beta}_2$ in equation [4]) for different distance measures when controlling for ZIP and year-month fixed effects. Considering dispensing of all opioids as well as only oxycodone, Figure 4 shows that the effect of competition for independent pharmacies is a decreasing function of the radius. The smaller the radius, the higher the effect of competition on the dispensing of opioids. A new competitor in geographically close areas has strong competitive pressure on independent pharmacies, and thus leniency increases. Comparing all opioids and OxyContin, the effect of distance is similar. The relative sizes of the coefficients for OxyContin in Figure 4 are higher than for all opioids, inde-

Table 5: Regression, Competition Analysis

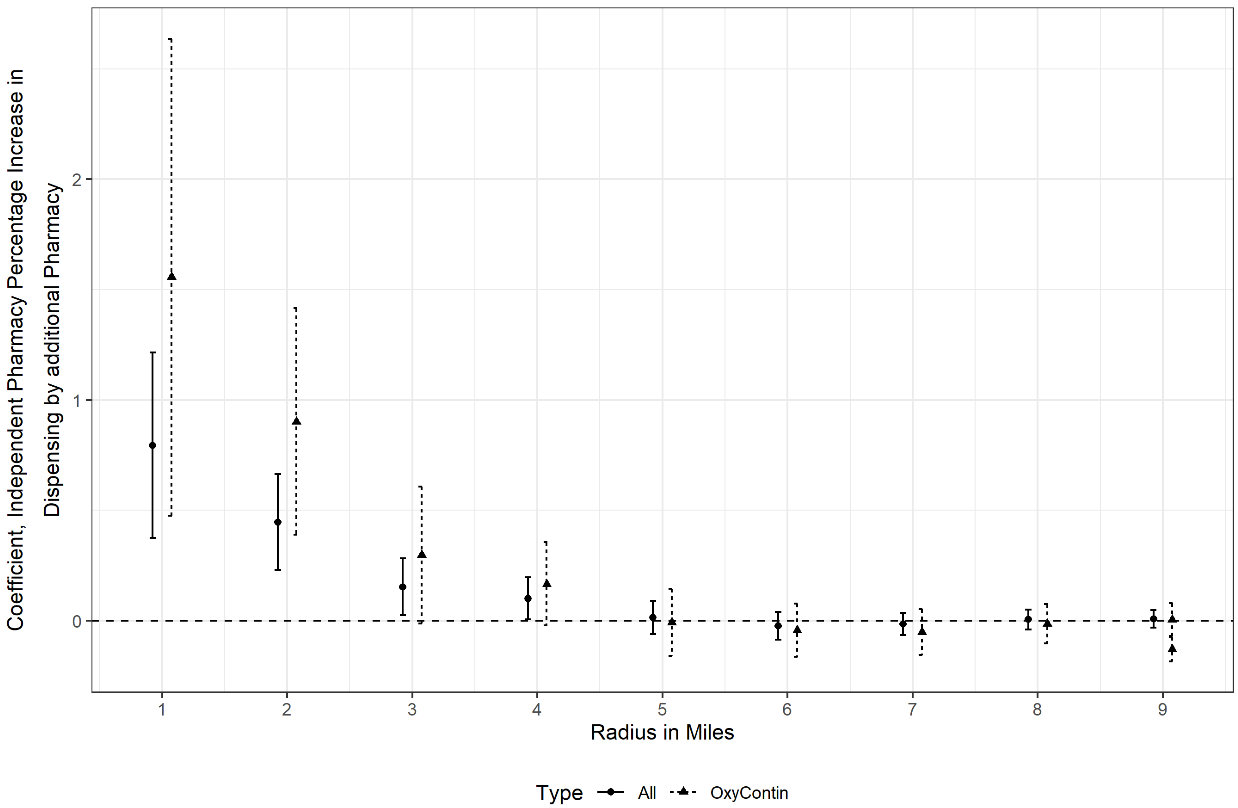
	OxyContin							
		Full Sample			Before Reformulation		After Reformulation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competition	0.138	-0.045	-1.502^{***}	-1.049^{***}	-0.714^{***}	-1.338^{***}	-0.555^{***}	-0.241^{**}
	(0.106)	(0.132)	(0.113)	(0.077)	(0.254)	(0.147)	(0.111)	(0.095)
Independent		16.018^{***}						
		(0.718)						
Competition*Independent		0.167^{*}		-0.725^{***}		1.095^{**}		-0.506^{***}
		(0.091)		(0.190)		(0.451)		(0.193)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP FE	Yes	Yes	No	No	No	No	No	No
Pharmacy FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	27.3	27.3	27.3	27.3	25.97	25.97	29.76	29.76
Observations	5,024,251	5,024,251	5,024,251	5,024,251	3,255,365	3,255,365	1,768,886	1,768,886
R-squared	0.145	0.153	0.629	0.629	0.678	0.678	0.779	0.779

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the competition analysis in equation (4). One observation corresponds to a pharmacy within a month. In all models we consider monthly dispensed OxyContin in MED as an outcome. In models (1) to (4) we consider the full sample. In model (5) and (6) we show results for the period before the OxyContin reformulation in August 2010. In model (7) and (8) we solely consider the period after the OxyContin reformulation. *Competition* displays the coefficient β_1, the effect of an additional competitor in a 1-mile radius. *Independent* displays the effect of independent pharmacies. *Competition* displays the coefficient β_1, the effect of an additional competitor in a 1-mile radius. *Comp*$\times$*Indep* displays the coefficient β_2, the effect of an additional competitor in a 1-mile radius on independent pharmacies. Year-month, ZIP FE and pharmacy FE indicate the use of fixed effects. We show the mean outcome of the outcome variable. Standard errors are clustered at the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

pendent of the radius. This observation is in line with the interpretation that higher competition increases dispensing, and the demand for leniency is higher for abusive opioids.

Figure 4: The Effect of Competition on Independent Pharmacies for Different Spatial Measures



Notes: The figure shows the effect of an additional competitor within a radius on an independent pharmacy's dispensing relative to a chain pharmacy before the OxyContin reformulation divided by the average dispensing of pharmacies in the sample before reformulation. The effect is based on coefficients from a regression that estimates the effect of competition on independent pharmacies within different radii on the dispensing of (1) all opioids and (2) OxyContin, as described by β_2 in equation (4). Each displayed coefficient corresponds to an individual regression that includes ZIP and year-month specific fixed effects, i.e. specification (6) of Table 5 with different measures of competition. The error bars correspond to the 95% confidence interval.

7.2 Geographic Variation in Diversion Demand

We now explore geographical heterogeneity of the ownership effect. The analysis is useful in two dimensions. First, we investigate whether differences in opioid dispensing between independent pharmacies and chain pharmacies are concentrated in some US states. Second, we evaluate whether higher dispensing differentials between independent and chain pharmacies are positively related to local drug abuse prevalence. We discussed in our analysis of the OxyContin reformulation that a higher demand for diversion is associated with higher dispensing by independent pharmacies. We therefore expect that higher drug abuse in local areas could also increase dispensing of independent pharmacies compared with chain pharmacies.

We first consider the following regression model equivalent to model for each state separately:

$$Y_{it} = \beta Indep_i + \gamma_{FE} + \mu_t + \varepsilon_{it}. \tag{5}$$

For each of the regressions, γ_{FE} are ZIP and μ_t year-month fixed effects. Figure 5 shows the relative size of the $\hat{\beta}$ coefficients compared to the average dispensing across all pharmacies for each specific state. We differentiate between two different coefficients, one for all opioids and one for OxyContin. The results indicate that in the vast majority of states, independent pharmacies dispense more opioids than chain pharmacies. In addition, the relative sizes of the $\hat{\beta}$ coefficients are in most states higher when considering only OxyContin.

Next, we evaluate whether the local drug abuse prevalence is related to the dispensing difference between independent and chain pharmacies. Although we cannot perfectly measure the local demand for legal medical use and illegal recreational use, we approximate each with the following two measures.

To approximate the market size for recreational use u_g^A in county g, we use the drug poisoning death rates from the National Center for Health Statistics' National Vital Statistics System (NVSS). The data provide county age-adjusted death rates due to drug poisoning in each year.[18] The data include deaths from all types of drug poisoning, not only prescription opioids.[19] Indeed the majority of death is due to illicit opioids, such as illicitly manufactured fentanyl (CDC 2019*a*). However, we believe that it is reasonable to assume that a higher death rate due to drug poisoning is positively correlated with the market size for recreational opioid use. We further approximate the county-level market size for medically appropriate use by the 2006–2012 county opioid prescription rates from the Centers for Disease Control and Prevention (CDC n.d.*b*).[20]

We estimate the following model at the pharmacy level:

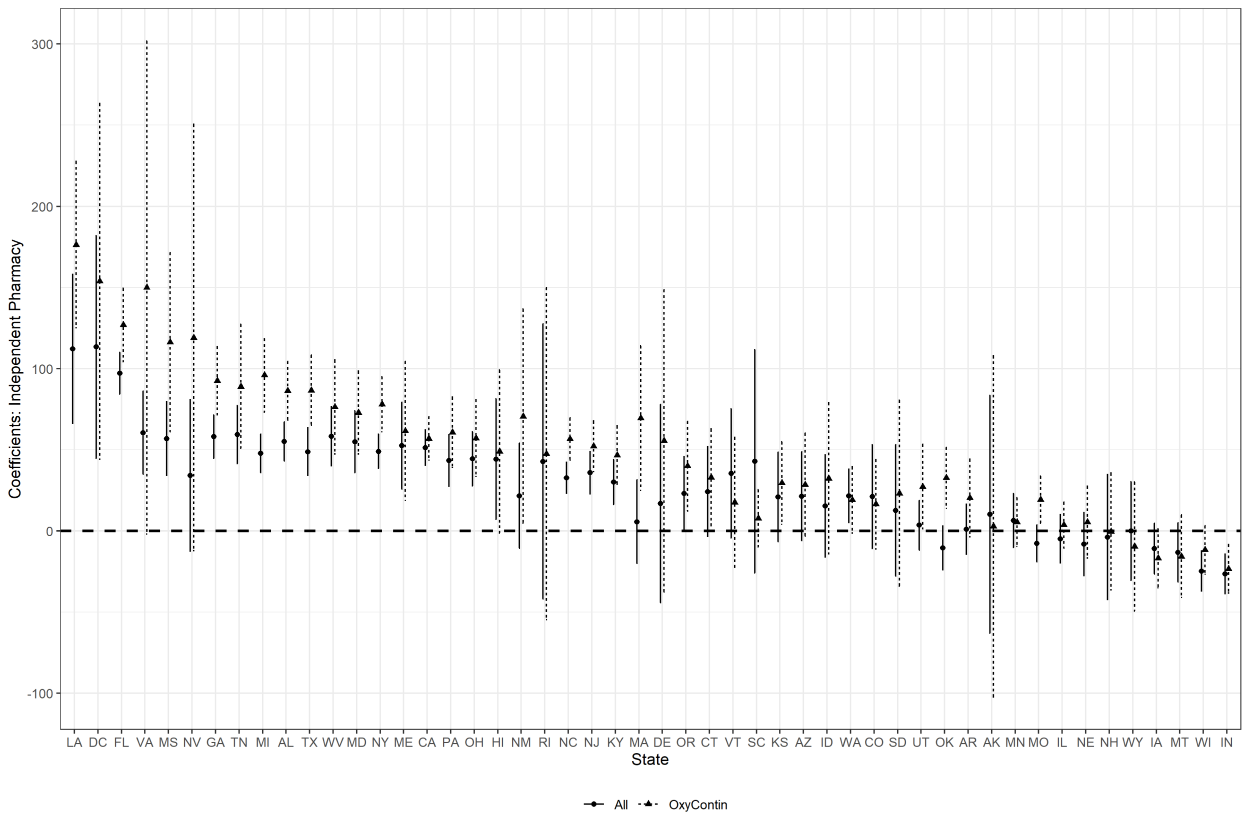
$$Y_{igt} = \beta_1 Indep_i + \beta_2 Indep_i * \hat{u}^A_{gz-1} + \beta_3 Indep_i * \hat{u}^M_{gz} + \hat{u}^A_{gz-1} + \hat{u}^M_{gz} + \alpha_i + \mu_t + \varepsilon_{igt}, \tag{6}$$

[18] For details, see https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/index.htm.

[19] The causes of death are classified using the International Classification of Diseases (ICD–10). We consider the drug-poisoning deaths that are defined as having one of the following underlying cause-of-death codes: X40–X44 (unintentional), X60–X64 (suicide), X85 (homicide), or Y10–Y14 (undetermined intent) (CDC n.d.*a*).

[20] The source of prescription data is the IQVIA Xponent 2006–2018, a sample of almost 50,000 retail pharmacies that dispense more than 90% of all retail prescriptions (CDC n.d.*b*). We acknowledge that not all of the opioid prescriptions are medically appropriate as for example doctors also play a crucial role for diversion when writing inappropriate prescriptions, but nevertheless the prescription rate is a good approximation of the medical market size.

Figure 5: Dispensing Regressions Across States



Notes: The figure shows heterogeneous effects of ownership in different states on average dispensing of all opioids as well as OxyContin only. We show relative effect of coefficient $\hat{\beta}$, i.e., $\frac{\hat{\beta}}{\bar{Y}}$ where $\bar{Y}$ is the mean outcome across population and $\hat{\beta}$ is based on regression in model (5). Each coefficient is based on a state-specific regression with either all opioid dispensing in MED or dispensing of OxyContin in MED. The regression model includes ZIP and year-month fixed effects. North Dakota is not included as only independent pharmacies exist in the state. The error bars correspond to the 95% confidence interval.

where y_{igt} is the dispensing of all prescription opioids and OxyContin by pharmacy i in county g in month t of year z. $\hat{u}^{A}_{gz-1}$ is the approximation for the market size of recreational use in county g, for which we use the age-adjusted county-level death rate due to drug poisoning in the past year $z-1$ to minimize the bias due to reverse causality. $\hat{u}^{M}_{gz}$ is the approximation for the market size of medical use in county g in the current year z, that is, the county-level prescription rate. $Indep_i$ is a dummy variable that takes the value 1 if a pharmacy is independent. We expect to see a positive $\hat{\beta}_2$ in the pre-OxyContin reformulation period if independent pharmacies are more responsive to the local recreational (diversion) demand.

Table 6 shows estimates from equation (6). Columns (1)–(4) include the period before the

OxyContin reformulation, and columns (5)–(8) include the post-period. Our key interest is the coefficient of $Independent * \hat{u}^A$, as we expect to see a positive coefficient in the pre-reformulation period for the dispensing of OxyContin and all prescription opioids if independent pharmacies respond more to the recreational (diversion) demand. The estimates support our hypothesis, as shown by column (2) and (4). During the period when prescription opioids are the main driver for drug abuse before the OxyContin reformulation, the higher the local diversion demand (in the past year), the more doses dispensed by independent pharmacies relative to chain counterparts. Local medical demand is also positively associated with the higher dispensing of OxyContin by independent pharmacies, but the effect size is smaller that that of local diversion demand. After the OxyContin reformulation, heroin became a popular substitute for OxyContin (Alpert et al. 2018; Evans et al. 2019. Therefore, independent pharmacies may lose more sales due to this reform given that they serve more recreational demand before, which is confirmed by the estimate of $Independent * \hat{u}^A$ in column (8). Compared with the different responses to diversion demand, independent and chain pharmacies are more similar in response to the medical demand. As the prescription rate increases, both chains and independent pharmacies increase dispensing similarly. The only exception is the OxyContin dispensing before the reformulation. Counties with higher prescription rates saw higher dispensing of OxyContin by independent pharmacies, consistent with the doctor-shopping explanation.

Overall, the results in Table 6 support our prediction. Controlling for the prescription rate, a larger market for recreational use increases the difference in dispensing between independent and chain pharmacies. The previous results for the OxyContin reformulation show that independent pharmacies' response to the recreational market accounts for 50% of the extra average dispensing of OxyContin by independent pharmacies. Our analysis using the geographic variation in local diversion demand and medical demand further confirms that independent pharmacies distribute more prescription opioids, especially OxyContin, to the recreational market.

8 What Explains the Larger Diversion from Independent Pharmacies?

Our results above demonstrate that independent pharmacies on average dispense more prescription opioids than chain pharmacies, and 50% of the excessive dispensing of OxyContin is associated with the diversion market. In this section, we discuss the potential reasons behind the difference in dispensing (to the diversion market) between independent and chain pharmacies.

First, independent pharmacies may have stronger financial incentives to divert. According to data from the National Association of Chain Drug Stores (NACDS), from 2000 to 2010, the number

Table 6: Prescription Rate, Lagged Drug Death Rate, and Pharmacy Ownership

	Before OxyContin Reformulation				After OxyContin Reformulation			
	All	All	OxyContin	OxyContin	All	All	OxyContin	OxyContin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	-10.005		-0.011		24.616		6.825^{***}	
	(24.046)		(3.265)		(18.089)		(1.824)	
Independent*$\hat{u}^A$	13.602^{***}	4.138^{***}	1.904^{***}	0.467^{**}	5.522^{***}	1.126	0.075	-0.580^{***}
	(3.353)	(1.241)	(0.382)	(0.235)	(1.361)	(2.300)	(0.119)	(0.120)
Independent*$\hat{u}^M$	-0.534^{**}	0.374	-0.058^{*}	0.190^{***}	-0.116	0.624	0.012	0.062
	(0.240)	(0.229)	(0.032)	(0.048)	(0.192)	(0.735)	(0.017)	(0.038)
$\hat{u}^A$	0.878	0.450	-0.232	-0.034	4.415^{***}	4.260^{***}	0.161	0.106^{*}
	(1.414)	(0.432)	(0.202)	(0.180)	(1.308)	(0.985)	(0.148)	(0.062)
$\hat{u}^M$	1.062^{***}	0.532^{***}	0.088^{***}	-0.039	1.222^{***}	1.640^{***}	0.034^{*}	0.076^{***}
	(0.176)	(0.162)	(0.026)	(0.047)	(0.190)	(0.238)	(0.019)	(0.017)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No	Yes	No	Yes	No
Pharmacy FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean outcome	304.3	304.3	25.92	25.92	384.5	384.5	29.70	29.70
Mean prescription rate	82.13				86.36			
Mean death rate (lagged)	12.34				13.25			
Observations	2,578,144	2,578,144	2,578,144	2,578,144	1,779,853	1,779,853	1,779,853	1,779,853
R-squared	0.054	0.625	0.055	0.738	0.009	0.141	0.067	0.797

* $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$

Notes: Regressions are at the pharmacy-month level. In model specifications (1) to (2) and (5) to (6), the outcome is monthly dispensed opioids in MED. In models (3) to (4) and (7) to (8) we consider monthly dispensed OxyContin in MED as an outcome. *Independent* is an indicator that takes the value one if a pharmacy is independent. $\hat{u}^A$ is the approximation of the recreational market size, measured by the county-level age-adjusted death rate due to drug poisoning (per 100,000 population) in the past year; $\hat{u}^M$ approximates the medical market size, measured by the county-level prescription rate of opioids (per 100 population) in the current year. Year-month, ZIP FE and pharmacy FE indicate the use of fixed effects. Standard errors are clustered at the county level, adjusted for serial correlation and heteroskedasticity.

of chain drugstores increased by 11% while the the number of independent pharmacies remained about the same, which implies that the market is more favorable to chains; the average prescription revenue per pharmacy outlet increased by 62% among chain pharmacies whereas it increased only 34% among independent pharmacies (Fein 2011*b*). Therefore, independent pharmacies indeed face tougher competition. Moreover, column (6) of Table 5 suggests that independent pharmacies may have compensated for their loss of revenue from OxyContin in the medical market when facing more competitors by increasing their dispensing to the diversion market before the OxyContin reformulation.

While they face greater incentive to divert due to competition, independent pharmacies may also perceive a lower probability of being caught and therefore a lower likely cost of wrongdoing. Given that most lawsuits were against major chain pharmacies (Hoffman 2020), it is likely that big pharmacies are more closely watched by both regulators and the media. If firm size matters for the likelihood of committing a crime, we should find that smaller chains behave more similarly to independent pharmacies. To test this hypothesis, we divide chains into three categories: (1) the three major pharmacy chains: CVS, Walgreens and Rite Aid; (2) major supermarket chains (with total revenue equal or above Rite Aid in 2012): Walmart, Costco, Kroger, Target, Ahold, Sears, Albertsons, and Publix; and (3) the remaining smaller chains. Figure 6 shows the comparison between smaller chains, independent pharmacies, and major pharmacy chains.[21] Compared with the three major pharmacy chains, independent pharmacies still on average dispensed the most OxyContin before the reformulation, but smaller chains on average dispensed less than their larger chain counterparts. After the reformulation, although all of them reduced OxyContin dispensing, smaller chains and independent pharmacies reduced it more than major pharmacy chains. As shown in columns (2) and (4) of Table 7, smaller chains reduced their dispensing by about 4.5 more MED than major chains after the reformulation, while independent pharmacies reduced their dispensing by 10.2 more MED than the major chains. This evidence supports our hypothesis that smaller firms are more likely to divert prescription opioids.

Second, compared with chain pharmacies, independent pharmacies may have lower non-human capital, such as insufficient internal tracking systems.[22] Independent pharmacies have up to three stores, and thus their internal databases naturally have less complete information on patients' pre-

[21] We exclude large supermarket chains from this analysis as their behavior is more complicated. On the one hand, they are large businesses with similar total revenue as major pharmacy chains, so their behavior might be more similar to large pharmacy chains. On the other hand, prescription drug sales account for only a small share of total revenue for these supermarket chains. Therefore, if we consider only their pharmacy business, they might behave more similarly to smaller chains.

[22] Another difference is the security level. However, as pharmacy theft and robberies account for only 1.5% of drug diversion, we think security has only a limited impact. In fact, regarding security, existing studies do not find an average difference between independent and chain pharmacies. If anything, chain pharmacies have more cases of theft and robbery of controlled substances (Pharmacists Mutual 2016).

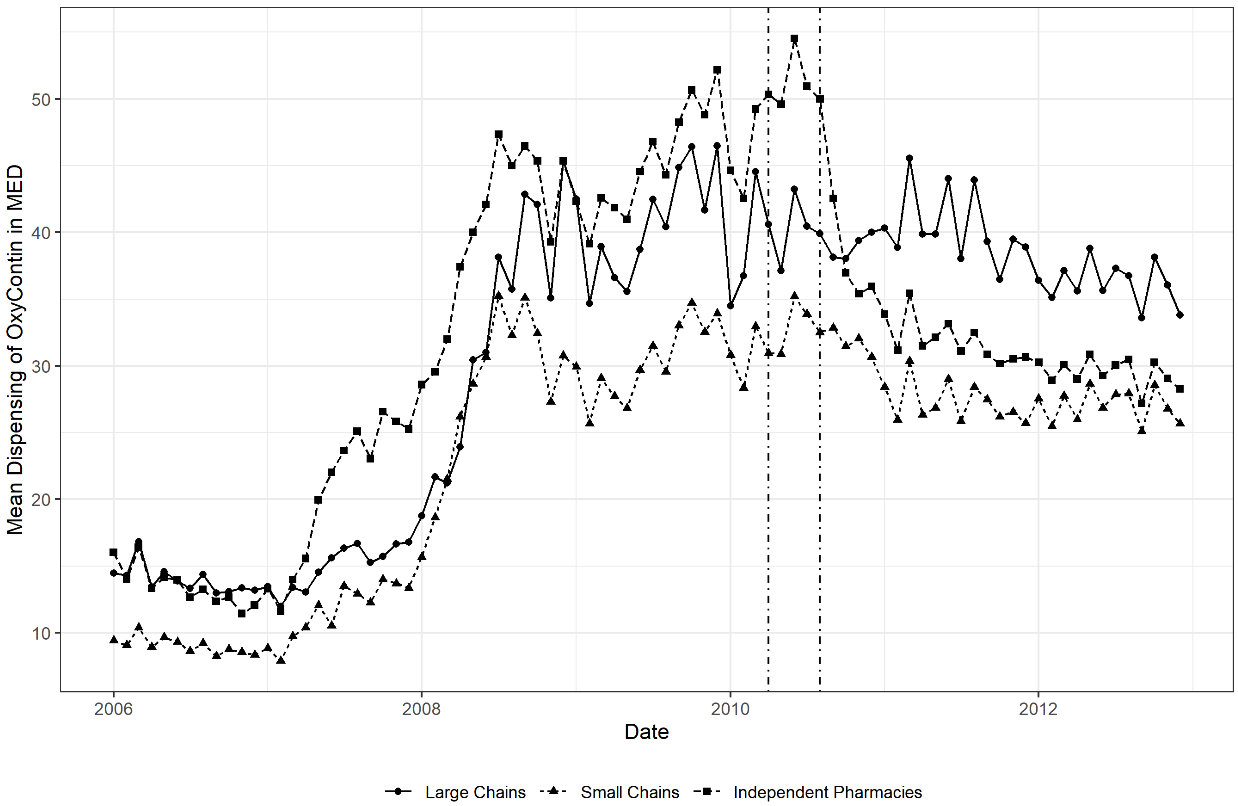
Table 7: OxyContin Reformulation: Smaller Chains, Independent Pharmacies, and Large Chains

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	Small chains	Small chains	Independent	Independent	Small chains	Small chains	Independent	Independent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Small Chain*Post	-3.832^{***}	-4.458^{***}			-2.877^{***}	-2.497^{***}		
	(0.395)	(0.393)			(0.480)	(0.486)		
Small Chain	-6.624^{***}				-7.579^{***}			
	(0.671)				(0.858)			
Independent*Post			-10.764^{***}	-10.217^{***}			-12.766^{***}	-11.061^{***}
			(0.589)	(0.582)			(0.632)	(0.554)
Independent			4.646^{***}				6.647^{***}	
			(0.710)				(0.862)	
Post	10.609^{***}		10.609^{***}		1.106^{***}		1.106^{***}	
	(0.220)		(0.220)		(0.230)		(0.230)	
Constant	27.807^{***}		27.807^{***}		37.310^{***}		37.310^{***}	
	(0.318)		(0.318)		(0.416)		(0.416)	
Year-month FE	No	Yes	No	Yes	No	Yes	No	Yes
Pharmacy FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean outcome	27.25	27.25	27.25	27.25	27.25	27.25	27.25	27.25
Mean effect in percent	−14.06	−16.36	−39.50	−-37.49	−10.56	−9.163	−46.85	−40.59
Observations	2,051,262	2,051,262	3,345,868	3,345,868	1,486,052	1,486,052	2,417,074	2,417,074
R-squared	0.011	0.662	0.000	0.093	0.005	0.710	0.002	0.699

* $p < 0.1$, ** $p < 0.05$, *** $p<0.01$

Notes: Large chains are CVS, Walgreens, and Rite Aid. Major supermarket chains, such as Walmart, Costco, Kroger, Target, Ahold, Sears, Albertsons, and Publix, are excluded. The rest of the chains are small chains. The outcome variable is the monthly OxyContin dispensing at the pharmacy level. Models (1), (2), (5), and (6) compare small chains with large chains before and after the 2010 OxyContin reformulation. Models (3), (4), (7), and (8) compare independent pharmacies with large chains before and after the OxyContin reformulation. Columns (1)–(4) keep the full sample; columns (5)–(8) only keep observations from 2008 to 2012. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

Figure 6: OxyContin Dispensing: Smaller Chains, Independent Pharmacies, and Large Chains



Notes: The figure presents average OxyContin dispensing in MED by three type of pharmacies between 2006 and 2012. Large chains are the three major pharmacy chains: CVS, Walgreens, and Rite Aid. Major supermarkets (Walmart, Costco, Kroger, Target, Ahold, Sears, Albertsons, and Publix) are excluded. Smaller chains are the rest of the chains. The first vertical line corresponds to April 2010, when the new OxyContin was approved by the FDA. The second vertical line corresponds to August 2010, when the new formula was delivered to pharmacies.

scription history than their chain counterparts unless patients stick with only one pharmacy. As a result, they may lack information to identify potential drug abusers and drug dealers who often engage in doctor shopping and pharmacy shopping. To test this, we exploit the implementation of must-access PDMPs for dispensers in four states during 2006 and 2012 under the assumption that the timing of a PDMP implementation is not correlated with other concurrent factors that would affect chain and independent pharmacies' prescription opioid dispensing differently.[23] We estimate the following model to examine if the must-access PDMP helped independent pharmacies to

[23] Although Buchmueller and Carey (2018) show that eight states implemented must-access PDMP for prescribers during the same period, only four states required dispensers to access the PDMP database before dispensing controlled substances: Arizona in July 2011, Delaware in January 2012, New Mexico in August 2012, and Ohio in August 2011.

reduce their dispensing compared with chains:

$$Y_{it} = \beta_1 Indep_i \cdot PostPDMP_{it} + \beta_2 PostPDMP_{it} + \beta_3 Indep_i \cdot PostReform_{it} + \mu_t + \alpha_i + \varepsilon_{it}, \qquad (7)$$

where $PostPDMP_{it}$ takes the value 1 for pharmacy i located in one of the four states after the implementation of the state-level PDMP. $\hat{\beta}_1$ is our key interest, as we want to investigate whether independent pharmacies reduced their dispensing relative to chains after being required to access the same database of patients' prescription history as their chain counterparts. Here we also control for $Indep_i \cdot PostReform_{it}$ because the implementation dates in these four states are all in 2011 and 2012, after the OxyContin reformulation. As we have found from Figure 2 and Table 4, the OxyContin reformulation greatly reduced the gap in OxyContin dispensing between independent and chain pharmacies. Without controlling for the aggregate effect on independent pharmacies due to the reformulation, we may overestimate the PDMP's impact as $PostPDMP_{it}$ is positively correlated with $PostReform_{it}$.

Table 8 shows the results. The first four columns show the effect of the must-access PDMP on the dispensing of all prescription opioids, and columns (5)–(8) show the effect on OxyContin dispensing. Column (4) demonstrates that the gap between independent and chain pharmacies in dispensing of all prescription opioids closed by about 12.4 MED (3.7%) after the implementation of the must-access PDMP for dispensers, although not statistically significant. Column (8) shows that the gap between independent and chain pharmacies shrank by 4.2 MED (15.2%) after the must-access PDMP for dispensers. This evidence supports our hypothesis that the difference in the tracking system of distribution of prescription opioids can explain some of the difference in dispensed amounts between independent and chain pharmacies.

Third, independent pharmacies may have lower levels of human capital, because they have older employees whose knowledge might be outdated, and they may also provide less rigorous on-the-job training. For the former, it is true that pharmacists in independent pharmacies are on average slightly older (47 vs. 43 years) than their chain pharmacy counterparts (Schommer et al. 2007). However, medical and pharmacy schools only added opioid curricula very recently (National Institute on Drug Abuse 2017). In addition, the CDC guidelines on prescription opioids for prescribers and pharmacists were only issued in 2016 (CDC 2016; Dowell et al. 2016).[24] Therefore, neither the older nor the younger pharmacists would have had this information prior to 2016. For the latter, both the 2007 and 2012 surveys done by the American Pharmacists Association indicated that independent pharmacists had higher average ratings of additional training on the job (9.5 vs. 8.6 in 2007; 5.9 vs. 5.2 in 2012) than their chain counterparts (Schommer 2013; Schommer et al. 2007). Therefore, differences in human capital during our study period are not likely to

[24] Prior to 2016, states had their own guidelines but mainly for prescribers only.

Table 8: Regression, Must-access PDMP

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	65.211***	66.174***	145.033***		11.137***	11.433***	19.474***	
	(4.396)	(4.398)	(5.330)		(0.672)	(0.672)	(0.864)	
Independent*PostPDMP	0.247	0.356	−27.445	−12.359	−1.696	−1.716	−4.517*	−4.154**
	(27.754)	(27.756)	(26.197)	(13.009)	(2.733)	(2.733)	(2.573)	(2.013)
PostPDMP	89.469***	90.258***	25.497***	20.590***	12.621***	14.721***	1.162	1.276**
	(8.233)	(8.479)	(7.489)	(4.025)	(0.955)	(0.972)	(0.966)	(0.554)
Independent*PostReform	−20.357***	−21.310***	−24.342***	−16.069***	−6.475***	−6.728***	−7.338***	−5.864***
	(4.566)	(4.571)	(4.440)	(4.717)	(0.565)	(0.563)	(0.577)	(0.561)
Constant	277.344***				21.316***			
	(1.468)				(0.221)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean Outcome	332.5	332.5	332.5	332.5	27.25	27.25	27.25	27.25
Mean Effect in Percent	0.0743	0.107	−8.253	−3.716	−6.223	−6.295	−16.58	−15.24
Observations	5,104,770	5,104,770	5,079,419	5,103,585	5,104,770	5,104,770	5,079,419	5,103,585
R-squared	0.002	0.002	0.048	0.186	0.001	0.003	0.025	0.106

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the impact of the must-access PDMP on dispensing in equation (7). Columns (1)–(4) show the impact on the dispensing of all prescription opioids; columns (5)–(8) show the impact on OxyContin dispensing. One observation corresponds to a pharmacy within a month. During 2006 and 2012, four states had implemented must-access PDMPs for dispensers: Arizona in July 2011, Delaware in January 2012, New Mexico in August 2012, and Ohio in August 2011. *PostPDMP* takes the value 1 in an implementation state after the must-access PDMP was in effect. We show the mean of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\hat{\beta}_1}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity and correlation, and reported in parentheses.

explain the pattern.

In summary, although we are not able to investigate an exhaustive list of all possible differences between chain and independent pharmacies, we show that financial incentives and prescription drug tracking systems are the two likely reasons to explain why independent pharmacies dispensed more to the diversion market.

9 Conclusion

The opioid epidemic is a serious public health crisis in the United States. Although studies have documented the roles played by other suppliers, such as physicians, manufactures, and regulators, the role of retail pharmacies has not been explored in detail. In this study, we document that retail pharmacies, specifically independent pharmacies, also contribute to the opioid crisis.

The direct comparison on a granular local level indicates that independent pharmacies on average dispense 40.9% MED of all prescription opioids and 61.7% of OxyContin, one of the most popular drugs among drug abusers. Our acquisition analysis further confirms that these differences are due to the pharmacy ownership, as independent pharmacies acquired by chains reduced dispensing of all prescription opioids and OxyContin by 31.7% and 43% MED, respectively. In addition, by making use of the OxyContin reformulation, which affected the diversion demand but not the medical market, we show that about 50% of the difference in OxyContin dispensing can be explained by independent pharmacies' response to the diversion demand. Furthermore, we show that spatial competition exacerbates independent pharmacies' incentives to divert, and counties with higher drug abuse prevalence see larger differences in dispensing between independent and chain pharmacies. The evidence therefore points to misdoing by independent pharmacies during the opioid epidemic from 2006 to 2012.

Although many reasons might explain why independent pharmacies are more likely to divert drugs, we show that stronger financial incentives due to greater competitive pressure and lower expected cost of wrongdoing are a likely reason. In addition, the introduction of the must-access PDMP for dispensers helped to overcome the lack of efficient tracking systems among independent pharmacies. Given these findings, policymakers might need to reconsider competition in the retail pharmacy industry and strengthen monitoring and regulations of small (independent) pharmacies, which might be overlooked by the media and the public in contrast to major chains.

Appendix

A Exits

In our sample we observe 10,175 exiting pharmacies between 2006 and 2012. Further, a large fraction of those exiting pharmacies are independent. It may be possible that the exiting independent pharmacies, rather than the general ownership, drive our effect of more dispensing. In this section we show that exiting pharmacies generally do not dispense more but rather less opioids. We observe that exiting pharmacies decrease dispensing in the month before exit. Independent and chain pharmacies that exit do not differ from each other.

In Figure A.1 we present dispensing of OxyContin by pharmacies before the date of exit. From the descriptive statistics we observe that OxyContin dispensing decreases gradually in the months before a pharmacy exits. This may be due to two reasons. First, it may be possible that pharmacies lose business, such that the observed decline in dispensing is the reason for the exit. Second, the pharmacy may anticipate the forthcoming exit and therefore decrease its dispensing and stockpiling.

We further investigate the impact of exits on dispensing in the following two regression models:

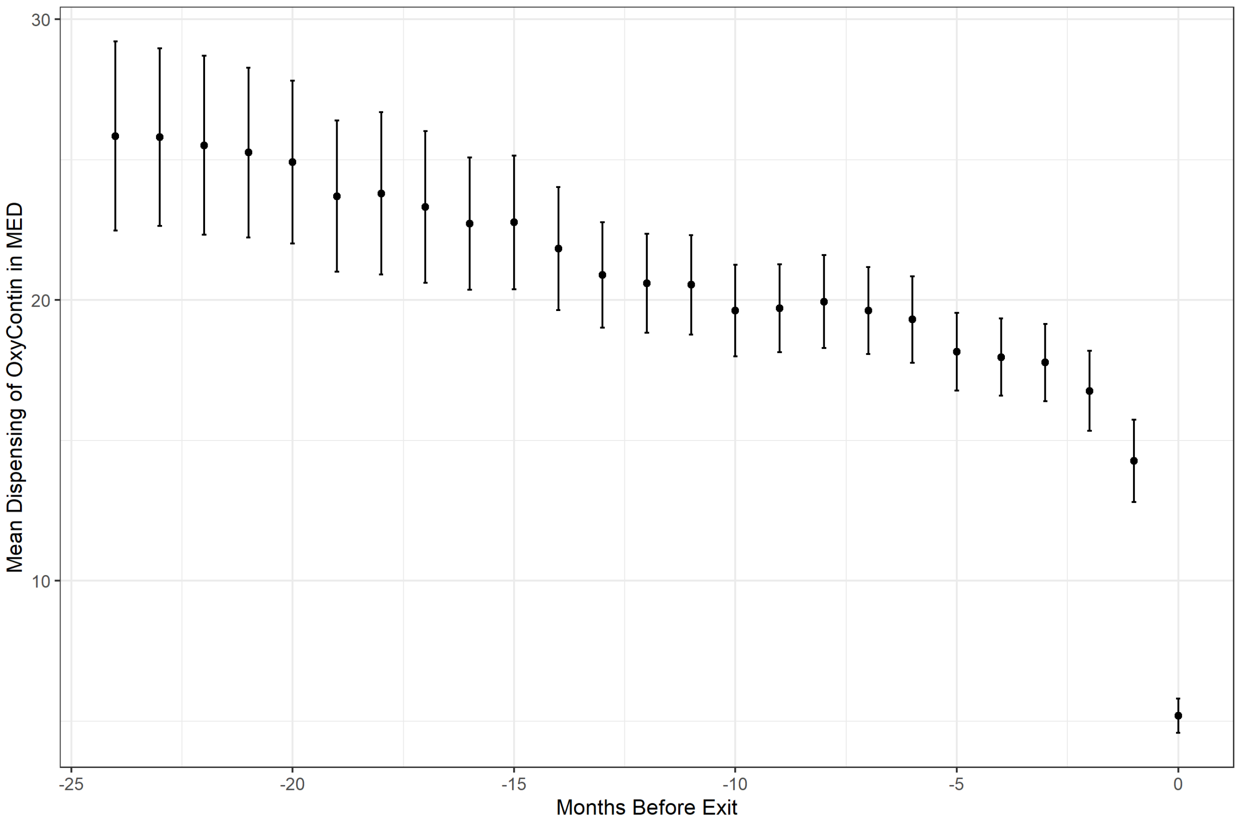
$$Y_{it} = \beta_1 Exit_i \cdot Independent_i + \alpha_{FE} + \mu_t + \varepsilon_{it} \tag{8}$$

$$Y_{it} = \beta_2 MonthBeforeExit_{it} \cdot Independent_i + \alpha_{FE} + \mu_t + \varepsilon_{it}, \tag{9}$$

where Y_{it} is the usual outcome of opioid and OxyContin dispensing by pharmacy i in time t. $Exit$ is an dummy variable that takes the value 1 if pharmacy i exits during the time of our sample. Indicator $Independent_i$ takes the value 1 if pharmacy i is independent. $MonthBeforeExit_{it}$ is the difference in months before the month of exit for pharmacy i in t. $MonthBeforeExit_{it}$ is positive. Finally, α_i are ZIP code month-year specific effects, and μ_t are month-year fixed effects. In the first model we test whether there is a general difference between pharmacies that exit or do not exit. In comparison, the second model evaluates how dispensing changes in the months before the exit and excludes comparison with pharmacies that do not exit.

First, we consider dispensing of all opioids and present results for both models in Table A.1. Second, we consider OxyContin dispensing only in Table A.2. In both tables, regression specification (1) solely includes the $Exit_{it}$ indicator and therefore compares the mean of exiting and nonexiting pharmacies, controlling for year-month fixed effects. For all opioids as well as OxyContin we observe that exiting pharmacies dispense less opioids. Specification (2) and (3) refer to the first regression model, with year-month and ZIP code and year-month fixed effects. After

Figure A.1: Exiting Pharmacies, Dispensing Before Exit



Notes: The figure reports dispensing of OxyContin in MED for pharmacies that exit. We consider monthly average dispensing in the two years before the date of exit. The error bars correspond to the 95% confidence interval.

controlling for ZIP code specific fixed effects, we still observe that exiting pharmacies dispense less opioids as well as less OxyContin. Further, we do not observe that independent pharmacies are statistically different from chain pharmacies when considering the difference between exiting and nonexiting pharmacies. Specifications (4) and (5) refer to the second model, consisting of solely those pharmacies that exit. Again, independent of fixed effects, we see that closer to the date of exit (smaller regressor $MonthBeforeExit_{it}$), the pharmacy reduces its dispensing. The effect is not significantly different from zero when including ZIP code year-month fixed effects. Finally, we do not observe any statistically significant differences between chain and independent pharmacies. However, the point estimates show that independent pharmacies potentially reduce dispensing more when they are close to the date of exit. Results are comparable for all opioids and OxyContin.

Overall, the analysis shows that exiting pharmacies dispense less opioids, especially close to the date of exit. Therefore our general result showing that ownership matters is not driven by exiting independent pharmacies.

Table A.1: Exit Regression, All Opioids

	All Opioids				
	(1)	(2)	(3)	(4)	(5)
Exit	-66.043^{***}	-108.161^{***}	-139.972^{***}		
	(6.473)	(6.648)	(10.338)		
MonthsBeforeExit				-1.122^{***}	-1.134^{***}
				(0.231)	(0.423)
Independent		63.208^{***}	145.396^{***}	86.686^{***}	163.566^{***}
		(4.879)	(5.846)	(11.172)	(18.786)
Exit:Independent		31.533^{***}	26.657^{*}		
		(11.485)	(14.332)		
MonthsBeforeExit:Independent				-0.292	-0.658
				(0.409)	(0.449)
Year-month FE	Yes	Yes	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	Yes
Observations	5,079,419	5,079,419	5,079,419	315,948	315,948
R-squared	0.002	0.003	0.049	0.006	0.309

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of regressions that investigate dispensing of exiting pharmacies. One observation corresponds to a monthly pharmacy. In models (4) and (5) we solely consider pharmacies that exit between 2006 and 2012. The outcome variable is all opioid dispensing in MED. *Exit* is a dummy that takes the value 1 if a specific pharmacy exited between 2006 and 2012 and zero otherwise. *Independent* is an indicator that takes the value 1 if a pharmacy is independent. We interact the dummies *Exit* and *Independent* in models (2) and (3). *MonthsBeforeExit* are the months before the date of exit for those pharmacies that exit. We evaluate whether the months before an exit have different effects for independent and chain pharmacies by interacting *MonthsBeforeExit* and *Independent* in models (4) and (5). Year-month FE and ZIP FE indicate the use of fixed effects. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

Table A.2: Exit Regression, OxyContin

	OxyContin				
	(1)	(2)	(3)	(4)	(5)
Exit	-2.280^{**}	-5.591^{***}	-9.520^{***}		
	(1.115)	(0.706)	(1.199)		
MonthsBeforeExit				-0.184^{***}	-0.207^{***}
				(0.030)	(0.071)
Independent		9.375^{***}	17.532^{***}	6.870^{***}	18.886^{***}
		(0.586)	(0.769)	(1.485)	(3.082)
Exit*Independent		0.500	1.283		
		(1.712)	(1.982)		
MonthsBeforeExit:Independent				−0.110	−0.064
				(0.068)	(0.076)
Year-month FE	Yes	Yes	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	Yes
Observations	5,079,419	5,079,419	5,079,419	315,948	315,948
R-squared	0.002	0.003	0.025	0.014	0.345

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of regressions that investigate dispensing of exiting pharmacies. One observation corresponds to a monthly pharmacy. In models (4) and (5) we solely consider pharmacies that exit between 2006 and 2012. The outcome variable is OxyContin dispensing in MED. *Exit* is a dummy that takes the value 1 if a specific pharmacy exited between 2006 and 2012 and zero otherwise. *Independent* is an indicator that takes the value 1 if a pharmacy is independent. We interact the dummies *Exit* and *Independent* in models (2) and (3). *MonthsBeforeExit* are the months before the date of exit for those pharmacies that exit. We evaluate whether the months before an exit have different effects for independent and chain pharmacies by interacting *MonthsBeforeExit* and *Independent* in models (4) and (5). Year-month FE and ZIP FE indicate the use of fixed effects. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

B Dispensing Per Capita

In our main analysis, we use the dispensed MED at the pharmacy level. In this section, we present results with an alternative outcome measure: dispensed MED per capita by each pharmacy, where the population is measured in 2010 at the ZIP code level. Table B.1 shows results of the direct comparison between independent and chain pharmacies, and Table B.2 corresponds to the acquisitions of independent pharmacies. Table B.3 evaluates the OxyContin reformulation. Table B.4 shows results of the competition analysis, and Table B.5 shows that the gap in prescription opioid dispensing between independent and chain pharmacies is positive correlated with local diversion demand. Table B.6 further evaluates small chains' and independent pharmacies' behavior relative to that of the major pharmacy chains. Table B.7 shows the impact of must-access PDMPs on pharmacies' dispensed MED per capita.

In general, the estimated effects (mean effect in percent) are smaller than those for pharmacy-level dispensed MED but of the same direction, and thus the interpretations are similar to our main results.[25]

Table B.1: Regression, Direct Comparison Per Capita

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	0.0096***	0.0096***	0.0089***	0.0058***	0.0009***	0.0009***	0.0010***	0.0007***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.00003)	(0.00003)	(0.00004)	(0.00003)
Constant	0.0152***				0.0012***			
	(0.0001)				(0.00001)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP FE	No	No	No	Yes	No	No	No	Yes
Mean Outcome	0.0191	0.0191	0.0191	0.0191	0.0015	0.0015	0.0015	0.0015
Mean Effect in Percent	50.22	50.49	47.38	31.38	59.24	60	65.41	48.8
Observations	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385
R-squared	0.0057	0.0079	0.0813	0.2153	0.0021	0.0052	0.0292	0.0931

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the direct comparison between independent and chain pharmacies. One observation corresponds to a pharmacy within a month. In model specifications (1) to (4), the outcome is monthly dispensed opioids per capita (population in 2010) in MED. In models (5) to (8) we consider monthly dispensed OxyContin per capita in MED as an outcome. Independent displays the coefficient β. Year-month FE, county FE, and ZIP FE indicate the use of fixed effects. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

[25] Except for the impact of the must-access PDMP on the OxyContin dispensing, we find a larger effect in percent when using the per capita MED dispensed.

Table B.2: Acquisitions, Per Capita

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before	-0.006^{***}	-0.004^{**}	-0.001		-0.0005^{**}	-0.0002	-0.0001	
	(0.002)	(0.002)	(0.001)		(0.0002)	(0.0002)	(0.0002)	
After	-0.010^{***}	-0.012^{***}	-0.008^{***}	-0.005^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.0004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Chain	-0.009^{***}	-0.009^{***}	-0.006^{***}		-0.001^{***}	-0.001^{***}	-0.001^{***}	
	(0.0003)	(0.0003)	(0.0002)		(0.00003)	(0.00003)	(0.00003)	
Constant	0.025^{***}				0.002^{***}			
	(0.0003)				(0.00003)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.0191	0.0191	0.0191	0.0191	0.0015	0.0015	0.0015	0.0015
Mean effect in percent	−53.25	−62.75	−40.36	−23.96	−49.68	−65.32	−55.85	−29.39
Observations	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385	5,028,385
R-squared	0.006	0.008	0.215	0.333	0.002	0.005	0.093	0.157

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the acquisition regression analysis in equation (2). One observation corresponds to a pharmacy within a month. In model specifications (1) to (4), the outcome is monthly dispensed opioids in MED per capita (population in 2010). In models (5) to (8) we consider monthly dispensed OxyContin in MED per capita as an outcome. *Before* displays the coefficient β_0, the effect of independent pharmacies before acquisition. *After* displays the coefficient β_1, the effect of chain pharmacies that were independent before acquisition. *Chain* displays the coefficient β_C, the effect of chain pharmacies that did not change ownership. The baseline effect is independent pharmacies that did not change ownership. Year-month FE, ZIP FE, and pharmacy FE indicate the use of fixed effects. When using pharmacy fixed effects, only the variation of changing ownership can be used. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta_1}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

Table B.3: Regression, OxyContin Reformulation, Per Capita

	OxyContin							
	Full sample: 2006-2012				Subsample: 2008-2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-0.0001^{***}	-0.0002^{***}	-0.0001^{***}	-0.0001^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0004^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Independent	0.0009^{***}	0.0010^{***}	0.0008^{***}		0.0013^{***}	0.0013^{***}	0.0010^{***}	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Post	0.0003^{***}				-0.0000^{**}			
	(0.0000)				(0.0000)			
Constant	0.0010^{***}				0.0014^{***}			
	(0.0000)				(0.0000)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152
Mean effect in percent	−9.622	−10.67	−9.299	−5.791	−32.28	−32.40	−30.19	−27.15
Observations	5,039,527	5,039,527	5,028,508	5,038,211	3,631,971	3,631,971	3,625,387	3,630,766
R-squared	0.0024	0.0052	0.0931	0.1739	0.0094	0.0111	0.3653	0.6415

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the OxyContin reformulation regression analysis in equation (3). The outcome variable is the per-capita OxyContin dispensing in MED per month at the pharmacy level, where the population is at the ZIP code level and from the 2010 census. *Independent*Post* displays the coefficient $\hat{\beta}$, the change of independent pharmacies after the reformulation. *Independent* displays the effect of independent pharmacies. *Post* is an indicator showing months after the reformulation of OxyContin. Year-month FE, ZIP FE, and pharmacy FE indicate different fixed effects. We show the mean of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\hat{\beta}}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

Table B.4: Regression, Competition Analysis, Per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OxyContin per Capita*100							
	Full Sample				Before Reformulation		After Reformulation	
Competition	0.0004 (0.0004)	0.0001 (0.0004)	-0.007^{***} (0.0005)	-0.006^{***} (0.0004)	-0.008^{***} (0.001)	-0.009^{***} (0.001)	-0.002^{***} (0.001)	-0.001 (0.001)
Independent		0.072^{***} (0.003)						
Competition*Independent		-0.0001 (0.0003)		-0.002^{**} (0.001)		0.002 (0.002)		-0.002^{*} (0.001)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP FE	Yes	Yes	No	No	No	No	No	No
Pharmacy FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.152	0.152	0.152	0.152	0.1421	0.1421	0.1702	0.1702
Observations	4,973,924	4,973,924	4,973,924	4,973,924	3,222,065	3,222,065	1,751,859	1,751,859
R-squared	0.327	0.331	0.585	0.585	0.682	0.682	0.555	0.555

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the competition analysis in equation (4). One observation corresponds to a pharmacy within a month. In all models we consider monthly dispensed OxyContin per capita $\times 100$ in MED as an outcome. In models (1) to (4) we consider the full sample. In models (5) and (6) we show results for the time before the OxyContin reformulation in August 2010. In models (7) and (8) we solely consider the time after the OxyContin reformulation. *Competition* displays the coefficient β_1, the effect of an additional competitor in a five miles radius. *Independent* displays the effect of an independent pharmacies. *Competition* displays the coefficient β_1, the effect of an additional competitor in a 1-mile radius. *Comp*$\times$*Indep* displays the coefficient β_2, the effect of an additional competitor in a 1-mile radius on independent pharmacies. Year-month FE, ZIP FE and pharmacy FE indicate the use of fixed effects. We show the mean outcome of the outcome variable. Standard errors are clustered at the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

Table B.5: Prescription Rate, Lagged Drug Death Rate, and Pharmacy Ownership

	Before OxyContin Reformulation				After OxyContin Reformulation			
	All*100		OxyContin*100		All*100		OxyContin*100	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	−0.3051**		−0.0495***		−0.2956**		0.0150	
	(0.1336)		(0.0183)		(0.1491)		(0.0125)	
Independent*$\hat{u}^A$	0.0783***	0.0245***	0.0105***	0.0048***	0.0581***	0.0056	0.0021**	−0.0049***
	(0.0159)	(0.0088)	(0.0017)	(0.0015)	(0.0139)	(0.0092)	(0.0010)	(0.0009)
Independent*$\hat{u}^M$	0.0035**	0.0073***	0.0005**	0.0023***	0.0053***	0.0036	0.0005***	0.0004*
	(0.0014)	(0.0022)	(0.0002)	(0.0004)	(0.0015)	(0.0030)	(0.0001)	(0.0002)
$\hat{u}^A$	0.0588***	0.0023	0.0039***	−0.0002	0.0880***	0.0175***	0.0037***	−0.0004
	(0.0122)	(0.0033)	(0.0014)	(0.0012)	(0.0132)	(0.0040)	(0.0009)	(0.0004)
$\hat{u}^M$	−0.0010	0.0015	−0.0002	−0.0005*	−0.0000	0.0099***	−0.0004**	0.0003***
	(0.0019)	(0.0013)	(0.0002)	(0.0003)	(0.0023)	(0.0013)	(0.0002)	(0.0001)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No	Yes	No	Yes	No
Pharmacy FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean outcome	1.741	1.741	0.142	0.142	2.207	2.207	0.170	0.170
Prescription rate	82.13				86.36			
Death rate (lagged)	12.34				13.25			
Observations	2,541,178	2,541,178	2,541,178	2,541,178	1,755,616	1,755,616	1,755,616	1,755,616
R-squared	0.0774	0.4961	0.0858	0.7374	0.0554	0.3626	0.0825	0.5841

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Regressions are at the pharmacy-month level. In all models we consider monthly dispensed all opioids/OxyContin per capita $\times 100$ in MED as an outcome. *Independent* is an indicator that takes the value one if a pharmacy is independent. $\hat{u}^A$ is the approximation of the recreational market size, measured by the county-level age-adjusted death rate due to drug poisoning (per 100,000 population) in the past year; $\hat{u}^M$ approximates the medical market size, measured by the county-level prescription rate of opioids (per 100 population) in the current year. Standard errors are clustered at the county level, adjusted for serial correlation and heteroskedasticity.

Table B.6: OxyContin Reformulation: Smaller Chains, Independent Pharmacies, and Large Chains, Per Capita

	Full sample 2006–2012				2008–2012			
	Small chains	Small chains	Independent	Independent	Small chains	Small chains	Independent	Independent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Small chain*Post	−0.0001***	−0.0002***			−0.0001***	−0.0001***		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Small chain	−0.0003***				−0.0003***			
	(0.0000)				(0.0000)			
Independent*Post			−0.0003***	−0.0003***			−0.0006***	−0.0005***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Independent			0.0006***				0.0009***	
			(0.0000)				(0.0001)	
Post	0.0005***		0.0005***		0.0001***		0.0001***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Constant	0.0013***		0.0013***		0.0018***		0.0018***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Year-month FE	No	Yes	No	Yes	No	Yes	No	Yes
Pharmacy FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean outcome	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152	0.00152
Mean effect in percent	−8.106	−11.78	−21.27	−18.69	−5.857	−5.343	−37.09	−31.49
Observations	2,034,868	2,034,868	3,282,693	3,282,693	1,474,197	1,474,197	2,372,415	2,372,415
R-squared	0.005	0.463	0.001	0.162	0.001	0.495	0.003	0.702

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Large chains are CVS, Walgreens, and Rite Aid. Major supermarket chains, such as Walmart, Costco, Kroger, Target, Ahold, Sears, Albertsons, and Publix, are excluded. The rest of the chains are small chains. The outcome variable is the per capita OxyContin dispensing in MED per month at the pharmacy level, where the population is at the ZIP code level and from the 2010 census. Models (1), (2), (5), and (6) compare small chains with large chains before and after the 2010 OxyContin reformulation. Models (3), (4), (7), and (8) compare independent pharmacies with large chains before and after the OxyContin reformulation. Columns (1)–(4) keep the full sample; columns (5)–(8) only keep observations from 2008 to 2012. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

Table B.7: Regression, Must-Access PDMP, Per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		All				OxyContin		
Independent	0.0094***	0.0095***	0.0055***		0.0010***	0.0010***	0.0008***	
	(0.0003)	(0.0003)	(0.0002)		(0.0000)	(0.0000)	(0.0000)	
Independent*PostPDMP	0.0013	0.0014	−0.0024**	−0.0004	0.0001	0.0001	−0.0005***	−0.0004***
	(0.0016)	(0.0016)	(0.0010)	(0.0007)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
PostPDMP	0.0008	0.0006	0.0004	−0.0001	0.0003***	0.0004***	0.0000	−0.0000
	(0.0005)	(0.0005)	(0.0003)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Independent*PostReform	0.0004	0.0003	0.0008***	0.0012***	−0.0001***	−0.0002***	−0.0001***	−0.0001***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0135***				0.0010***			
	(0.0001)				(0.0000)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.0191	0.0191	0.0191	0.0191	0.00152	0.00152	0.00152	0.00152
Mean effect in percent	7.063	7.123	−12.57	−2.121	8.914	8.842	−31.92	−25.74
Observations	5,028,385	5,028,385	5,028,385	5,027,218	5,028,385	5,028,385	5,028,385	5,027,218
R-squared	0.0070	0.0079	0.2153	0.3641	0.0024	0.0053	0.0931	0.1740

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the impact of the must-access PDMP on dispensing in equation (7). Columns (1)–(4) show the impact on the dispensing of all prescription opioids; columns (5)–(8) show the impact on OxyContin dispensing. The outcome variable is the per capita dispensing in MED per month at the pharmacy level, where the population is at the ZIP code level and from the 2010 census. During 2006 and 2012, four states had implemented must-access PDMPs for dispensers. Arizona, Delaware, New Mexico, and Ohio implemented PDMPs in July 2011, January 2012, August 2012, and August 2011, respectively. *PostPDMP* takes the value 1 in an implementation state after the must-access PDMP was in effect. We show the mean of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\hat{\beta}_1}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity and correlation, and reported in parentheses.

C Quarterly Analysis

Within this section we use quarterly instead of monthly data to compare independent to chain pharmacies on a local geographical level. One concern with the use of monthly ARCOS data is that orders from pharmacies may not be on a monthly basis. Instead, it is possible that pharmacies order products on a bimonthly frequency, for example. Such a pattern would impact our results. To show robustness we create a quarterly pharmacy-level data set and compare independent pharmacies with chain pharmacies in the same model as the main paper:

$$Y_{it} = \beta Indep_i + \mu_t + \gamma_{FE} + \varepsilon_{it}, \tag{10}$$

where Y_{it} is the dispensed MED of opioids at pharmacy i in quarter t as well as the dispensed MED of OxyContin. $Indep_i$ is a dummy that takes the value 1 if a pharmacy is independent, μ_t are year-quarter fixed effects, and γ_{FE} represents different geographic fixed effects. Table C.1 shows results of the direct comparison between independent and chain pharmacies. The relative effects are comparable to our main analysis using monthly data. Using ZIP and year-quarter fixed effects, independent pharmacies dispense 37.4% more opioids compared with chain pharmacies. Using monthly data, the effect size was 40.9%. Considering only OxyContin, we find an effect of 58.1% more dispensing for independent pharmacies when using quarterly data. This result also is comparable to the result of 61.7% using monthly data. Therefore, we find that the monthly analysis is robust to a quarterly analysis.

D Quantile Regression

In addition to looking at how pharmacy ownership affects the average level of prescription opioid dispensing, because the dispensing is right-skewed, we also conduct quantile regressions to examine how pharmacy ownership affects dispensing at different quantiles.

Figure D.1 reports the unconditional quantile regression coefficients. As expected, ownership plays a bigger role for pharmacies with higher dispensing. For pharmacies dispensing prescription opioids under the median level, independent pharmacies dispense less prescription opioids than their chain counterparts. However, for pharmacies dispensing more than the median, we find clearly that independent pharmacies dispense much more opioids than their chain counterparts. At the 90th percentile, an independent pharmacy on average dispenses about 300 more MED of all prescription opioids than a chain pharmacy in the same ZIP code in the same month. Similarly, for pharmacies dispensing OxyContin under the median level, there is no difference between independent and chain pharmacies. However, for pharmacies dispensing at or above the median,

Table C.1: Regression, Quarterly Direct Comparison

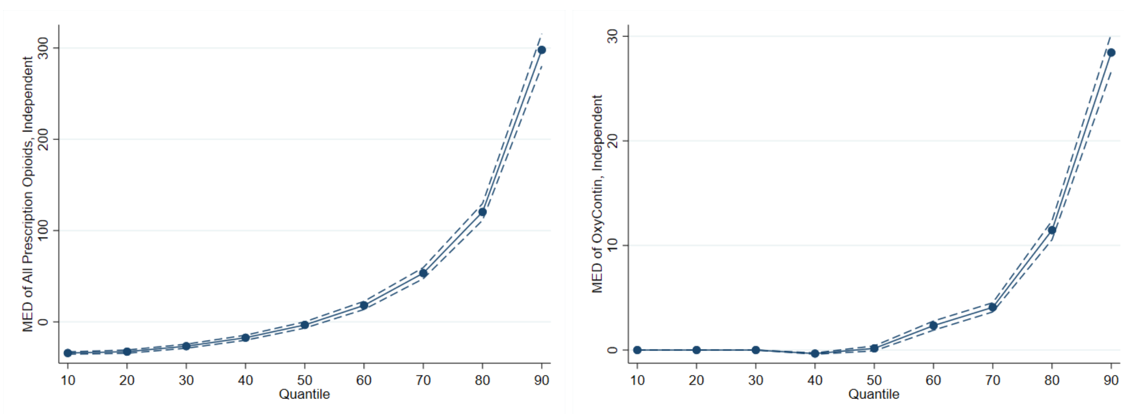
	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	139.331***	141.748***	303.915***	363.713***	23.299***	23.862***	40.530***	46.353***
	(13.013)	(13.022)	(15.760)	(15.723)	(1.594)	(1.593)	(2.000)	(2.116)
Constant	915.253***				70.051***			
	(4.667)				(0.618)			
Year-quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	973.61	973.61	973.61	973.61	79.81	79.81	79.81	79.81
Mean effect in percent	14.31	14.56	31.22	37.36	29.19	29.9	50.78	58.08
Observations	1,737,739	1,737,739	1,737,739	1,737,739	1,737,739	1,737,739	1,737,739	1,737,739
R-squared	0.001	0.004	0.039	0.099	0.001	0.006	0.023	0.056

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of a direct comparison between independent and chain pharmacies in equation (1). One observation corresponds to a pharmacy within a quarter. In model specifications (1) to (3), the outcome is quarterly dispensed opioids in MED. In models (4) to (6) we consider quarterly dispensed OxyContin in MED as an outcome. *Independent* displays the coefficient β. Year-quarter FE, county and ZIP FE indicate the use of fixed effects. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

independent pharmacies dispense more OxyContin. At the 90th percentile, an independent pharmacy generally dispenses about 30 more MED of OxyContin than a chain counterpart in the same ZIP code in the same month.

Figure D.1: Ownership Effect at Different Quantiles: Chain vs Independent



Notes. The figure reports regression coefficients of the effects of independent ownership on all opioids and OxyContin MED at different quantiles from unconditional quantile regressions. Year-month and ZIP fixed effects are included. The dashed lines are the 95% confidence interval based on standard errors clustered at the pharmacy level.

E Acquisitions: Chains That Became Independent Pharmacies

In this section we evaluate the acquisition of chain pharmacies by independent pharmacies.[26] In our main analysis we show that independent pharmacies that get acquired by chains reduce their opioid dispensing. Here, we evaluate whether we see an reverse effect when chain pharmacies become independent. We do not show the analysis in the main part of the paper as cases of such acquisition are less common (223 acquisitions), Furthermore, our results suggest that we have reasons to believe that in comparison to the acquisitions of independent pharmacies by chains, where the behavior before acquisition is the same, those chains that become independent pharmacies are different from other chains in general. In detail, the chains that become independent dispense less opioids than other chains that do not change ownership. Nevertheless, we expect that chain pharmacies that become independent increase their opioid dispensing.

Figure E.1 shows monthly dispensing of opioids in MED for chain pharmacies 12 months before and after becoming an independent pharmacies. From the raw data we observe an increase of dispensing after the ownership change. However, in comparison to the reverse case when independent pharmacies getting acquired by chain pharmacies we do not observe a discontinuity after the ownership change. Instead, the new independent owner increases dispensing gradually over the months following the ownership change. A possible interpretation is that the new independent owner increases the number of patients over time. However, overall we observe the expected result in the raw data, the independent owner increases opioid dispensing.

In Table E.1 we report the regression evidence of the following model:

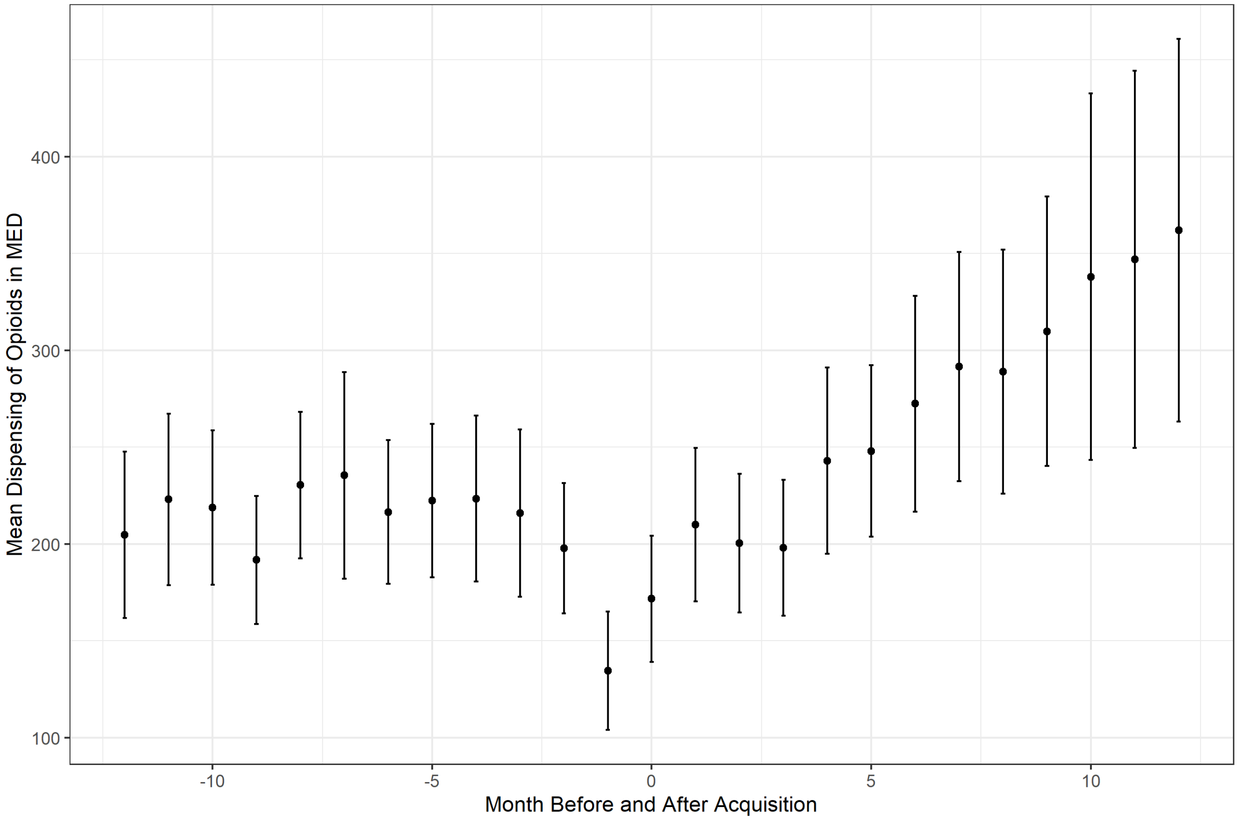
$$Y_{it} = \beta_0 D_{it}^{PRE} + \beta_1 D_{it}^{POST} + \beta_I D_{it}^{Independent} + \alpha_i + \mu_t + \varepsilon_{it}. \tag{11}$$

Interpretation is similar to the model in the main analysis. Y_{it} are the dispensed dosage of all opioids and OxyContin. We compare the sample of pharmacies that remained independent during the entire period and the sample of pharmacies that changed from chain to independent, with the baseline being those pharmacies that were always chains. D_{it}^{PRE} is an indicator that takes the value 1 for pharmacies before acquisition. Similarly, D_{it}^{POST} takes the value 1 if a pharmacy has been acquired. $D_{it}^{Independent}$ takes the value 1 if a pharmacy has always been owned by a chain. α_i are pharmacy fixed effects. Note that we drop D_{it}^{PRE} and D_{it}^{CHAIN} when including α_i due to multicollinearity. μ_t are time fixed effects.

After controlling for year-month fixed effects (models 2 and 6) the $\hat{\beta}_0$ coefficients in Table E.1 are comparable to the coefficients of $\hat{\beta}_C$. Therefore chain pharmacies that change to independent differ slightly (but not always significantly) from pharmacies that are chains and do not change

[26] Note that we call the ownership change from chain to independent an acquisition for consistency with the main analysis.

Figure E.1: Monthly Dispensing of Opioids Before and After Acquisition



Notes: The figure represents monthly mean dispensing of all opioids in MED for chain pharmacies in the 12 months before and after becoming independent. The error bars correspond to the 95% confidence interval.

their ownership structure. In detail, those pharmacies do start with slightly lower opioid dispensing. Thus, in comparison to the main analysis, we observe differences in acquired pharmacies that could affect the analysis. It is possible that chain pharmacies that get acquired by independent pharmacies differ from other chains. In our preferred model specification using pharmacy fixed effects, model specifications (4) and (8), we observe that after chain pharmacies become independent they increase their dispensing of all opioids as well as OxyContin. However, the results are not significant.

Table E.1: Regression of Acquisition Analysis, Chain to Independent

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before	-78.620^{***}	-33.672	-93.880^{***}		-5.852^{***}	0.728	-4.484	
	(23.016)	(23.197)	(26.859)		(2.191)	(2.193)	(3.251)	
After	73.971	48.500	-22.438	45.852	13.408^{**}	10.297^{*}	4.976	1.500
	(46.846)	(46.839)	(45.266)	(35.947)	(5.489)	(5.475)	(5.756)	(2.905)
Independent	49.889^{***}	50.609^{***}	130.832^{***}		8.525^{***}	8.700^{***}	16.904^{***}	
	(4.324)	(4.324)	(5.241)		(0.535)	(0.536)	(0.642)	
Constant	313.182^{***}				23.896^{***}			
	(2.111)				(0.262)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	333.09	333.09	333.09	333.09	27.3	27.3	27.3	27.3
Mean effect in percent	22.21	14.56	-6.74	13.77	49.11	37.71	18.22	5.49
Observations	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419	5,079,419
R-squared	0.0004	0.002	0.048	0.148	0.0005	0.003	0.025	0.091

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the acquisition regression analysis in equation (2). One observation corresponds to a pharmacy within a month. In model specifications (1) to (4), the outcome is monthly dispensed all opioids in MED. In models (5) to (8) we consider monthly dispensed OxyContin in MED as an outcome. *Before* displays the coefficient β_0, the effect of chain pharmacies before acquisition. *After* displays the coefficient β_1, the effect of independent pharmacies that were a chain before acquisition. *Independent* displays the coefficient β_I, the effect of independent pharmacies that did not change their ownership. The baseline effect is chain pharmacies that did not change ownership. Year-month FE, ZIP FE, and pharmacy FE indicate the use of fixed effects. When using pharmacy fixed effects, only the variation of changing ownership can be used. We show the mean outcome of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\beta_1}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered on the pharmacy level, adjusted for heteroskedasticity, and reported in parentheses.

F Robustness Check: The OxyContin Reformulation

F.1 Excluding Florida

By the clinics' peak in 2010, 90 of the nation's top 100 opioid prescribers were Florida doctors, according to federal officials, and 85% of the nation's oxycodone was prescribed in the state. That year alone, about 500 million pills were sold in Florida. The number of people who died in Florida with oxycodone or another prescription opioid in their system hit 4,282 in 2010, a four-fold increase from 2000, with 2,710 of the deaths deemed overdoses, according to a state medical examiner's report (Los Angeles Time 2019). Figure F.1 shows the average OxyContin dispensing excluding Florida, and we find the pattern is similar to our main Figure 2. Therefore, the OxyContin reformulation results are not driven by the Florida "outlier." Column (2) of Table F.1 also demonstrates that the estimated effect (-4.3, -16%) is similar to our baseline estimate (-5.9, -22%).

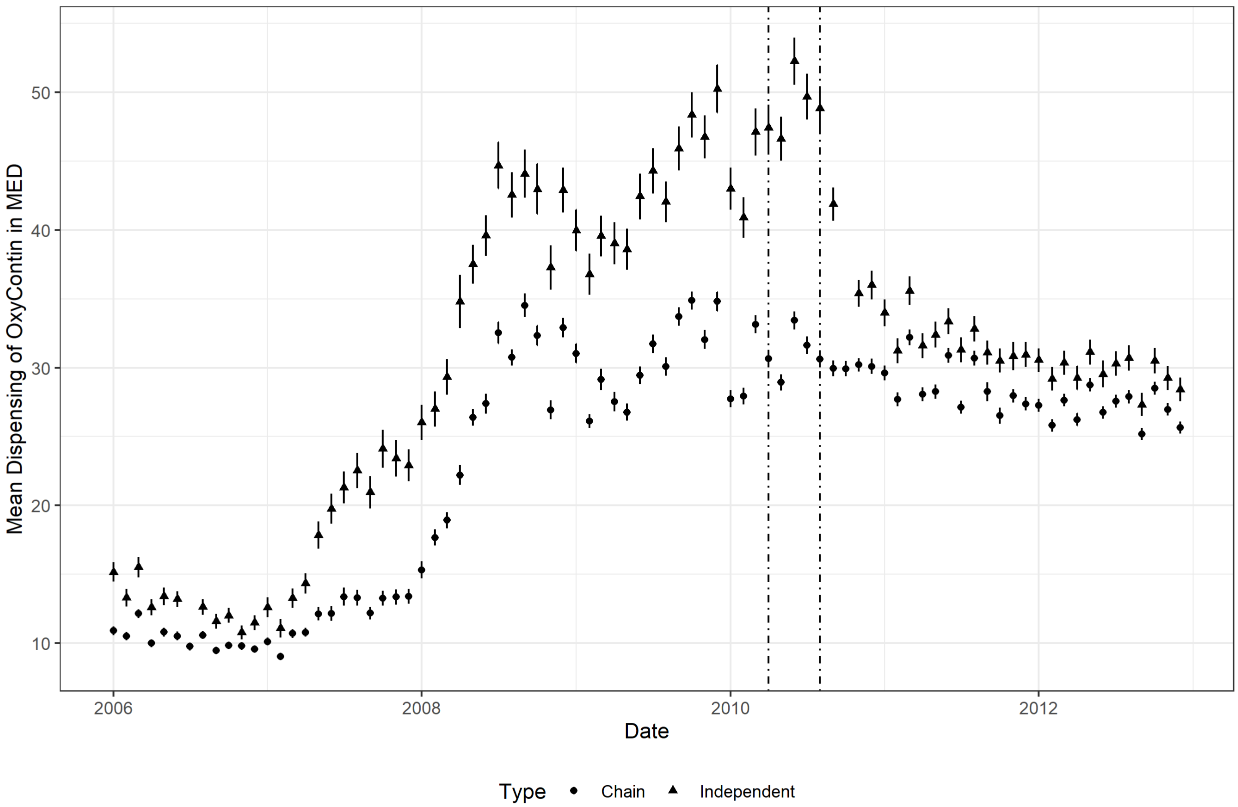
F.2 Excluding Pharmacies with Dispensing in Top Percentiles

Since drug diversion is a crime, it is possible that perhaps only a few outlier pharmacies dispense extremely large quantities of OxyContin and thus drive up the average dispensing before the reformulation. To test if this is the case, we gradually drop pharmacies with per capita dispensing in the top 1st, 5th, and 10th percentiles and redo the analysis. Although we find shrinkage of the estimated effect when excluding more pharmacies in the top percentiles, the estimated effect is still robust.

F.3 Adding ZIP$\times$Time Fixed Effects

In our preferred specification, we include year-month fixed effects and pharmacy fixed effects. However, we don't have data on time-varying characteristics of pharmacies and/or their neighborhood to control for possible confounding factors that may also affect pharmacies' dispensing before and after the OxyContin reformulation. Therefore, as a robustness check, we add ZIP$\times$ year-month fixed effects to capture these possible factors in the model, and the results are shown in Table F.2. Columns (3), (4), (7), and (8) present new estimates with ZIP$\times$ year-month fixed effects added, which have the same sign as our main estimates. Compared to Table 4, estimates in columns (4) and (8) of Table F.2 is about 5% and 26.6% larger than the corresponding estimates in Table 4, respectively. This exercise demonstrates that our results are robust to richer, time-varying fixed effects.

Figure F.1: OxyContin Reformulation, Excluding Florida



Notes: The figure shows the average dispensing of OxyContin in MED for chain and independent pharmacies between 2006 and 2012 without Florida. The first vertical line is April 2010, when the new OxyContin was approved by the FDA. The second vertical line corresponds to August 2010, when the new formula was delivered to pharmacies. The error bars correspond to the 95% confidence interval.

Table F.1: Robustness Checks, OxyContin Reformulation

	OxyContin				
	Baseline	Exclude FL	Exclude 1%	Exclude 5%	Exclude 10%
	(1)	(2)	(3)	(4)	(5)
Independent*Post	−5.973***	−4.327***	−2.579***	−1.108***	−0.908***
	(0.557)	(0.529)	(0.261)	(0.198)	(0.174)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Pharmacy FE	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.25	26.93	24.53	20.23	17.02
Mean effect in percent	−21.92	−16.07	−10.51	−5.477	−5.332
Observations	5,104,770	4,760,913	4,907,066	4,685,851	4,406,889
Number of pharmacies	85,417	79,457	76,928	73,821	69,935
R-squared	0.106	0.095	0.589	0.566	0.524

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the OxyContin reformulation regression analysis in equation (3) with different samples. Column (1) includes the full sample. Pharmacies in Florida are excluded in column (2). 6,864 pharmacies with only post-reformulation records and 847 pharmacies with unknown ZIP code or small population size (< 1 percentile, 1,644 people in a ZIP code area) are excluded from analyses in columns (3)–(5). Pharmacies with the average pre-reformulation monthly OxyContin dispensing per capita (divided by ZIP-code-level population) in the top 1st, 5th, and 10th percentiles are excluded in columns (3), (4), and (5), respectively. One observation corresponds to a pharmacy within a month. *Independent*Post* displays the coefficient $\hat{\beta}$, the change of independent pharmacies after the reformulation. We show the mean of the outcome variable as well as the mean effect in percent across each sub-sample, which is defined as $\frac{\hat{\beta}}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

Table F.2: Robustness Checks, OxyContin Reformulation

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-6.740^{***}	-7.031^{***}	-7.547^{***}	-6.267^{***}	-10.854^{***}	-10.892^{***}	-13.926^{***}	-11.924^{***}
	(0.564)	(0.562)	(0.979)	(0.922)	(0.609)	(0.609)	(0.916)	(0.727)
Independent	11.137^{***}	11.433^{***}	20.135^{***}		15.251^{***}	15.294^{***}	26.515^{***}	
	(0.672)	(0.672)	(1.105)		(0.806)	(0.806)	(1.176)	
Post	6.584^{***}				-0.806^{***}			
	(0.139)				(0.158)			
Constant	21.316^{***}				28.706^{***}			
	(0.221)				(0.282)			
Observations	5,104,770	5,104,770	5,079,419	4,705,777	3,679,675	3,679,675	3,661,471	3,396,173
R-squared	0.001	0.003	0.158	0.233	0.006	0.008	0.240	0.754
Year-month FE	No	Yes	No	No	No	Yes	No	No
ZIP Year-month FE	No	No	Yes	Yes	No	No	Yes	Yes
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	27.25	27.25	27.25	27.25	27.25	27.25	27.25	27.25
Mean effect in percent	−24.73	−25.80	−27.69	−23	−39.83	−39.97	−51.10	−43.76

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Results of the OxyContin reformulation regression analysis in equation (3). The outcome variable is OxyContin dispensing in MED per month at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation. *Independent* displays the effect of independent pharmacies. *Post* is an indicator showing months after the reformulation of OxyContin. We show the mean of the outcome variable as well as the mean effect in percent across the population, which is defined as $\frac{\hat{\beta}}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the pharmacy level, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

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