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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. Using data of prescription opioid orders, we show that compared with chain pharmacies, independent pharmacies dispense 39.1% more opioids and 60.5% more OxyContin. After an independent pharmacy becomes a chain pharmacy, opioid dispensing decreases. Using the OxyContin reformulation, which reduced non-medical demand but not the legitimate medical demand, we show that at least a third of the difference in the amount of OxyContin dispensed can be attributed to non-medical demand. We show that differences in competitive pressure and whether pharmacists own the pharmacy drive our estimates.

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 (Substance Abuse and Mental Health Services Administration 2018). In the same year, on average 130 Americans died every day from an opioid overdose (Centers for Disease Control and Prevention 2019*a*). Prescription opioid analgesics are at the root of the current opioid epidemic (Okie 2010; Dart et al. 2015), 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. 2022; Hadland et al. 2019; Nguyen et al. 2019), the role of dispensing pharmacies is not well understood.[2]

Drug diversion, defined as when prescription medicines are obtained or used illegally (Centers for Disease Control and Prevention 2019*b*), is an important source of opioid drug abuse. In particular, police and regulatory agencies perceive that pharmacies are involved in nearly 80% of all prescription drug diversion (Inciardi et al. 2007).[3] As the last line of defense ensuring that prescriptions are filled and drugs are dispensed only for legitimate medical use, pharmacies play an important role in several diversion channels. In fact, surveys show that compared with physicians, pharmacists have better knowledge of whether patients abuse drugs (Cicero et al. 2011). Moreover, 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). Empirically, we know little about how pharmacies use their discretion and what factors may affect pharmacies' discretion in dispensing prescription opioids.[4]

During recent years, large chains increased their market power in the health care market in general and specifically in the pharmaceutical market (Gaynor et al. 2015). Many existing studies reveal the downside of large chains. For example, large chains may exploit market power by

[1] The 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] Prescription opioids account for a substantial share of revenue for retail pharmacies. For example, OxyContin always ranked top 20 in retail sales among all prescription drugs in the US between 2008 and 2012, and it was one of the top 10 drugs between 2008 and 2010 (Drugs.com n.d.).

[3] Specifically, 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. Pharmacies are involved in all four of these sources. The rest 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%).

[4] Small-scale interviews with both pharmacists and drug abusers show that different pharmacists treat suspicious prescriptions differently (Rigg et al. 2010; Hartung et al. 2018).

increasing prices or reducing the quality of service (Cuellar and Gertler 2006; Dafny et al. 2012; Eliason et al. 2020; Gaynor and Town 2011). High concentration and monopolization are common in many markets, not just health care. In particular, concentration in digital markets has received recent interest from lawmakers as it may threaten innovation, privacy and data protection, the existence of a free and diverse press, and political and economic liberty (US House, Subcommittee on Antitrust, Commercial and Administrative Law of the Committee on the Judiciary, 2020). However, whether firm ownership affects the incentive to comply with regulations remains unexplored. If large firms are more likely to follow regulations, a full cost-benefit analysis of ownership, such as in antitrust investigations, should incorporate possible benefits of an industry's consolidation.

This paper analyzes whether pharmacy ownership affects prescription opioid dispensing and drug diversion. As a starting point, we present two stylized facts showing that independent and chain pharmacies have big differences in prescription opioid dispensing. First, we find that within a ZIP code, independent pharmacies, compared with chain pharmacies, dispense on average 128 (39.1%) more Morphine Equivalent Doses (MED, in grams) of all prescription opioids and 16.4 (60.5%) more MED of OxyContin, which is a type of prescription opioid especially prone to abuse and therefore diversion (Alpert et al. 2018; Cicero et al. 2011). Second, following the identification strategy of Eliason et al. (2020), we show that when a facility switches from being an independent pharmacy to being part of a chain, it dispenses 110.5 less MED of all opioids (33.8%) and 14.3 less MED of OxyContin (52.8%). Although both analyses reveal a large difference in dispensing between independent and chain pharmacies, we do not know what drives the differences: medical needs or drug diversion.

To examine whether 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 non-medical demand for OxyContin.[5] By comparing the dispensing of OxyContin before and after the reformulation between independent and chain pharmacies, we find that the difference greatly narrowed after the reformulation, mainly driven by the reduction among independent pharmacies. The difference in dispensing of OxyContin shrank by approximately 5.3 MED, a 19.7% reduction from the average MED dispensed per pharmacy. 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

[5] We use "non-medical demand" to refer to the demand for recreational or abusive use. Previous research shows that the reformulation of OxyContin reduced non-medical demand and led recreational users to substitute other drugs. For discussion, see, for example, Alpert et al. (2018), Butler et al. (2013), Chilcoat et al. (2016), Coplan et al. (2016), Dart et al. (2015), Evans et al. (2019), Havens et al. (2014), Larochelle et al. (2015), Sessler et al. (2014), Severtson et al. (2013), and Zhang and Guth (2021).

pharmacies (estimated from the analysis in ownership changes) can be attributed to their different responses to non-medical demand. A back-of-envelope calculation shows that 37.2% of the higher dispensing in independent pharmacies is due to drug diversion.[6]

As more than 37% of the difference in dispensing between independent and chain pharmacies resulted from diversion, we identify two mechanisms behind why independent pharmacies are more likely to be involved in drug diversion: (1) competitive pressure from chains and (2) pharmacists who are owners of independent pharmacies having stronger financial incentives to dispense than pharmacists who are employees. For the former, we show that independent pharmacies are more likely to compensate for their profit loss due to competition by dispensing more OxyContin before the reformulation than after the reformulation. Moreover, the response is mainly due to the competition from chain pharmacies but not independent pharmacies. For the latter, we compare the headquarters and branches of multi-store independent pharmacies, with the presumption that independent pharmacist owners are more likely to work in the headquarters if they are still actively involved in drug dispensing.[7] We find that headquarters dispensed on average 45.6% more OxyContin than their branch counterparts. After the reformulation, although both headquarters and branches decreased their OxyContin dispensing, headquarters reduced their dispensing on average 7.6 more MED than branches did. As a result, the gap in OxyContin dispensing disappeared, indicating that headquarters are more likely to dispense OxyContin in response to non-medical demand.

Our analysis suggests that we might need to reconsider competition in the retail pharmacy market. Although independent firms are often associated with high-quality services, in terms of opioid dispensing, they perform worse than their chain counterparts in deterring opioid dispensing for non-medical demand. In addition, stricter monitoring and regulation of independent pharmacies may be important, since a pharmacist in an independent pharmacy may also be the owner of the pharmacy and thus have a stronger financial incentive to increase sales than a salaried pharmacist employee would have. Moreover, unlike large firms, which are more closely watched by stakeholders, the media, and the government, small firms attract less notice. Stricter monitoring and regulation can lower independent pharmacies' tendency toward over-dispensing due to higher expected costs of misdoing.

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 side of prescription opioids focuses on the roles played by physi-

[6] Our estimate of the difference in dispensing due to ownership change in column (9) of Table 3 indicates that on average independent pharmacies dispense 14.34 more MED than chain pharmacies. Column (4) in Table 4 shows that after the OxyContin reformulation, the difference decreases by 5.34 MED, a 37.2% reduction (5.34/14.34).

[7] Headquarters are identified from the Orbis database and defined as where a company is registered in the national corporation registry (Orbis 2021).

cians, pain clinics, manufacturers, and the government (Alpert et al. 2018, 2022; Ayres and Jalal 2018; Buchmueller and Carey 2018; Grecu et al. 2019; Maclean et al. 2020; Meinhofer 2016, 2018; Powell et al. 2020; Schnell 2017; Schnell and Currie 2018), but pharmacies are often overlooked (Simeone 2017). Although we may think pharmacies merely fill prescriptions from prescribers, our analysis reveals that pharmacies can significantly influence the dispensing of prescription opioids. In particular, more than a third of the over-dispensing by independent pharmacies relative to chains is to meet the non-medical demand, and competition exacerbates their incentives to dispense for non-medical demand.

Our paper also contributes to the literature on 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. We show that besides economic efficiency, the higher opportunity costs of misbehavior may cause chain pharmacies to behave closer to the social optimum. As we also investigate the effect of ownership change 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 ownership change, Eliason et al. (2020) 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: after independent pharmacies become part of a chain, the former independent pharmacies behave more like chain pharmacies, with less dispensing of opioids. Due to larger chains' better compliance with regulations, our article is relevant for antitrust regulators. When evaluating the costs and benefits of large chains, competition authorities should consider the possibility that large chains may be easier to regulate because of the higher opportunity costs of misbehavior.

In addition, we provide new empirical evidence on the effect of competition on illegal/unethical behavior. Under standard assumptions, competition is beneficial 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 literature specifies such a mechanism in theory.[8] Empirically, there is limited evidence on the relation between competition and illegal behavior. Existing studies have examined the areas of vehicle inspection

[8]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 of illegal behavior. Dewatripont and Tirole (2019) show that competition may promote unethical behavior when firms are profit maximizing.

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. We add to the literature by presenting additional evidence of the positive relationship between competition and leniency in the market of opioid-dispensing pharmacies. Furthermore, leniency results in higher drug dispensing and drug diversion for non-medical demand, deviating from the social optimum and resulting in negative health effects.

2 Institutional Background

2.1 The Retail Pharmacy Market

Over 84,000 retail pharmacies existed in the United States between 2006 and 2012. Pharmacies filled 3.6 billion prescriptions a year, and nearly all Americans (93%) lived within a 5-mile radius of a pharmacy (Fein 2011*a*). Retail pharmacies include independent and chain pharmacies. Chain pharmacies include stand-alone pharmacy chains, supermarket pharmacies, and mass merchandiser pharmacies; the rest are independent pharmacies. During our study period, approximately 53.3% (44,812/84,111) of pharmacies were 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 (Aungst 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; Starc and Swanson 2018). Often, independent pharmacies get paid less than larger chains for the medicines they dispense from PBMs and insurers. 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 about 10%, almost solely due to increase in chains. 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.

2.2 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 from 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 post-surgery 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 in 1999 (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 Substance Abuse and Mental Health Services Administration (SAMHSA) defines opioid misuse as taking a prescription opioid that was "not prescribed for you or only for the experience or feeling it caused." The 2017 National Survey on Drug Use and Health showed that 53.1% of people who misused pain relievers obtained their most recent pain reliever from a friend or relative (Substance Abuse and Mental Health Services Administration 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' Role in Opioid Dispensing

Pharmacists are legally required to ensure that controlled substances are prescribed for a medical purpose and are not diverted for non-medical use (Drug Enforcement Administration 2010). Therefore, pharmacists should screen for prescriptions and behaviors that suggest diversion (Bach and Hartung 2019). Nevertheless, pharmacists may face a conflict of interest, as their profit depends on filling prescriptions. Small-scale interviews with both pharmacists and drug abusers show that different pharmacists treat suspicious prescriptions differently (Rigg et al. 2010; Hartung et al.

2018). Some pharmacists are stricter and question and reject suspicious prescriptions confidently, while others are lax in their standards and may never question or reject any prescriptions.

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 non-medical 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, 2022). 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 cannot easily be broken, crushed, or dissolved, and thus it greatly reduces the possibility of OxyContin abuse, although it cannot eradicate oral misuse by taking more pills or higher doses (Alpert et al. 2018). The reformulation resulted in an increase use of illicit drug use and overdose death (Powell and Pacula, 2021).

3 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 delivered to pharmacies in the United States.[9] We aggregate the data at the pharmacy level by 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 other health care facilities.[10] The ARCOS data differentiate between chain and other retail pharmacies, where the chain pharmacy category includes stand-alone

[9] The national raw data were downloaded from the website of The Washington Post (2019). After adjusting for destroyed and returned orders from deliveries to pharmacies, we assume that all the deliveries from manufacturers/distributors to pharmacies are finally dispensed by pharmacies to customers. Furthermore, we exclude large outliers.

[10] Note that this exclusion also excludes "pill mills" that prescribed and dispensed opioids within one facility.

chain pharmacies, supermarket pharmacies, and mass merchandiser pharmacies.[11] We connect the data set with geographical information on pharmacies offered by the *Washington Post* (Rich et al. 2019).

Table 1 provides basic summary statistics of our sample. We observe 84,111 pharmacies during 2006 and 2012. Of these, 44,812 are chain pharmacies while the remaining ones are independent pharmacies. Compared with chain pharmacies, independent pharmacies face more competition nearby. Panel B of Table 1 focuses on the concentration of pharmacies. We observe pharmacies in 38% of all ZIP codes. In 21% of ZIP codes, both independent and chain pharmacies are present. Panel C shows 15,056 entries and 10,752 exits over these seven years.[12] Among these entries, 6,413 (43%) were chain pharmacies, and 8,643 (57%) were independent pharmacies. However, exits among independent pharmacies (7,830) were more than double those among chain pharmacies (2,922).[13] As a result, the relative number of chains increased between 2006 and 2012. We also observe ownership changes.[14] In detail, we observe 304 independent pharmacies that became a chain. Panel D of Table 1 describes the dispensing. On average, pharmacies dispense 327 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 became part of a chain, the comparison between the last two rows and the first two rows in Panel D shows that prior to the ownership change, they did not differ strongly in terms of opioid dispensing from other independent pharmacies that did not change ownership.

[Table 1 about here.]

[11] In our main analyses, we use the chain and independent pharmacies (other retail pharmacies) defined in the ARCOS data directly. In online Appendix A, we conduct robustness checks by differentiating independent pharmacies with a single store, two stores, three stores, and four or more stores and compare them respectively with chain pharmacies. We find that "independent" pharmacies with four or more stores are fundamentally different from independent pharmacies with no more than three stores, and these large "independent" pharmacies are more similar to chains.

[12] We identify an entry as a new DEA license issued for a pharmacy in a geographical location without a pharmacy operating there beforehand during 2006–2012, and we only consider entries after June 2006. Exits are identified if we do not observe a pharmacy for the remaining time during our sample period and for at least six months.

[13] In online Appendix B we analyze the role of exiting and entering pharmacies. We observe decreasing opioid dispensing by both independent and chain pharmacies before exit and increasing dispensing after entry. While more independent pharmacies exit and enter, they do not drive our results for the impact of ownership, as shown in online Appendix B.

[14] We define an ownership change as the combination of changes in the DEA registration number, buyer name, and pharmacy type at the same geographical location. We further require that the change from an old to a new owner take at most three months, to reduce the likelihood of a shutdown of a pharmacy before the opening of a new pharmacy. Finally, each ownership change happened after at least six months since the beginning of the sample period. There are likely many ownership changes within the same pharmacy type, i.e., an independent pharmacy that changes owners but still maintains independent ownership. However, we cannot necessarily relate such a case to an ownership change with a new registration number alone, because a pharmacy might also update its DEA registration number occasionally without changing ownership.

4 Differences in Dispensing between Independent and Chain Pharmacies

In this section, we document the differences in prescription opioid dispensing between chain and independent pharmacies using two empirical models. First, we use a direct comparison with rich geographic and time fixed effects. Second, we employ an analysis of ownership changes that compares independent pharmacies' dispensing before and after the facilities became chain pharmacies.

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:

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

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. $Independent_i$ 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 code 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. $\hat{\beta}$ indicates the difference between independent and chain pharmacies in prescription opioid dispensing.[15]

Table 2 presents results from regression (1). Columns (1)–(4) evaluate the relation between pharmacy ownership and all opioid dispensing, and columns (5)–(8) examine OxyContin specifically. The effects are robust to different geographic fixed effects. When we gradually add county and ZIP code fixed effects to compare pharmacies within a county or a ZIP code, the effects become stronger and the R^2 increases, supporting our hypothesis that pharmacy ownership plays a role in determining the amount of opioids dispensed (Altonji et al. 2005; Oster 2019). Column (4) indicates that independent pharmacies on average dispense 128 (39.1%) more MED of all opioids. Moreover, if independent and chain pharmacies respond differently to non-medical demand, the

[15]For our specification (1) as well as equation (2) and (3), we provide several robustness checks in online Appendix C. First, we replace Y_{it} with the per capita dispensed MED by each pharmacy i in month t as an alternative outcome variable. For the denominator of per capita dispensed MED, we use the ZIP code-level population from the 2010 census of pharmacy i's location. Second, we replace the separate geographic and time fixed effects with geographic identifier $\times$ year-month fixed effects. Third, instead of month-level analysis, we also conduct quarter-level analysis in case some pharmacies do not order stock frequently. In addition, for specification (1), we also show unconditional quantile regression results in online Appendix D to examine the impact of pharmacy ownership on prescription opioid dispensing at different quantiles.

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 16.4 (60.5%) 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 non-medical demand.

[Table 2 about here.]

Change in Ownership

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 pharmacies' 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 became part of 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 ownership change to the ownership. We identify 304 ownership changes from independent pharmacies becoming chain pharmacies.

Following the difference-in-differences approach of Eliason et al. (2020), we show effects of the ownership change of an independent pharmacy becoming a chain pharmacy on dispensing of all opioids and OxyContin by comparing independent pharmacies that became a chain to those that never changed ownership. The identification assumption is that the change in ownership is uncorrelated with characteristics of the independent pharmacy. We use the following model:

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

where Y_{it} are the dispensed doses of all opioids and OxyContin at pharmacy i in month t. 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 independent pharmacies before the ownership change. Similarly, D_{it}^{POST} takes the value 1 if an independent pharmacy has changed ownership and becomes a chain. Adding the two indicators D_{it}^{PRE} and D_{it}^{POST} would be equivalent to a treatment group dummy. We decided to split the dummy as the coefficient of D_{it}^{PRE} allows us to evaluate whether independent pharmacies that become chains differ from independent pharmacies without a change in ownership before the date of the ownership change. $CHAIN_i$ takes the value 1 if a pharmacy has always been owned by a chain. We include facility fixed effects

(α_i).[16] Note that we drop D_{it}^{PRE} and D_{it}^{CHAIN} when including α_i due to multicollinearity. μ_t are time fixed effects.[17] In our final model we use two-way fixed effects. Recent literature shows that average treatment effects from linear regressions with period and group fixed effects could be biased in case of a staggered treatment design and heterogeneous treatment effects (Athey and Imbens 2021; Baker et al. 2021; Borusyak et al. 2021; Callaway and Sant'Anna 2020; De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021). We therefore also estimate a robust estimator based on De Chaisemartin and d'Haultfoeuille (2020).

If independent pharmacies that change ownership dispense similarly to independent pharmacies not changing ownership before the date of the ownership change, 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 become chain pharmacies reduce their dispensing of opioids. Thus $\hat{\beta}_1$ is expected to be negative.

Figure 1 depicts the monthly average dosage of all opioids dispensed by pharmacies before and after an ownership change. It shows a clear reduction in opioid dispensing after the ownership change. Surrounding the date of an ownership change, we observe that an independent pharmacy decreases its dispensing slightly during the months prior to the ownership change. As we measure dispensing through orders shipped to pharmacies, this can be explained by a stock reduction in anticipation of the forthcoming ownership change.

[Figure 1 about here.]

Table 3 further demonstrates that a pharmacy's ownership affects its dispensing behavior, as after independent pharmacies became chain pharmacies, they decreased their opioid dispensing. Columns (1) to (5) show the impact on dispensing of all opioids, while columns (6) to (10) solely evaluate OxyContin. As shown in columns (1) to (3), we observe non-significant coefficients of the D^{PRE} regressor, meaning that before the ownership change, those pharmacies that started as independent and then became chain pharmacies are not significantly different from the all-time independent pharmacies. However, after the ownership change, formerly independent pharmacies decreased their dispensing. Using ZIP code and year-month specific effects, specification (3) shows that they dispense 153.2 (46.8%) less MED per month than their independent counterparts that do not change ownership. Including facility fixed effects in column (4) gives us a slightly smaller but still significant estimate that independent pharmacies dispense 110.5 (33.8%) less MED of all opioids per month after becoming chain pharmacies. Considering the estimator of De Chaisemartin and d'Haultfoeuille (2020) in column (5), our result gets stronger. Similarly to

[16] Note that facility fixed effects differ from pharmacy fixed effects. The former are based on location, while the latter are based on the DEA number. We can solely include facility fixed effects as we would not identify ownership changes with pharmacy fixed effects.

[17] We present an event study of the analysis in online Appendix E.

the findings for all opioids, independent pharmacies that change ownership do not differ before the ownership change from the all-time independent pharmacies in terms of OxyContin dispensing, as shown in columns (6) to (10). However, after the ownership change, the former independent pharmacies reduced their OxyContin dispensing by 14.3 (52.8%) MED per month, as shown in column (9). Column (10) reports the estimator De Chaisemartin and d'Haultfoeuille (2020) that corrects for a potential bias due to heterogeneous treatment effects in a staggered treatment adoption setting. Using this estimator, our results get slightly stronger. We conclude that the estimates are robust to different specifications. Therefore, we show that the differences are due to the ownership rather than facility-specific factors such as geography.

[Table 3 about here.]

5 The OxyContin Reformulation and Dispensing for Non-medical Demand

Our stylized facts reveal big differences in opioid dispensing between independent and chain pharmacies. However, it is impossible to distinguish whether the differences are due to medically appropriate dispensing or dispensing for non-medical demand. Therefore, in this section, we provide a simple conceptual framework and use the OxyContin reformulation as a quasi-experiment to identify the dispensing for non-medical demand in the retail pharmacy market.

Conceptual Framework

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 or abusive use (the non-medical market). While the market for medically necessary usage is solely based on legitimate prescriptions, the market for non-medical demand 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. The size of the medically necessary market is determined by legitimate prescriptions, while for the non-medical use, the size of the market is based on 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 above analysis we show that $q_I > q_C$. However, higher dispensing by independent pharmacies itself does not imply more dispensing for non-medical demand, because market A 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.[18]

Therefore, 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 (Mastropietro and Omidian 2015). 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 non-medical 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 non-medical market before the reformulation.

Identification and Results

Given our conceptual framework, we use the following model to test whether the over-dispensing of independent pharmacies is partially driven by their misdoing in dispensing for non-medical demand:

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

where Y_{it} represents OxyContin dispensing at pharmacy i in month t. $Post_t$ takes the value 1 for all months since August 2010, when the new OxyContin formulation entered the market and shipment of the old OxyContin ceased. $Independent_i$ 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 non-medical demand.[19] In online Appendix E, we show the event study results.[20]

Figure 2 depicts the average dispensing of OxyContin before and after the reformulation by

[18] On the other hand, chain pharmacies also have their own advantages, such as being more likely to be included in a preferred provider network, and thus may attract more insured customers (Jones 2019; Starc and Swanson 2018).

[19] Since we have simultaneous treatment for all pharmacies, our two-way fixed effects model estimate does not suffer from a bias due to heterogeneous treatment effects when some weights of the average treatment effect are negative (Baker et al. 2021; Borusyak et al. 2021).

[20] Our main analysis is based on the classification of independent and chain pharmacies. In online Appendix F, we also divide chain pharmacies into small chains and large chains, and we find that large chains are least likely, small chains are more likely, and independent pharmacies are the most likely to dispense for non-medical demand.

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 more than half a year earlier than that of chain pharmacies. From 2008 to 2010, 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 about here.]

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 5.3 MED (19.7%) per month. In addition, as we notice that the pre-reformulation parallel trends for independent and chain pharmacies in Figure 2 are more evident since 2008, we also limit the sample to 2008–2012 only and show the estimates in columns (5)–(8). The estimated effect in column (8) is about 70% ([9.0-5.3]/5.3) larger than the counterpart estimate in the whole sample.

[Table 4 about here.]

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 reduced the non-medical demand. We have two assumptions here. First, we assume that the reformulation 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 non-medical demand 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 about here.]

Since it is possible that the results are driven by a small proportion of misbehaving pharmacies, we conduct robustness checks in online Appendix G by excluding Florida (the state with the highest dispensing of OxyContin in 2010) and pharmacies whose dispensing is in the top percentiles. The estimates are still negative and significant, though with smaller magnitudes, as shown in online Appendix Table G.1. Moreover, we also estimate the unconditional quantile treatment effects of the OxyContin reformulation and plot the estimates in online Appendix Figure G.2. We find that, compared with chain counterparts whose OxyContin dispensing was at or below the median, independent pharmacies in the similar quantiles did not significantly reduce their OxyContin dispensing. However, among pharmacies that dispensed more than the median level of OxyContin, independent pharmacies reduced their OxyContin dispensing significantly after the reformulation, compared with chain pharmacies. Then, we further examine the changes in dispensing of 80 mg OxyContin vs. other lower dosages in online Appendix Table G.2, as the former dosage is more likely to be sought for non-medical use due to its popularity among drug abusers. We find a 33.1% decline in 80 mg OxyContin dispensing but only a 7.5% decline in non–80 mg OxyContin dispensing by independent pharmacies, which provides further evidence that independent pharmacies are more involved in drug dispensing for non-medical demand. In addition, as another robustness check, in online Appendix Table C.6 we also add ZIP code $\times$ year-month fixed effects to control for possible neighborhood-specific time-varying characteristics that may affect pharmacies' dispensing. The estimated treatment effect is -5.1, similar to our main estimate (-5.3).

Identifying Top Diverting Pharmacies via the OxyContin Reformulation

Following the logic of our OxyContin reformulation analysis, we examine which pharmacies dispense the most OxyContin for non-medical demand and where they are located. We calculate the changes in OxyContin dispensing using the difference in per capita monthly dispensed OxyContin one year after (August 2010–July 2011) and one year before (August 2009–July 2010) the reformulation. Not surprisingly, over half of the pharmacies reduced their OxyContin dispensing after the reformulation. Table 5 shows the characteristics of the top and bottom diverting pharmacies in this regard. The top diverting pharmacies are those whose change in dispensed OxyContin is very negative, i.e., reducing their dispensing the most after the reformulation. The bottom diverting pharmacies are those whose dispensing of OxyContin increased the most after the reformulation.

[Table 5 about here.]

As shown in Table 5, 61,410 pharmacies existed from August 2009 to July 2011. Among these pharmacies, 41% are independent pharmacies. An average pharmacy in column (1) and an average independent pharmacy in column (2) are comparable, indicating independent pharmacies and chain pharmacies are distributed similarly. As an exception, we observe that independent pharmacies more likely to locate in a rural area. However, consistent with our previous findings, independent pharmacies on average reduced more OxyContin dispensing after the reformulation. As a result, the shares of independent pharmacies among the top 5% and top 10% diverting pharmacies are much higher: 70% and 60%, respectively. However, we should note that independent pharmacies account for a higher share of the bottom diverting pharmacies as well: 53% of the bottom 5% and 47% of the bottom 10%. This is consistent with the observation that the chain pharmacies' dispensing is more concentrated while the independent pharmacies' dispensing is more dispersed. The top 10% (5%) diverting pharmacies on average reduced their monthly OxyContin dispensing by 73 (114) MED, whereas the bottom 10% (5%) on average increased their monthly OxyContin dispensing by 22 (28) MED.

In terms of ZIP code-level characteristics, both the top and bottom diverting pharmacies are more likely to be located in a less populous area compared with the average pharmacies in column (1) and have a lower median and mean household income, larger rural share, larger white share, and larger share of vacant houses. However, compared with the bottom diverting pharmacies, the top diverting pharmacies are located in areas that have a larger population, are less rural, and have a lower share of white people. When looking at the county-level characteristics, the top diverting pharmacies are located in areas with much higher opioid prescription rates and drug poisoning death rates, but a little surprisingly, the bottom pharmacies in this regard are also located in areas with slightly higher opioid prescription rates and drug poisoning death rates than the national average. In summary, the top diverting pharmacies are more likely to be located in more populous and less rural areas with high drug-related death rates than the bottom diverting pharmacies.

In addition to the descriptive characteristics, we also plot where the top diverting pharmacies are located. Figure 4 depicts the geographic distribution of the top 10% independent and chain pharmacies dispensing for non-medical demand, respectively. Since independent pharmacies account for a larger share in the top 10% diverting pharmacies, we find a higher density of independent pharmacies in Figure 4. Furthermore, compared with the top diverting chains, the top diverting independent pharmacies are more concentrated in the following areas: (1) the intersection of Kentucky, West Virginia, and Virginia, (2) South Louisiana, and (3) the west and east coasts of Florida. When we compare these two maps with the maps on county-level death rates due to drug poisoning in 2006 and 2011 in Figure 5, we find that the counties with a greater share of top diverting independent pharmacies and the counties with the highest mortality rates due to drug poisoning are quite coincident.

[Figure 4 about here.]

[Figure 5 about here.]

6 What Explains Independent Pharmacies' Larger Dispensing for Non-medical Demand?

Our results have demonstrated that independent pharmacies on average dispense more prescription opioids than chain pharmacies, and 37.2% of the excessive dispensing of OxyContin is associated with the non-medical demand. In this section, we discuss the potential reasons behind the difference in dispensing for non-medical demand between independent and chain pharmacies.

6.1 Competitive Pressure

First, due to the consolidation of the pharmaceutical market in the past two decades, independent pharmacies have seen narrowing profit margins relative to chains and smaller market shares in total prescriptions, and thus they have a greater need to tip the balance. According to data from the National Association of Chain Drug Stores and the National Community Pharmacy Association, from 2000 to 2010, the number of chain pharmacies increased by 11% while the number of independent pharmacies remained about the same. In addition, the average prescription revenue per pharmacy outlet increased by 62% among chain pharmacies, whereas it increased by only 34% among independent pharmacies (Fein 2011*b*). This evidence implies that the market is more favorable to chains, and independent pharmacies face a tougher business environment. In addition, the gross margin of independent pharmacies was 22% in 2014 (Fein 2019), while the gross margin for all retail pharmacies in the same year was 26.7% (US Census Bureau 2018), demonstrating the lower profit margin of independent pharmacies relative to chains. In the following analysis we show that compared with chains, independent pharmacies are more likely to compensate for their loss of revenue from competition by dispensing more OxyContin prior to the reformulation.

We evaluate the effect of competition on OxyContin dispensing using the following model:

$$Y_{it} = \beta_1 Comp_{it} + \beta_2 Comp_{it} \cdot Independent_i + \alpha_i + \mu_t + \varepsilon_{it}, \quad (4)$$

where Y_{it} is 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 the reformulation and the response to the aggregate demand (both the medical and the non-medical demand) in the period before the 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. $Comp_{it} \cdot Independent_i$ is the interaction between competition and the independent pharmacy indicator, to test whether independent pharmacies and chain pharmacies respond differently to 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).

Using data between 2006 and 2012, the regression with pharmacy fixed effects cannot differentiate these two effects. Therefore, we evaluate pharmacies' response in OxyContin dispensing both before and after the OxyContin reformulation. The post-reformulation dispensing reflects more of the pure competition effect, as the non-medical demand hugely declined. In comparison, the pre-reformulation dispensing includes both competition and compensation effects. While both analyses do not reveal a causal estimate of competition as the number of competitors within a geographical area as well as entries and exits are potentially endogenous, we argue that the result on how pharmacies respond to competition (especially the difference in response between independent and chain pharmacies) offers insights on the incentives that pharmacies face.

Table 6 shows estimates from equation (4). Panel A shows the overall competition effects, and Panel B and Panel C consider competition from independent pharmacies and chain pharmacies separately. In Panel A, without pharmacy fixed effects, we find that higher density of pharmacies is associated with more OxyContin dispensed by independent pharmacies (at 10% significance level), as shown by column (2). This evidence supports our hypothesis that independent pharmacies tend to be more lenient in dispensing more opioids for non-medical demand under greater competition pressure, as competition could lead to more unethical behavior. Compared with chain pharmacies, independent pharmacies respond to an additional competitor within a 1-mile radius by increasing their dispensing of OxyContin by 0.185 MED on average. Columns (3) and (4) add pharmacy fixed effects, which estimate the effects of increased competition on each specific pharmacy's OxyContin dispensing. It is not surprising to find that competition has a negative aggregate impact on

OxyContin dispensing. However, although we expect that independent pharmacies may compensate for their loss from the medical market by being more lenient in dispensing for non-medical demand than their chain counterparts, we do not find a positive coefficient on the interaction term during the entire period in column (4).

[Table 6 about here.]

As the OxyContin reformulation substantially decreased the non-medical demand, we expect to see a much smaller compensation impact after the reformulation but a larger compensation impact before the reformulation among independent pharmacies. Columns (6) and (8) in Table 6 support our hypothesis. Before the reformulation, independent pharmacies suffer less from competition than chains (positive $\hat{\beta}_2$). However, after the reformulation, the negative impact of competition was more heavily borne by independent pharmacies (negative $\hat{\beta}_2$).

When examining competition effects from independent pharmacies and chain pharmacies separately in Panel B and C of Table 6, we find that our main finding, the compensation effect among independent pharmacies before the reformulation as shown in column (6), is almost solely driven by the competition from chain pharmacies. This is in line with the observed general pattern in the retail pharmacy market during 2000–2010 that independent pharmacies underwent great competitive pressure from chain pharmacies.

Our competition results are robust to different distance measures. The smaller the radius, the stronger the competition effect. In addition, the effect is stronger for more abusive opioids, such as OxyContin. Figure 6 demonstrates the effect of competition for independent pharmacies ($\hat{\beta}_2$ in equation [4]) for different distance-based competition measures before the OxyContin reformulation when controlling for pharmacy and year-month fixed effects. Considering dispensing of all opioids as well as only OxyContin, Figure 6 shows that the effect of competition for independent pharmacies relative to chain pharmacies is a decreasing function of the radius. A new competitor in geographically close areas puts strong competitive pressure on independent pharmacies, and thus leniency increases more. The relative size of the coefficients for OxyContin in Figure 6 are higher than that for all opioids, independent of the radius.

[Figure 6 about here.]

6.2 The Owner of a Pharmacy

Second, in addition to a greater incentive to dispense for non-medical demand due to competition, one of the major differences between independent and chain pharmacies is whether a pharmacist is also the owner of a pharmacy. For chain pharmacies, pharmacists are salaried employees or employees on an hourly wage basis, so they follow corporate rules, and their compensation is mostly pre-determined. However, many independent pharmacies are owned by a pharmacist, so such a pharmacist is not only working in a pharmacy but also the owner of it. Therefore, when dispensing opioids, these pharmacist owners are likely to have more discretion power and greater financial incentives to dispense more. If pharmacist ownership is an underlying factor to explain the differences in opioid dispensing for non-medical demand, we should be able to find such a pattern within multi-store independent pharmacies, because a pharmacist owner can work mostly in one store only.

If we can pinpoint which pharmacies are owned directly by a pharmacist working there, then we can compare the dispensing practices of the pharmacies with and without a pharmacist owner. However, a challenge is that it is hard to acquire such detailed information for small businesses. To provide evidence on this, we utilize an alternative approach by focusing on multi-store independent pharmacies and comparing the dispensing between headquarters and non-headquarters, with the assumption that, if a multi-store pharmacy is owned by a pharmacist who still works as an active dispenser, this pharmacist owner is more likely to work in the pharmacy's headquarters. To identify headquarters, we rely on the Orbis database (Orbis 2021), a database on private companies. It has information on close to 400 million companies and entities across the globe. Its strengths include (1) comparable information, (2) extensive corporate ownership structures, and (3) a holistic view of companies. However, a weakness of the Orbis database is that it only has the latest company information as of 2021, but our ARCOS data were from 2006 to 2012. Therefore, we can only successfully find the locations of headquarters and branches for a subset of multi-store independent pharmacies that are still in business.

In the ARCOS data, among the 27,974 independent pharmacy firms, 23,549 firms (84.2%) had only one store during the 2006–2012 period, 3,543 firms (12.7%) had two or three stores during the seven years, and the remaining 882 (3.2%) potentially had more than three stores as determined on the basis of the pharmacy name and the state identifier.[21] Among the 4,425 potential multi-store independent pharmacies, we successfully found headquarters for 1,378 firms (31.1%).

Table 7, Figure 7, and Table 8 show the comparison between headquarters and branches when the analysis is restricted to the multi-store independent pharmacies for which we successfully identify the headquarters from the Orbis database. As shown in columns (4) and (8) of Table 7, headquarters dispense 32.4% more prescription opioids and 45.6% more OxyContin than their branch counterparts. Figure 7 shows the dispensing of OxyContin among headquarters and branches over

[21] We recognize the limitations of our identification of independent pharmacy firms. On the one hand, we may overestimate the number of multi-store pharmacies because we use the first 10 letters of pharmacy names to assign the parent company, so some independent pharmacy stores may happen to have similar names but in fact be totally independent. On the other hand, we may underestimate the number of multi-store pharmacies because we define a pharmacy firm based on the pharmacy name and state combination, so a cross-state pharmacy firm may be identified as separate pharmacy firms if there is only one store in a state.

time. Initially, headquarters and branches dispensed similar amounts of OxyContin. Since 2007, the dispensing of OxyContin diverged between headquarters and branches, and from 2007 to August 2010, headquarters constantly dispensed about 20 MED more than branches. After the OxyContin reformulation, although we find reductions in OxyContin dispensing among both headquarters and branches, the decline among headquarters was much bigger than among branches. As a result, they again dispensed similar amounts of OxyContin after the reformulation. This evidence implies that both headquarters and branches of independent pharmacies dispensed OxyContin for non-medical demand before the reformulation, but the headquarters dispensed more than their branch counterparts. Table 8 quantifies this effect by regression analysis, showing that headquarters reduced dispensing of OxyContin by 7.6 MED (23.6%) more than branches after the OxyContin reformulation. This evidence supports that pharmacist ownership can lead to more dispensing of prescription opioids for non-medical demand.

[Table 7 about here.]

[Figure 7 about here.]

[Table 8 about here.]

Chain and independent pharmacies are also different in other aspects: (1) Compared with large chains, which may have an integrated database that covers all their locations, independent pharmacies may lack data to track patients' drug use history and thus cannot effectively identify drug abusers or drug dealers. (2) Independent pharmacies may offer lower prices. (3) Pharmacists in independent pharmacies may have outdated knowledge due to older age and/or may receive lower-quality on-the-job training. We discuss all these potential channels in online Appendix H. To summarize, we find little evidence that any of these differences can explain the difference in dispensing for non-medical demand between independent and chain pharmacies.

In summary, although we are not able to investigate an exhaustive list of all possible differences between chain and independent pharmacies, we show that competitive pressure (from chains) and whether a pharmacist is an employee or owner of the pharmacy are the two likely reasons to explain why independent pharmacies dispensed more for the non-medical demand.

7 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 39.1% more MED of all prescription opioids and 60.5% more MED of OxyContin, one of the most popular drugs among drug abusers. Our analysis of changes in ownership further confirms that these differences are due to the pharmacy ownership, as independent pharmacies that become chains reduced dispensing in MED of all prescription opioids and OxyContin by 33.8% and 52.8%, respectively. In addition, by making use of the quasi-experiment arising from the OxyContin reformulation, which affected the non-medical demand but not the medical market, we show that about 37.2% of the difference in OxyContin dispensing between independent and chain pharmacies can be explained by independent pharmacies' response to the non-medical demand.

Although many reasons might explain why independent pharmacies are more likely to dispense for non-medical demand, we show that competitive pressure (from chains) and whether a pharmacist is an employee or ownership of the pharmacy are two likely reasons.

Given these findings, policymakers might need to reconsider the effects of competition and consolidation in the retail pharmacy industry. Chain pharmacies may have less incentives for drug diversion, yet their growth may spur increased pressure toward wrongdoing for the remaining independent pharmacies. To counteract this tendency, policymakers may want to consider whether there is a need to strengthen monitoring and regulation of small independent pharmacies, which are often overlooked in the larger debate over consolidation in the health care industry.

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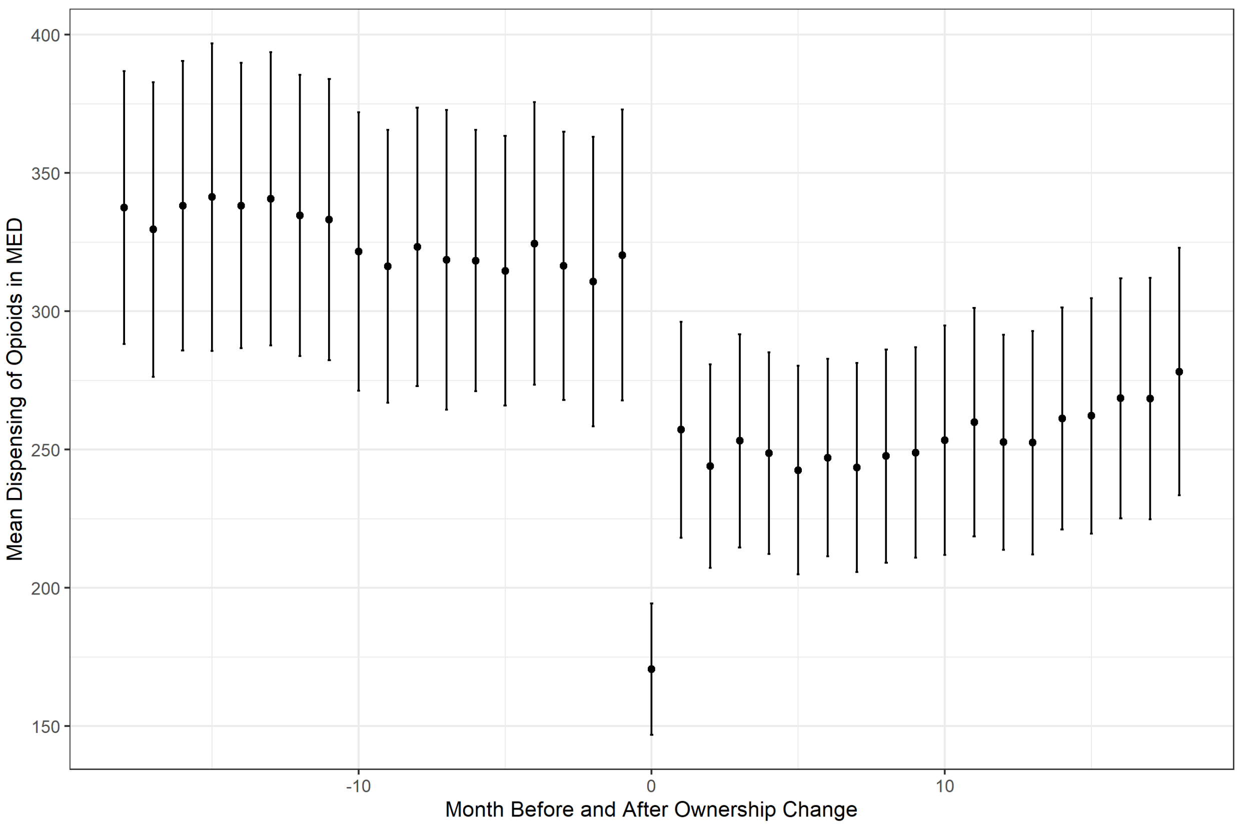
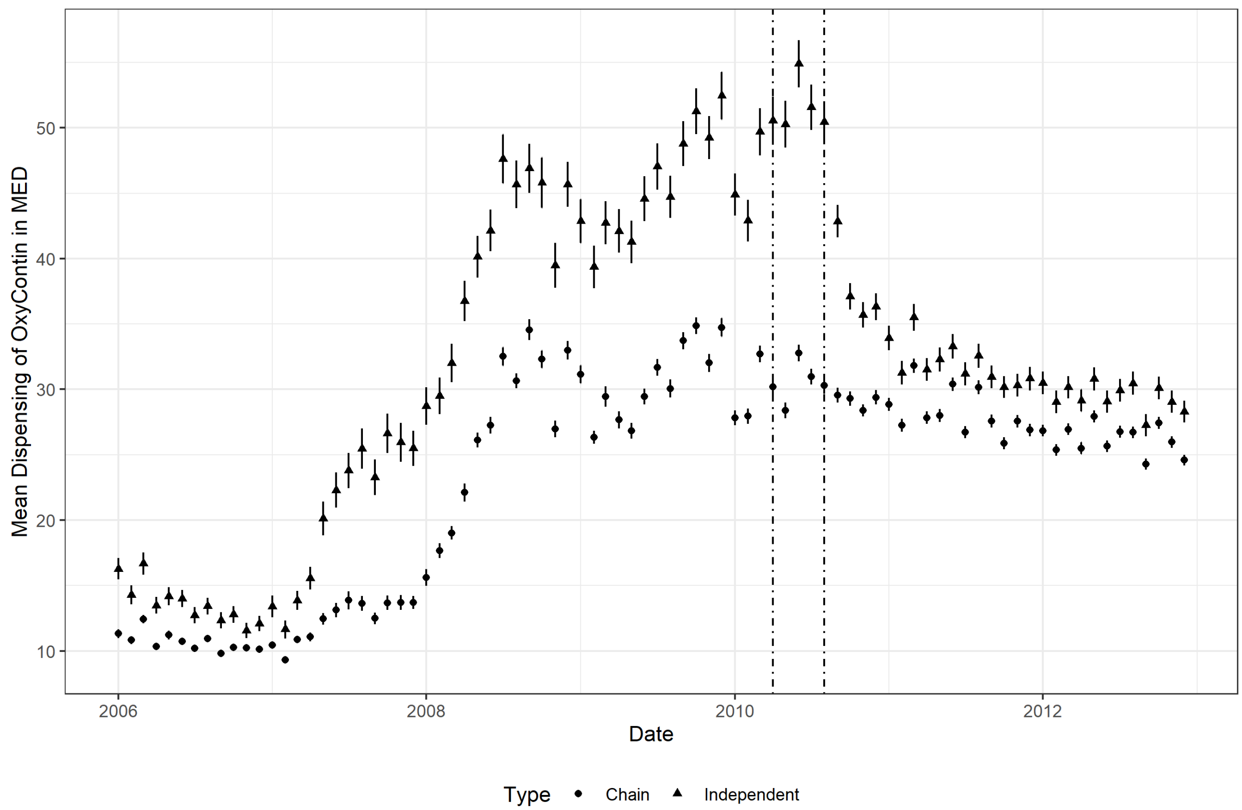
Figure 1: Dispensing of All Opioids in Months Before and After Ownership Change



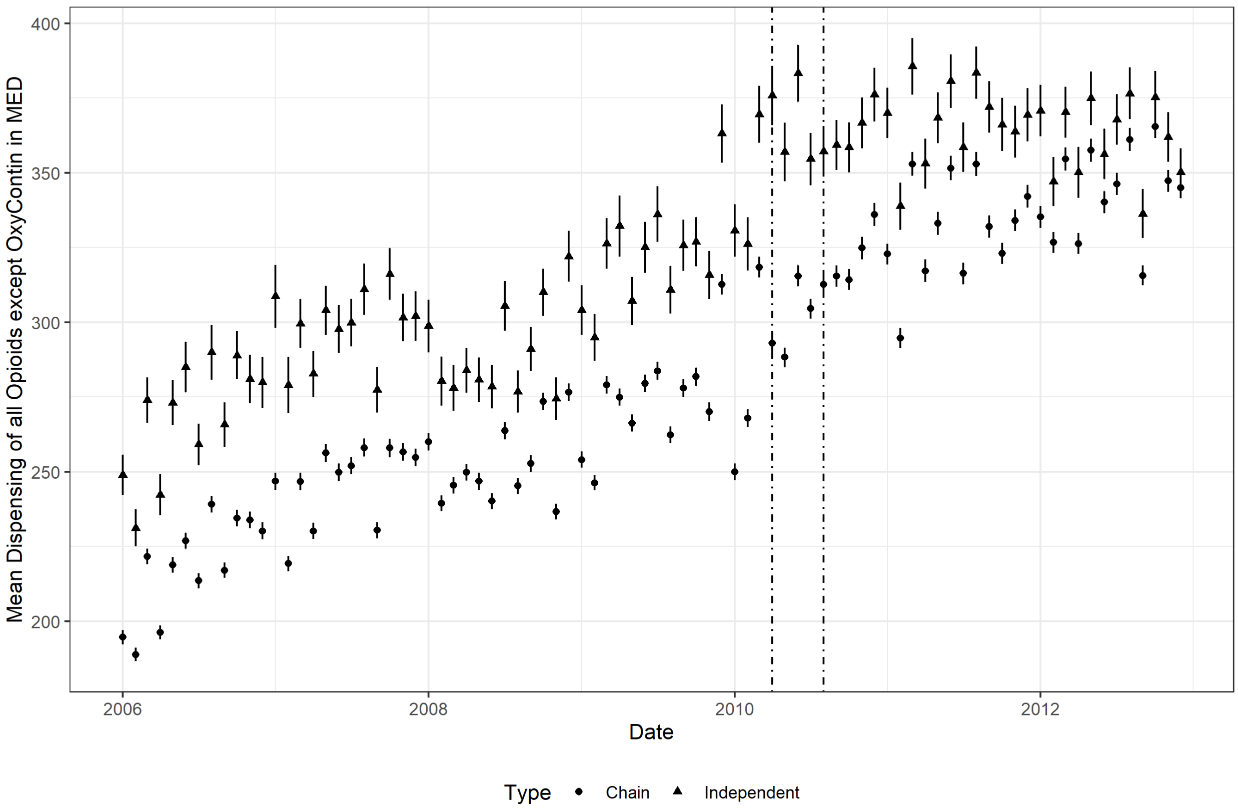
Notes: The figure represents monthly mean dispensing of all opioids in MED for independent pharmacies 18 months before and after becoming part of a chain. The 18th month before or after the ownership change includes all previous or following months. The error bars correspond to the 95% confidence interval.

Figure 2: OxyContin Dispensing, Chain vs. Independent Pharmacies



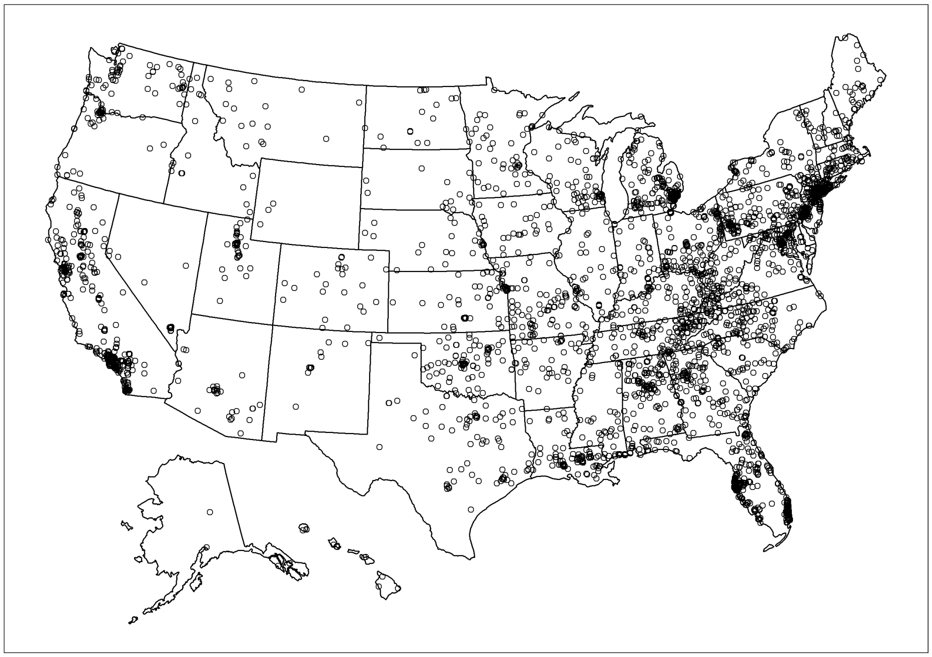
Notes: The figure shows average dispensing of OxyContin in MED for chain and independent pharmacies between 2006 and 2012. The first vertical line corresponds to April 2010, when the new OxyContin was approved by the FDA. The second vertical line corresponds to August 2010, when the new formula was delivered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

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

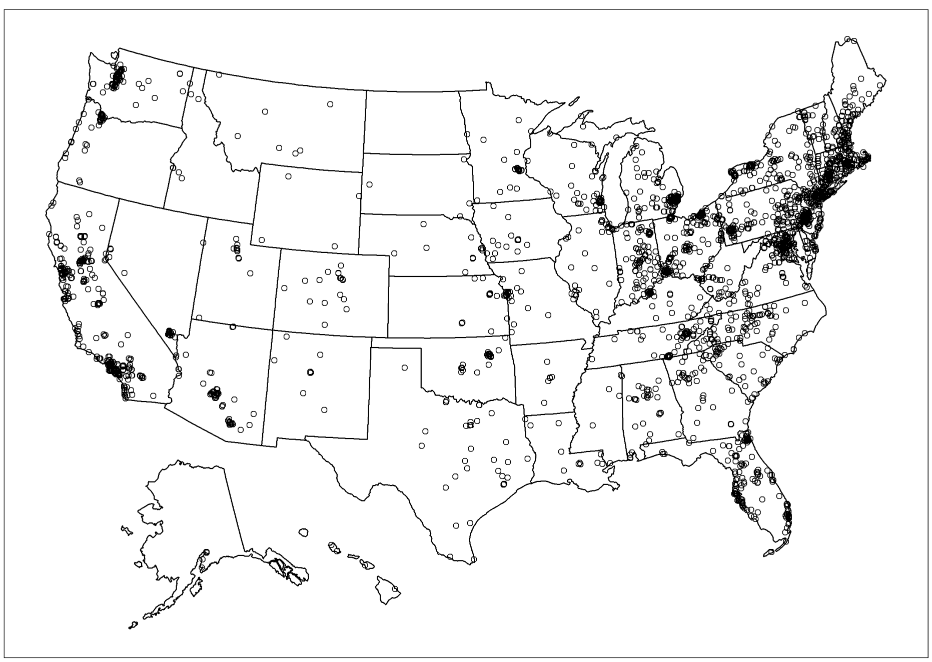


Notes: The figure shows average dispensing of all prescription opioids except OxyContin in MED for chain and independent pharmacies between 2006 and 2012. The error bars correspond to the 95% confidence interval.

Figure 4: Locations of Top 10% Diverting Pharmacies



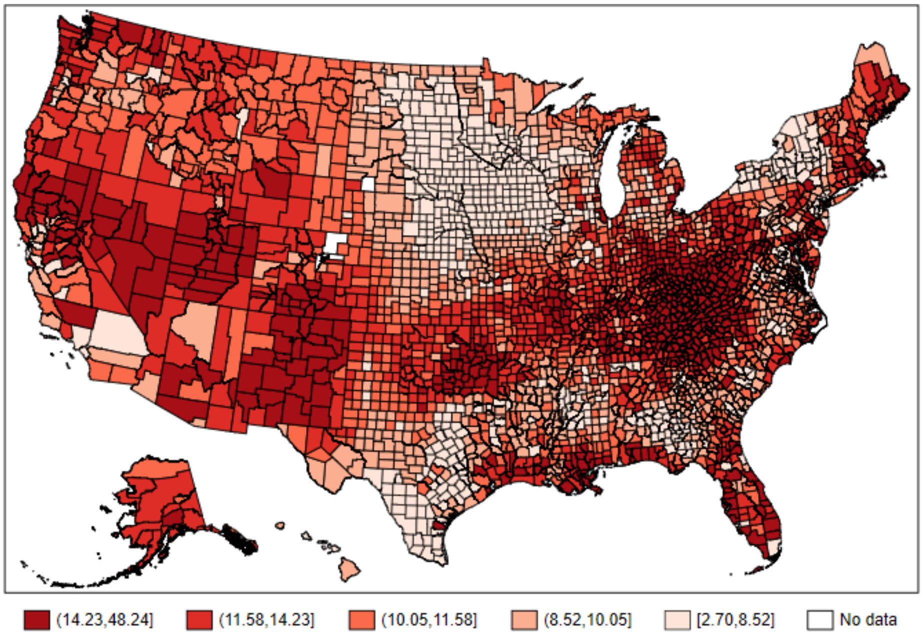
(a) Locations of independent pharmacies in the top 10 percentile



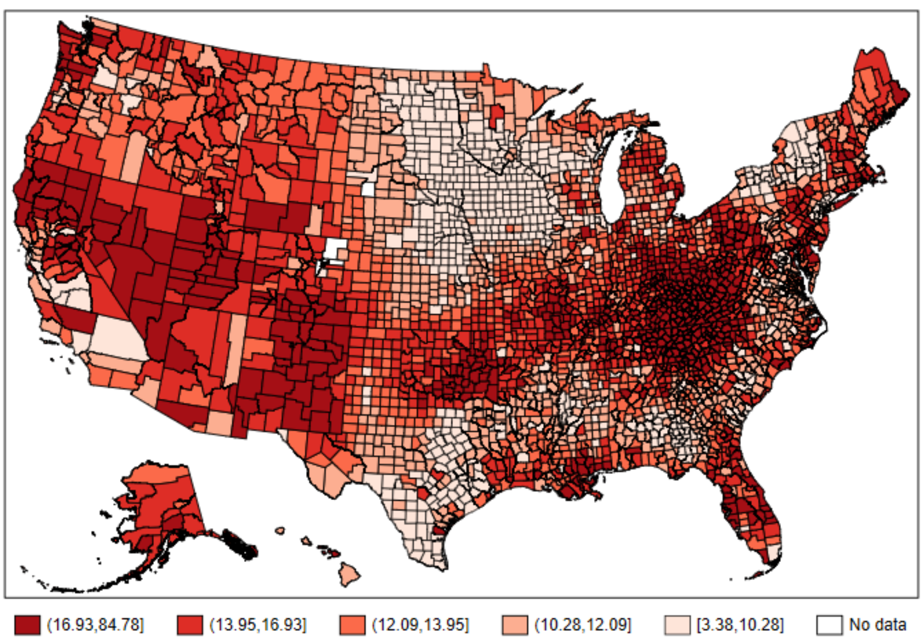
(b) Locations of chain pharmacies in the top 10 percentile

Notes: These two maps plot locations of the top 10% diverting pharmacies, by independent and chain ownership separately. Degree of diverting is calculated by the average monthly dispensing of OxyContin per capita from August 2010 to July 2011 minus the average monthly dispensing of OxyContin per capita from August 2009 to July 2010. The top pharmacies in this regard are those with the most negative changes in OxyContin dispensing.

Figure 5: Estimated Crude Death Rates for Drug Poisoning by County



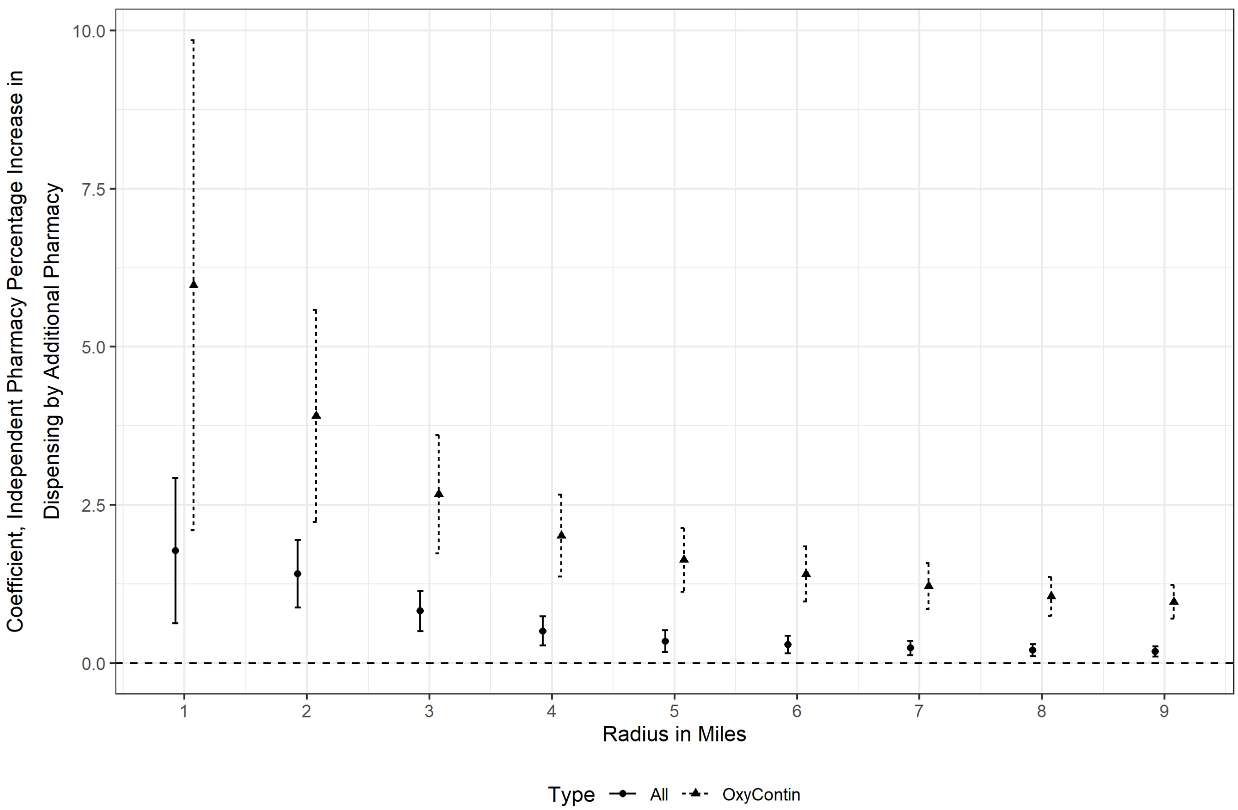
(a) 2006



(b) 2011

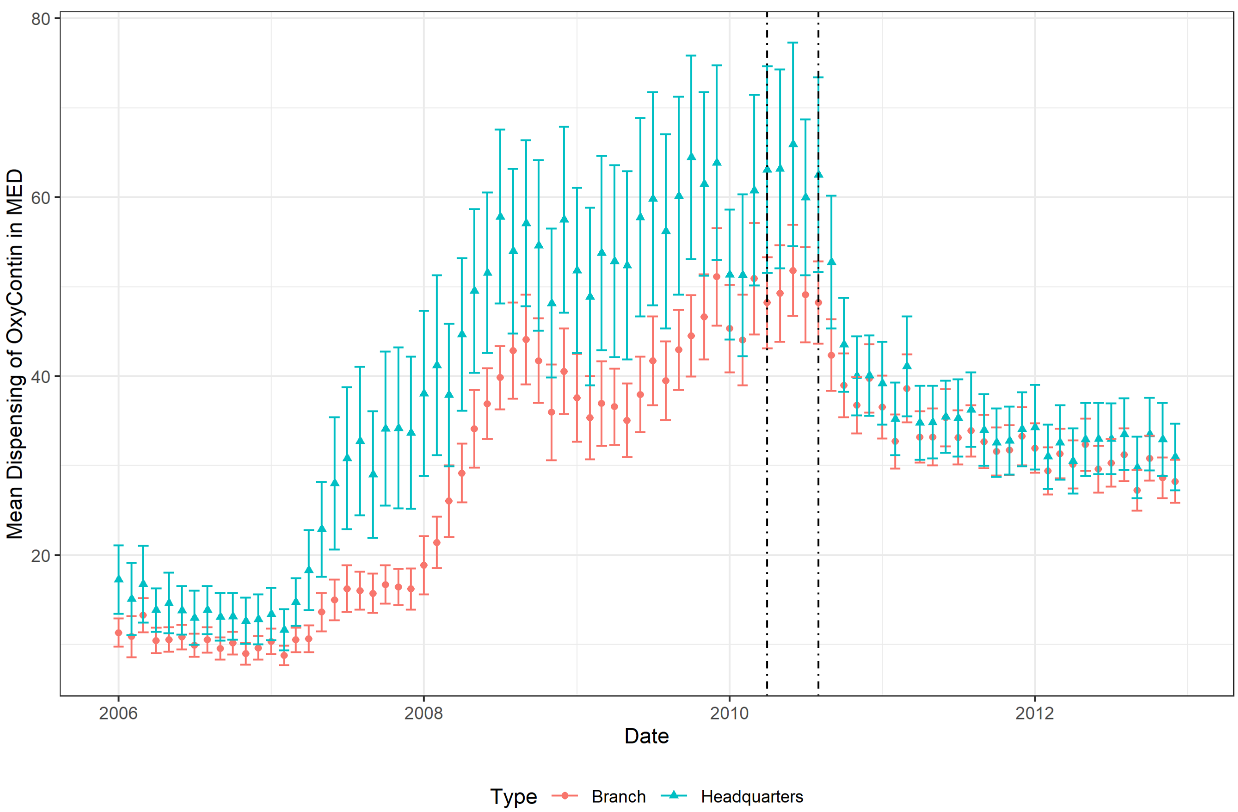
Notes: These maps show the quintiles of counties based on model-based crude death rates for drug poisoning per 100,000 population by county in 2006 and 2011. The darker the color, the higher the death rate is. The legend shows the range of death rates in each quintile. County-level crude death rates for drug poisoning are from National Center for Health Statistics (2021).

Figure 6: 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 pharmacy and year-month specific fixed effects with pre-reformulation observations, i.e., specification (6) of Table 6 panel A with different measures of competition. The error bars correspond to the 95% confidence interval.

Figure 7: OxyContin Dispensing by Headquarters and Branches



Notes: This analysis includes the subset of multi-store independent pharmacies that have headquarters found in the Orbis data. The first vertical line corresponds to April 2010, when the new OxyContin formulation was approved by the FDA. The second vertical line corresponds to August 2010, when the new formulation was delivered to pharmacies. The error bars correspond to the 95% confidence interval.

Table 1: Summary Statistics

	All	Chain	Independent
A: Pharmacies and Concentration			
Number of pharmacies	84,111	44,812	39,299
Competitors within 1-mile radius	4.47	3.7	5.57
	(9.09)	(7.18)	(11.18)
Competitors within 5-mile radius	52.95	43.64	66.30
	(114.02)	(86.82)	(11.18)
Chains within 1-mile radius	2.15	2.18	2.10
	(3.81)	(3.78)	(3.85)
Independent pharmacies within 1-mile radius	2.33	1.52	3.48
	(6.39)	(4.28)	(8.42)
B: Pharmacy Concentration in ZIP Code Areas			
Share of ZIP code areas with at least one pharmacy	0.38	0.26	0.32
Share of ZIP code areas with independent and chain pharmacies	0.21	-	-
Avg. number of pharmacies in same ZIP code area	2.03	1.08	0.95
	(4.14)	(2.41)	(2.33)
Avg. number of pharmacies in same ZIP code area, conditional on both types present	8.11	4.42	3.69
	(5.49)	(3.21)	(3.79)
C: Entries, Exits, and Ownership Changes			
Entries	15,056	6,413	8,643
Exits	10,752	2,922	7,830
Ownership change from independent to chain	304	-	-
D: Opioid Dispensing			
Monthly MED dispensing, all opioids	327.19	306.49	356.62
	(541.11)	(342.89)	(735.15)
Monthly MED dispensing, OxyContin	27.14	23.67	32.06
	(75.91)	(50.60)	(101.36)
Monthly MED, all opioids, independent before becoming chain	-	-	355.71
			(471.54)
Monthly MED OxyContin, independent before becoming chain	-	-	36.86
			(135.67)

Notes: Panel A describes the number of pharmacies as well as the number of competing pharmacies in different radii. Panel B describes the concentration of pharmacies on the ZIP code level. Panel C shows the number of entries, exits, and ownership changes. Note that entries are defined by the presence of a new owner at a new location, while exits are defined as a pharmacy that closes at a location without replacement. In comparison, an ownership change is defined by a new owner at the same geographic location within three months. Panel D describes opioid dispensing. We divide dispensing into dispensing of all opioids and of OxyContin only. The last two rows describe dispensing by independent pharmacies that became chains, prior to the date of the ownership change. Standard deviations are in parentheses.

Table 2: Regression, Direct Comparison

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	50.131***	51.362***	107.826***	128.016***	8.393***	8.640***	14.492***	16.407***
	(4.908)	(4.912)	(5.551)	(5.875)	(0.577)	(0.578)	(0.657)	(0.720)
Constant	306.488***				23.671***			
	(2.109)				(0.269)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP code FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	327.19	327.19	327.19	327.19	27.14	27.14	27.14	27.14
Mean effect in percent	15.32	15.7	32.96	39.13	30.93	31.84	53.41	60.46
N	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761
R^2	0.002	0.010	0.089	0.225	0.003	0.019	0.066	0.159

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

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. We show the mean outcome of the outcome variable as well as the mean effect in percent, which is defined as $\frac{\beta}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table 3: Change in Ownership: Independent to Chain

	All					OxyContin				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	DID-M	OLS	OLS	OLS	OLS	DID-M
D^{PRE}	1.516	32.777	-1.226			5.099	9.193	7.526		
	(33.915)	(33.655)	(32.747)			(6.886)	(6.832)	(7.314)		
D^{POST}	-102.89^{***}	-130.867^{***}	-153.215^{***}	-110.507^{***}	-154.392^{***}	-9.303^{***}	-13.306^{***}	-14.604^{***}	-14.339^{***}	-15.223^{***}
	(19.755)	(19.61)	(20.439)	(16.65)	(15.284)	(6.886)	(6.832)	(7.314)	(4.073)	(2.641)
CHAIN	-49.933^{***}	-50.89^{***}	-127.879^{***}			-8.362^{***}	-8.573^{***}	-16.361^{***}		
	(4.931)	(4.934)	(5.912)			(0.578)	(0.578)	(0.724)		
Constant	356.624^{***}					32.036^{***}				
	(4.883)					(0.554)				
Year-month FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	No	Yes	No	No
Facility FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Mean outcome	327.19	327.19	327.19	327.19	327.19	27.14	27.14	27.14	27.14	27.14
Mean effect in percent	−31.45	−40	−46.83	−33.77	−47.19	−34.28	−49.03	−53.82	−52.84	−56.1
N	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761
R^2	0.002	0.01	0.225	0.809		0.003	0.019	0.159	0.649	

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

Notes: Results of the regression analysis in equation (2). One observation corresponds to a pharmacy within a month. In model specifications (1) to (5), the outcome is monthly dispensed opioids in MED. In models (6) to (10), we consider monthly dispensed OxyContin in MED as an outcome. In models (5) and (10) we use a two-way fixed effects estimators that is robust to heterogenous treatment effects when weights of the average treatment effects are negative. Details of the estimator are described in De Chaisemartin and d'Haultfoeuille (2020). D^{PRE} displays the coefficient β_0, the effect of independent pharmacies before a change in ownership. D^{POST} displays the coefficient β_1, the effect of chain pharmacies that were independent before a change in ownership. *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. Facility fixed effects are based on the geographical location of a pharmacy. When using facility 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table 4: Regression, OxyContin Reformulation

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-6.097^{***}	-6.436^{***}	-6.996^{***}	-5.339^{***}	-10.475^{***}	-10.526^{***}	-10.892^{***}	-9.048^{***}
	(0.529)	(0.529)	(0.565)	(0.484)	(0.672)	(0.672)	(0.702)	(0.596)
Independent	10.569^{***}	10.912^{***}	18.886^{***}		14.947^{***}	15.002^{***}	24.353^{***}	
	(0.681)	(0.683)	(0.832)		(0.897)	(0.897)	(1.058)	
Post	6.095^{***}				-1.332^{***}			
	(0.154)				(0.178)			
Constant	21.495^{***}				28.923^{***}			
	(0.281)				(0.357)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	27.14	27.14	27.14	27.14	32.29	32.29	32.29	32.29
Mean effect in percent	−22.47	−23.72	−25.78	−19.67	−32.44	−32.60	−33.74	−28.02
N	5,055,761	5,055,761	5,055,761	5,054,885	3,653,388	3,653,388	3,653,388	3,652,557
R^2	0.004	0.019	0.159	0.650	0.006	0.008	0.174	0.727

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3). One observation corresponds to a pharmacy within a month. The outcome variable is monthly OxyContin dispensing in MED at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Independent* displays the dispensing of independent pharmacies relative to chains. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table 5: Characteristics of Top and Bottom Pharmacies Dispensing for Non-medical Demand

	All	Independent	Top 5%	Bottom 5%	Top 10%	Bottom 10%
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Mean	Mean	Mean	Mean	Mean
	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)
Share independent pharmacies	0.41	1.00	0.70	0.53	0.60	0.47
	(0.49)	(0.00)	(0.46)	(0.50)	(0.49)	(0.50)
Change in MED	-6.29	-12.11	-114.09	28.33	-72.88	22.15
	(53.48)	(78.33)	(199.71)	(33.73)	(148.00)	(25.68)
Change in per capita MED	-0.0003	-0.0006	-0.0069	0.0027	-0.0042	0.0017
	(0.0029)	(0.0042)	(0.0100)	(0.0030)	(0.0076)	(0.0023)
ZIP code-level characteristics						
Population	29,176	27,111	17,939	13,033	19,832	16,529
	(18,242)	(20,173)	(14,951)	(10,917)	(15,151)	(12,321)
Median household income	55,494	50,790	51,088	52,752	52,196	53,554
	(22,030)	(20,924)	(22,346)	(21,055)	(21,624)	(21,102)
Mean household income	69,660	64,657	64,890	66,263	66,051	67,230
	(28,588)	(28,040)	(29,354)	(27,447)	(28,546)	(27,445)
Share rural	0.16	0.23	0.29	0.37	0.26	0.31
	(0.27)	(0.33)	(0.37)	(0.38)	(0.34)	(0.35)
Share white	0.66	0.64	0.72	0.79	0.72	0.77
	(0.26)	(0.29)	(0.25)	(0.19)	(0.24)	(0.20)
Share elderly	0.14	0.14	0.15	0.16	0.15	0.16
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Share house vacant	0.10	0.11	0.13	0.13	0.12	0.12
	(0.07)	(0.08)	(0.10)	(0.11)	(0.09)	(0.10)
County-level characteristics						
Prescription rate 2006	76.93	76.21	87.85	78.90	85.40	79.87
	(36.53)	(40.91)	(45.24)	(35.46)	(42.66)	(34.87)
Death rate 2006	11.94	11.78	13.95	12.22	13.53	12.24
	(5.06)	(5.20)	(6.23)	(4.83)	(5.90)	(4.82)
Prescription rate 2010	86.36	85.97	98.40	89.61	95.73	90.75
	(40.45)	(45.38)	(48.71)	(39.02)	(46.27)	(38.85)
Death rate 2010	13.02	12.80	15.56	13.84	15.03	13.80
	(5.70)	(6.00)	(7.67)	(5.44)	(7.04)	(5.34)
Observations	61,410	25,299	3,070	3,071	6,141	6,141

Notes: The top 5th/10th and bottom 5th/10th percentiles are in terms of the change in OxyContin dispensing between August 2009–July 2010 (the year prior to the OxyContin reformulation) and August 2010–July 2011 (the year after the OxyContin reformulation), using the post-reformulation minus pre-reformulation dispensed OxyContin. Prescription rate is the opioid dispensing rate per 100 population. Death rate is model-based crude death rate for drug poisoning per 100,000 population. Standard deviations are reported in parentheses.

Table 6: Regression, Competition Analysis

	OxyContin							
	Full Sample				Before Reformulation		After Reformulation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Competition from Chain and Independent Pharmacies								
Competition	0.138	−0.063	-1.492^{***}	-1.106^{***}	-0.609^{**}	-1.504^{***}	-0.566^{***}	-0.308^{***}
	(0.137)	(0.168)	(0.137)	(0.091)	(0.297)	(0.175)	(0.137)	(0.097)
Independent		15.275^{***}						
		(0.821)						
Competition*Independent		0.185^{*}		-0.611^{***}		1.546^{***}		-0.416^{*}
		(0.109)		(0.217)		(0.512)		(0.226)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP code FE	Yes	Yes	No	No	No	No	No	No
Pharmacy FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	27.14	27.14	27.14	25.89	25.89	29.42	29.42
N	5,038,753	5,038,753	5,038,753	5,038,753	3,254,680	3,254,680	1,784,073	1,784,073
R^2	0.147	0.155	0.649	0.649	0.691	0.691	0.817	0.817
Panel B: Competition from Independent Pharmacies								
Competition	-0.245^{*}	−0.105	-1.545^{***}	-0.900^{***}	-0.628^{*}	-0.729^{***}	-0.505^{***}	-0.344^{***}
	(0.137)	(0.168)	(0.158)	(0.113)	(0.342)	(0.234)	(0.139)	(0.106)
Independent		16.154^{***}						
		(0.752)						
Competition*Independent		0.007		-0.972^{***}		0.162		−0.248
		(0.105)		(0.242)		(0.559)		(0.217)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP code FE	Yes	Yes	No	No	No	No	No	No
Pharmacy FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	27.14	27.14	27.14	25.89	25.89	29.42	29.42
N	5,038,753	5,038,753	5,038,753	5,038,753	3,254,680	3,254,680	1,784,073	1,784,073
R^2	0.147	0.155	0.649	0.649	0.691	0.691	0.817	0.817
Panel C: Competition from Chain Pharmacies								
Competition	0.897^{***}	−0.048	-1.378^{***}	-1.317^{***}	−0.495	-2.210^{***}	-0.737^{**}	−0.082
	(0.303)	(0.349)	(0.279)	(0.177)	(0.447)	(0.262)	(0.301)	(0.195)
Independent		13.791^{***}						
		(0.913)						
Competition*Independent		0.963^{***}		−0.165		4.454^{***}		-1.608^{**}
		(0.317)		(0.650)		(1.111)		(0.691)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP code FE	Yes	Yes	No	No	No	No	No	No
Pharmacy FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	27.14	27.14	27.14	25.89	25.89	29.42	29.42
N	5,038,753	5,038,753	5,038,753	5,038,753	3,254,680	3,254,680	1,784,073	1,784,073
R^2	0.148	0.155	0.649	0.649	0.691	0.691	0.817	0.817

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

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 models (5) and (6) we show results for the period before the OxyContin reformulation in mid-July 2010. In models (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 a pharmacy being independent. *Competition* displays the coefficient β_1, the effect of an additional competitor in a 1-mile radius. *Competition*Independent* displays the coefficient β_2, the effect of an additional competitor in a 1-mile radius on independent pharmacies. Year-month FE, ZIP code FE, and pharmacy FE indicate the use of fixed effects. We show the mean of the outcome variable. In Panel A we consider competition from chain and independent pharmacies, while Panel B considers only competition of independent pharmacies and Panel C considers only competition of chain pharmacies. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table 7: Direct Comparison with Headquarters Found

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HQ	74.440***	73.508***	102.259***	123.129***	8.468***	8.464***	13.154***	14.702**
	(24.504)	(24.502)	(35.085)	(47.487)	(2.860)	(2.861)	(4.473)	(6.489)
Constant	360.246***	360.502***	352.638***	346.921***	29.944***	29.945***	28.656***	28.232***
	(13.708)	(13.708)	(9.616)	(13.014)	(1.309)	(1.308)	(1.226)	(1.778)
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	380.6	380.6	380.6	380.6	32.26	32.26	32.26	32.26
Mean effect in percent	19.56	19.31	26.86	32.35	26.24	26.23	40.77	45.57
N	280,889	280,889	280,828	280,815	280,889	280,889	280,828	280,815
R^2	0.002	0.006	0.519	0.605	0.002	0.021	0.396	0.503

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

Notes: *HQ* represents whether a store is the headquarters of its pharmacy firm. A firm is identified using the pharmacy name-state combination. We only keep multi-store independent pharmacies whose headquarters are found in the Orbis database. 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. 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 ZIP code level area, adjusted for within-cluster correlation, and reported in parentheses.

Table 8: OxyContin Reformulation with Headquarters Found

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HQ*Post	-8.919^{***}	-8.921^{***}	-9.304^{***}	-7.602^{**}	-12.067^{***}	-11.943^{***}	-10.830^{***}	-9.304^{**}
	(2.819)	(2.812)	(3.008)	(3.151)	(4.022)	(4.020)	(4.145)	(4.076)
HQ	11.606^{***}	11.643^{***}	16.526^{***}		14.754^{***}	14.665^{***}	18.253^{***}	
	(3.501)	(3.494)	(4.870)		(4.992)	(4.991)	(6.006)	
Post	5.490^{***}				-6.298^{***}			
	(0.952)				(1.303)			
Constant	28.040^{***}				39.828^{***}			
	(1.368)				(2.060)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	32.26	32.26	32.26	32.26	39.18	39.18	39.18	39.18
Mean effect in percent	−27.64	−27.65	−28.84	−23.56	−30.80	−30.48	−27.64	−23.74
N	280,889	280,889	280,889	280,630	202,884	202,884	202,884	202,672
R^2	0.002	0.021	0.398	0.619	0.004	0.008	0.455	0.714

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

Notes: *HQ* represents whether a store is the headquarters of its pharmacy firm. A firm is identified using the pharmacy name-state combination. We only keep multi-store independent pharmacies whose headquarters are found in the Orbis database. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. The coefficient ($\hat{\beta}$) for *HQ*Post* is our key parameter of interest. 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 ZIP code level area, adjusted for within-cluster correlation, and reported in parentheses.

For Online Publication

Online Appendix

A Definition of Chain and Independent Pharmacies

In our main analyses, we borrow the coding of chain and independent pharmacies directly from the ARCOS data. However, as we notice some regional or local chains are coded as independent pharmacies, we conduct the following analyses to check the robustness of our main analyses.

We identify independent pharmacies with a single store, two stores, three stores, and four or more stores using a combination of the state, the month, and the pharmacy name (the first 10 letters), and we compare their dispensing behavior respectively to chains defined in the ARCOS data.[22] Table A.1 shows the direct comparison results, and Table A.2 compares single-store, two-store, three-store, and four-or-more-store independent pharmacies vs. chain pharmacies before and after the OxyContin reformulation. Figure A.1 plots the coefficients from column (8) of Table A.1 and the coefficients from column (4) of Table A.2. Both the tables and figures show that independent pharmacies with no more than three stores are distinct from independent pharmacies with more than three stores. Independent pharmacies with more than three stores behave much more similarly to chain pharmacies defined in the ARCOS data. These results assure us that the main results are driven by independent pharmacies even according to the strict definition of independent and chain pharmacies by the American Pharmacists Association.

B Entries and Exits

Our sample has frequent observations of entries and exits. Further, a large fraction of those entering and exiting pharmacies are independent. In Table B.1 we show some basic summary statistics of entries and exits. It may be possible that the exiting or entering independent pharmacies dispense less or more opioids than the non-exiting or non-entering counterparts. Note first that our main specification uses pharmacy fixed effects. Therefore, time-invariant differences between pharmacies do not affect our results. However, we may observe time-variant pharmacy-specific dispensing behavior that is correlated to entering or exiting the market. In the following, we investigate the effect of entries and exits in greater detail. Overall, we show that entering and exiting pharmacies act differently than non-entering and non-exiting pharmacies. However, they do not drive our main result that independent pharmacies serve a larger fraction of the non-medical demand.

[22] We vary the number of letters from 8 to 14 to identify the pharmacy firms, and our results are robust.

Table A.1: Direct Comparison of Pharmacies with Different Numbers of Stores

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of stores = 1	50.474***	51.718***	114.183***	141.614***	9.249***	9.505***	16.152***	18.819***
	(5.993)	(5.999)	(6.618)	(6.914)	(0.717)	(0.717)	(0.799)	(0.889)
No. of stores = 2	73.261***	73.757***	118.764***	137.835***	9.991***	10.185***	14.837***	16.835***
	(9.990)	(9.981)	(10.227)	(10.964)	(1.392)	(1.390)	(1.455)	(1.591)
No. of stores = 3	91.419***	92.857***	128.522***	143.841***	10.859***	11.053***	15.116***	15.898***
	(16.648)	(16.634)	(16.629)	(17.362)	(1.923)	(1.917)	(1.942)	(2.111)
No. of stores = 4	24.954***	26.514***	73.107***	74.575***	3.505***	3.763***	8.053***	8.374***
	(9.055)	(9.056)	(9.535)	(9.738)	(0.874)	(0.874)	(0.920)	(0.951)
Constant	306.488***	305.980***	282.547***	273.661***	23.671***	23.569***	21.124***	20.254***
	(2.109)	(2.110)	(1.723)	(2.440)	(0.269)	(0.269)	(0.222)	(0.301)
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP code FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	327.2	327.2	327.2	327.2	27.14	27.14	27.14	27.14
N	5,055,761	5,055,761	5,055,760	5,055,745	5,055,761	5,055,761	5,055,760	5,055,745
R^2	0.002	0.011	0.089	0.226	0.003	0.019	0.066	0.159

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

Notes: We identify number of stores using the pharmacy name-state-month combinations. The reference group is chain pharmacies in the ARCOS data. *No. of stores* measures the number of stores an independent pharmacy (as defined by the ARCOS data) has in a month. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation and heteroskedasticity, and reported in parentheses.

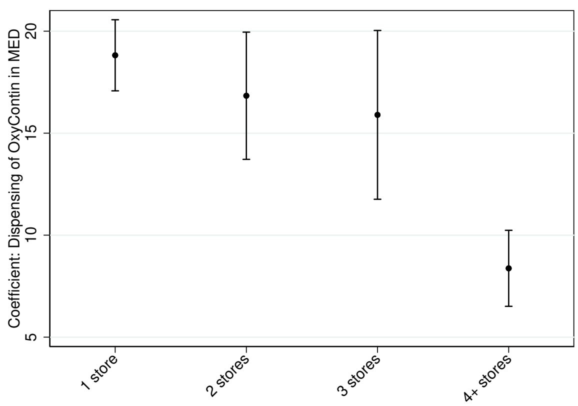
Table A.2: OxyContin Reformulation by Pharmacies with Different Numbers of Stores

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of stores = 1*Post	-7.845^{***}	-8.200^{***}	-8.802^{***}	-6.462^{***}	-12.351^{***}	-12.384^{***}	-12.765^{***}	-10.273^{***}
	(0.676)	(0.675)	(0.717)	(0.591)	(0.854)	(0.853)	(0.884)	(0.728)
No. of stores = 2*Post	-6.053^{***}	-6.319^{***}	-6.942^{***}	-6.227^{***}	-11.391^{***}	-11.396^{***}	-12.065^{***}	-10.574^{***}
	(1.533)	(1.528)	(1.547)	(1.475)	(1.991)	(1.991)	(1.964)	(1.766)
No. of stores = 3*Post	-3.729*	-4.011**	-3.912**	-4.637^{***}	-8.808^{***}	-8.844^{***}	-8.078^{***}	-9.061^{***}
	(2.039)	(2.034)	(1.971)	(1.552)	(2.496)	(2.496)	(2.382)	(1.850)
No. of stores = 4+*Post	0.031	-0.303	-0.746	-0.632	-3.605^{***}	-3.681^{***}	-3.999^{***}	-3.734^{***}
	(0.721)	(0.718)	(0.733)	(0.638)	(0.970)	(0.970)	(0.961)	(0.808)
No. of stores = 1	12.038^{***}	12.395^{***}	21.940^{***}	-0.091	16.543^{***}	16.579^{***}	27.814^{***}	7.550
	(0.855)	(0.856)	(1.037)	(3.542)	(1.125)	(1.124)	(1.305)	(4.718)
No. of stores = 2	12.152^{***}	12.445^{***}	19.347^{***}	-4.096	17.490^{***}	17.522^{***}	25.956^{***}	-2.186
	(1.729)	(1.725)	(1.937)	(2.913)	(2.376)	(2.376)	(2.580)	(4.103)
No. of stores = 3	12.219^{***}	12.468^{***}	17.300^{***}	-0.398	17.297^{***}	17.302^{***}	22.792^{***}	0.816
	(2.332)	(2.324)	(2.504)	(2.153)	(3.081)	(3.081)	(3.244)	(3.149)
No. of stores = 4+	3.562^{***}	3.898^{***}	8.693^{***}		7.197^{***}	7.276^{***}	12.519^{***}	
	(0.944)	(0.944)	(1.010)		(1.402)	(1.402)	(1.472)	
Post	6.095^{***}				-1.766^{***}			
	(0.154)				(0.178)			
Constant	21.495^{***}				29.356^{***}			
	(0.281)				(0.359)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	27.14	27.14	27.14	27.14	32.47	32.47	32.47	32.47
N	5,055,761	5,055,761	5,055,745	5,054,885	3,594,491	3,594,491	3,594,474	3,593,710
R^2	0.004	0.020	0.160	0.650	0.006	0.009	0.176	0.729

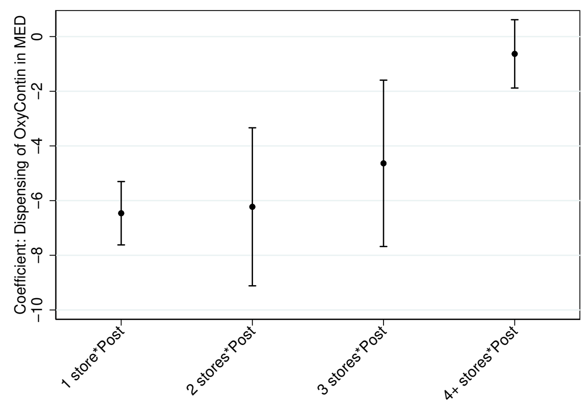
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: We identify the number of stores using the pharmacy name-state-month combinations. The reference group is chain pharmacies in the ARCOS data. *No. of stores* measures the number of stores an independent pharmacy (as defined by the ARCOS data) has in a month. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation and heteroskedasticity, and reported in parentheses.

Figure A.1: Independent Pharmacies with Different Numbers of Stores vs. Chain Pharmacies



(a) Direct Comparison: OxyContin



(b) OxyContin Reformulation

Notes: Figure (a) plots regression coefficients from Table A.1 (direct comparison) column (8), where the omitted group is chain pharmacies. Figure (b) plots regression coefficients from Table A.2 (OxyContin reformulation) column (4), where the omitted group is Chain*Post. Both graphs show that independent pharmacies with no more than three stores are drastically different from independent pharmacies with four or more stores. The latter group is much more similar to chain pharmacies.

Table B.1: Entries and Exits

	All	Chain	Indep.
	A: Total		
Entries	15,056	6,413	8,643
Exits	10,752	2,922	7,830
	B: Monthly		
Entries	193.03	110.81	82.22
Before reformulation	207.16	101.12	106.04
After reformulation	169.14	50.28	118.86
Exits	137.85	100.38	37.46
Before reformulation	141.02	43.05	97.96
After reformulation	130.26	24.09	106.17

Notes: Panel A of the table describes the total number of entries and exits of chain and independent pharmacies. An entry is defined as a new pharmacy at a specific location, while an exit is defined as the closure of a pharmacy at a specific location without a new opening. Panel B of the table describes average monthly entries and exits in the sample. Changes in ownership are neither entries nor exits. We show result divided by entries and exits of chains and independent pharmacies as well as before and after the OxyContin reformulation.

In Figure B.1 we present dispensing of OxyContin by pharmacies before the date of exit and after the date of entry respectively. We show raw means as in the first two subfigures and results from a basic regression framework in the lower two subfigures:

$$Y_{it} = \sum_{k=0}^{k=18} \beta_1^k Entry_{ik} + \mu_t + \alpha_i + \varepsilon_{it} \tag{5}$$

$$Y_{it} = \sum_{k=-18}^{k=0} \beta_1^k Exit_{ik} + \mu_t + \alpha_i + \varepsilon_{it}, \tag{6}$$

where Y_{it} are the dispensing of OxyContin. Additionally, $Entry_{ik} = 1$ if a pharmacy i enters k months ago. $Exit_{ik}$ takes the value 1 if a pharmacy exits in k months. The event study includes year-month and pharmacy fixed effects. We normalize the coefficients to periods after 18 months in the case of entry or to periods before 18 months for an exit.

From the results we observe that OxyContin dispensing increases gradually after an entry and decreases gradually in the months before a pharmacy exits. This may be due to two reasons. First, it may be possible that pharmacies increase business after an entry. Further, a pharmacy may lose business before an exit, such that the observed decline in dispensing is the reason for the exit. Second, in case of an exit the pharmacy may anticipate the forthcoming exit and therefore decrease its dispensing and stockpiling.

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

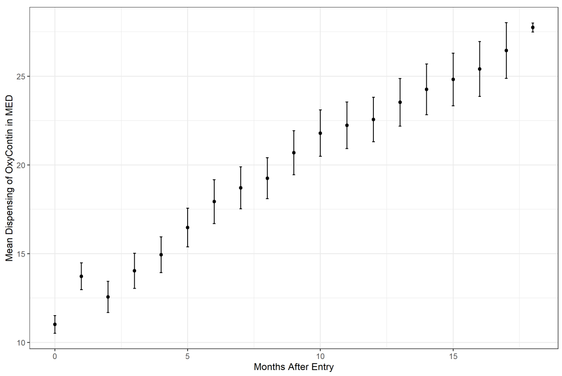
$$Y_{it} = \beta_1 Entry_i(Exit_i) \cdot Independent_i + \alpha_i + \mu_t + \varepsilon_{it} \tag{7}$$

$$Y_{it} = \beta_2 MonthAfterEntry_{it}(MonthBeforeExit_{it}) \cdot Independent_i + \alpha_i + \mu_t + \varepsilon_{it}, \tag{8}$$

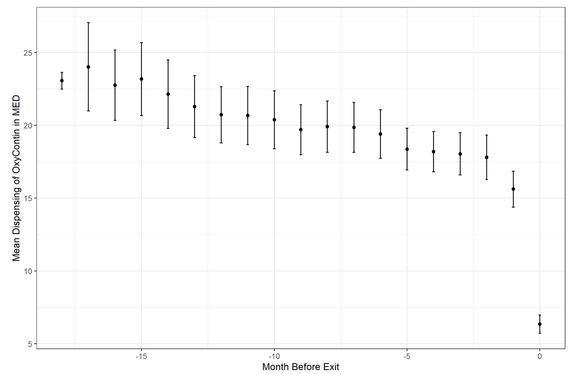
where Y_{it} is the usual OxyContin dispensing by pharmacy i in time t. $Entry$ is a dummy that indicates if pharmacy i entered within the years of the sample, while $Exit$ is an dummy variable that takes the value 1 if pharmacy i exits during the time of our sample. Indicator $Independent_i$ takes the value 1 if pharmacy i is independent. $MonthAfterEntry_{it}$ is the months since a pharmacy entered, and $MonthBeforeExit_{it}$ 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 fixed effects, and μ_t are month-year fixed effects. In the first model we test whether there is a general difference between pharmacies that enter or do not enter or between pharmacies that exit or do not exit. In comparison, the second model evaluates how dispensing changes in the months after an entry or before the exit and excludes pharmacies that do not exit or enter.

In Tables B.2 and B.3 we show the results for the regressions, considering entries and exits

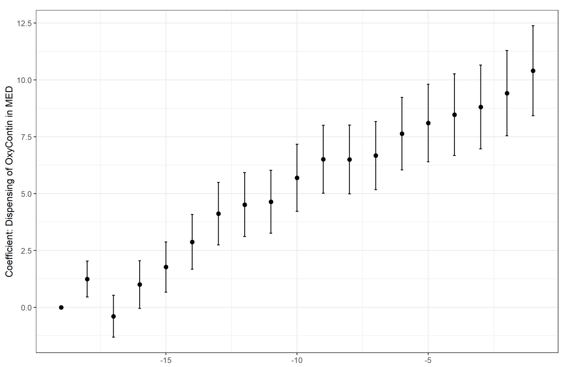
Figure B.1: Dispensing of OxyContin After Entry and Before Exits



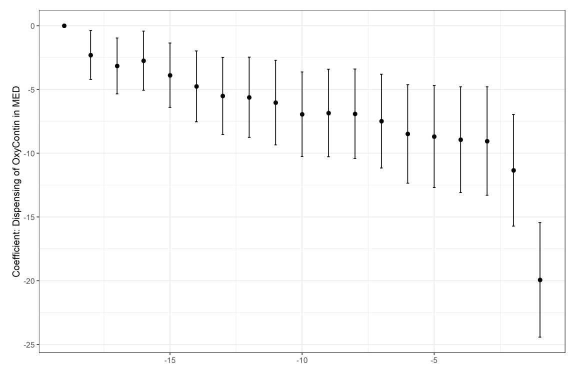
(a) Raw Trend of Dispensing After Entry



(b) Raw Trend of Dispensing Before Exits



(c) Event Study of Dispensing After Entry with Year-Month and Pharmacy Fixed Effects



(d) Event Study of Dispensing Before Exits with Year-Month and Pharmacy Fixed Effects

Notes: The figures present coefficients from dispensing of OxyContin by pharmacies after they enter a market as well as before they exit a market. One observation corresponds to a pharmacy within a month. The upper two subfigures show mean dispensing of OxyContin. The lower two subfigures show the plotted coefficient from an event study. The regression includes year-month and pharmacy fixed effects. The error bars represent 95% confidence intervals. Standard errors are clustered on the ZIP code area level and adjusted for heteroskedasticity.

separately. In both tables, regression specification (1) solely includes the $Entry_{it}$ or $Exit_{it}$ indicator and therefore compares the mean of entering or exiting to non-entering or non-exiting pharmacies, controlling for year-month fixed effects. Columns (2) and (3) refer to equation (7), with year-month and ZIP code and year-month fixed effects. Entering pharmacies dispense less OxyContin, and the negative effect of entry is greater for independent pharmacies. Entering independent pharmacies still dispense more than incumbent chain pharmacies. However, the difference is smaller than between incumbent chain and independent pharmacies. In comparison, exiting pharmacies dispense less OxyContin, but the difference is similar among chains and independent pharmacies. When considering equation (8) in columns (4) and (5), we solely observe those pharmacies that entered or exited. We see that entering pharmacies increase their dispensing after entering. The increase per month is lower (around 20%) for independent pharmacies. The observations are in line with the interpretation that entering pharmacies have fewer customers and may take longer to gain customers. Considering exits, 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 and 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.

Overall, the analysis shows that exiting and entering pharmacies dispense less opioids. We now turn to exploring robustness of the OxyContin reformulation to entries and exits. In principle our analysis of the OxyContin reformulation uses pharmacy fixed effects. Thus, if entering and exiting pharmacies are different from the remaining pharmacies, we do not expect a bias. However, a bias may be possible if entries and exits are correlated with the reformulation and we expect changes in dispensing within a pharmacy. Second, entries or exits of pharmacies correlated with the reformulation might influence existing pharmacies through competition. To address these concerns, first, we show results of the OxyContin reformulation when excluding entries and exits. Second, we control for the channel of competition by including competition-specific control variables.

As a first test of the possibility that entries and exits themselves are a threat to our main identification, we consider just the subsample of pharmacies that did not enter or exit. We believe this is a good check of whether the main effect holds up. However, we also need to emphasize that the result does not allow us to quantify the overall effect, as the subsample may be nonrandom (e.g., we may observe entries in locations with more drug abuse). We show the OxyContin reformulation in Tables B.4 for the sample of pharmacies that neither exited nor entered. With the selected sample, we observe an effect of the OxyContin reformulation, meaning that independent pharmacies decreased dispensing after the reformulation. However, the effect size is smaller compared to the findings in the main paper. Nevertheless, we argue that the selected sample shows that the difference between chain and independent pharmacies is not driven by entries or exits.

Table B.2: Entry Regression, OxyContin

	OxyContin				
	(1)	(2)	(3)	(4)	(5)
Entry	-7.612^{***}	-7.756^{***}	-6.229^{***}		
	(0.629)	(0.483)	(0.532)		
Independent		8.987^{***}	17.800^{***}	10.572^{***}	13.729^{***}
		(0.621)	(0.806)	(1.369)	(1.943)
MonthsAfterEntry				0.333^{***}	0.429^{***}
				(0.027)	(0.038)
Entry*Independent		-1.049	-7.398^{***}		
		(1.295)	(1.542)		
Independent*MonthsAfterEntry				-0.038	-0.087^{***}
				(0.035)	(0.034)
Year-month FE	Yes	Yes	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	Yes
N	5,055,761	5,055,761	5,055,761	560,357	560,357
R^2	0.017	0.020	0.160	0.015	0.382

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

Notes: Results of regressions that investigate dispensing of entering pharmacies. One observation corresponds to a monthly pharmacy. In models (4) and (5) we solely consider pharmacies that enter between 2006 and 2012. The outcome variable is OxyContin dispensing in MED. *Entry* is a dummy that takes the value 1 if a specific pharmacy entered 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 *Entry* and *Independent* in models (2) and (3). *MonthsAfterEntry* are the months after the date of entry for those pharmacies that enter. We evaluate whether the months after an entry have different effects for independent and chain pharmacies by interacting *MonthsAfterEntry* and *Independent* in models (4) and (5). Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

A second dimension is the effect of entries and exits on other non-exiting and non-entering pharmacies. As we observe more entries of independent pharmacies after reformulation, we may attribute part of the competition effect – as more entering independent pharmacies could in theory reduce individual dispensing – on incumbent pharmacies to the effect of the reformulation. We test such a threat to our identification. Consider the following regression model, which is similar

Table B.3: Exit Regression, OxyContin

	OxyContin				
	(1)	(2)	(3)	(4)	(5)
Exit	−1.885	−5.681***	−9.181***		
	(1.170)	(0.717)	(1.048)		
Independent		8.939***	17.053***	8.036***	21.726***
		(0.597)	(0.746)	(1.498)	(4.177)
MonthsBeforeExit				−0.170***	−0.155
				(0.030)	(0.112)
Exit*Independent		1.280	1.731		
		(1.764)	(2.104)		
Independent*MonthsBeforeExit				−0.086*	−0.041
				(0.051)	(0.081)
Year-month FE	Yes	Yes	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	Yes
N	5,055,761	5,055,761	5,055,761	324,053	324,053
R^2	0.016	0.019	0.159	0.014	0.368

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

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). Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table B.4: Oxycontin Reformulation without Entering and Exiting Pharmacies

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-4.240^{***}	-4.275^{***}	-4.370^{***}	-3.868^{***}	-8.190^{***}	-8.203^{***}	-8.279^{***}	-7.689^{***}
	(0.516)	(0.516)	(0.514)	(0.493)	(0.657)	(0.657)	(0.658)	(0.615)
Independent	10.894^{***}	10.926^{***}	20.894^{***}		14.844^{***}	14.854^{***}	26.785^{***}	
	(0.734)	(0.734)	(0.968)		(0.967)	(0.967)	(1.231)	
Post	6.352^{***}				-1.710^{***}			
	(0.163)				(0.192)			
Constant	22.207^{***}				30.269^{***}			
	(0.308)				(0.396)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	28.03	28.03	28.03	28.03	33.63	33.63	33.63	33.63
Mean effect in percent	−15.12	−15.25	−15.59	−13.8	−24.35	−24.39	−24.62	−22.86
N	4,191,644	4,191,644	4,191,644	4,191,644	2,995,313	2,995,313	2,995,313	2,995,313
R^2	0.005	0.022	0.192	0.650	0.006	0.009	0.211	0.734

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

Notes: Results of the OxyContin reformulation regression analysis excluding entering and exiting pharmacies. One observation corresponds to a pharmacy within a month. The outcome variable is monthly OxyContin dispensing in MED at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Independent* displays the dispensing of independent pharmacies relative to chains. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. 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 ZIP code level area, adjusted for serial correlation and heteroskedasticity, and reported in parentheses.

to our OxyContin reformulation in the main paper:

$$\begin{aligned} Y_{it} = & \beta Indep_i \cdot PostReform_t + \alpha_i + \mu_t + \sum_{k=1}^{K} \rho^k_{chain} CompChain_{itk}(\cdot County_i) + \\ & \sum_{k=1}^{K} \rho^k_{indep} CompIndep_{itk}(\cdot County_i) + \varepsilon_{it}. \end{aligned} \tag{9}$$

In comparison to the main analysis, we add individual regressors for the number of competing chains or independent pharmacies that a pharmacy faces ($CompChain_{itk}$ and $CompIndep_{itk}$ are indicators that take the value 1 if a firm faces k competitors of a type).[23] We also interact the flexible competition controls with an indicator of a county such that the coefficient for the number of competitors is different across counties. Overall, the new regressors control for confounding effects of entries on competition, which could be correlated with the reformulation.

We present the results of the analysis in Tables B.5 and B.6. The results show that even with the flexible controls the impact of the OxyContin reformulation is observable.

We argue that entries and exits do not affect the conclusion of our analysis either directly or via an effect on non-entering or non-exiting pharmacies.

C Robustness Checks of Main Specifications

C.1 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 C.1 shows results of the direct comparison between independent and chain pharmacies, and Table C.2 corresponds to the ownership changes of independent pharmacies. Table C.3 evaluates the OxyContin reformulation.

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

C.2 Adding ZIP code × Year-month Fixed Effects

In the following we extend the analysis of the direct comparison, the ownership change, and the OxyContin reformulation by replacing the separate geographic and year-month fixed effects with

[23] Note that K is the maximal number of competitors we observe.

Table B.5: Oxycontin Reformulation, with Competition Controls

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-6.325^{***}	-6.644^{***}	-7.099^{***}	-5.376^{***}	-10.479^{***}	-10.531^{***}	-10.855^{***}	-8.886^{***}
	(0.536)	(0.535)	(0.556)	(0.468)	(0.680)	(0.680)	(0.699)	(0.573)
Post	6.068^{***}				-1.335^{***}			
	(0.155)				(0.181)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Flexible competition × Pharmacy type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	27.14	27.14	27.14	32.29	32.29	32.29	32.29
Mean effect in percent	−23.31	−24.49	−26.16	−19.81	−32.46	−32.62	−33.62	−27.52
N	5,038,753	5,038,753	5,038,753	5,038,753	3,640,997	3,640,997	3,640,997	3,640,997
R^2	0.013	0.028	0.158	0.650	0.016	0.019	0.170	0.724

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

Notes: Results of the OxyContin reformulation regression analysis in equation (9) with flexible competition controls. One observation corresponds to a pharmacy within a month. The outcome variable is monthly OxyContin dispensing in MED at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table B.6: Oxycontin Reformulation, with County-specific Competition Controls

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-7.486^{***}	-7.635^{***}	-7.691^{***}	-5.715^{***}	-10.943^{***}	-10.988^{***}	-11.053^{***}	-8.587^{***}
	(0.624)	(0.623)	(0.603)	(0.481)	(0.735)	(0.736)	(0.724)	(0.567)
Post	5.752^{***}				-1.316^{***}			
	(0.175)				(0.200)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Flexible competition × Pharmacy type × County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	27.14	27.14	27.14	32.29	32.29	32.29	32.29
Mean effect in percent	−27.59	−28.14	−28.34	−21.06	−3.89	−34.03	−34.24	−26.6
N	5,038,753	5,038,753	5,038,753	5,038,753	3,640,997	3,640,997	3,640,997	3,640,997
R^2	0.172	0.186	0.259	0.662	0.205	0.208	0.292	0.737

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

Notes: Results of the OxyContin reformulation regression analysis in equation (9) with flexible competition controls. One observation corresponds to a pharmacy within a month. The outcome variable is monthly OxyContin dispensing in MED at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table C.1: Regression, Direct Comparison Per Capita

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	0.0103***	0.0104***	0.0095***	0.0057***	0.0010***	0.0010***	0.0011***	0.0007***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.00004)	(0.00004)	(0.00004)	(0.00003)
Constant	0.0153***				0.0012***			
	(0.0002)				(0.00002)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP code FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.02	0.02	0.02	0.02	0	0	0	0
Mean effect in percent	52.64	53.01	48.38	29.22	61.8	62.74	66.87	46.39
N	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318
R^2	0.0127	0.0169	0.1842	0.5367	0.0083	0.0196	0.1109	0.4022

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

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. 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

geographic $\times$ year-month fixed effects. Ideally, we want to include time-varying controls at the ZIP code level. However, we do not have such data 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 geographic $\times$ year-month fixed effects.

Table C.4 shows the result of the direct comparison. With ZIP code $\times$ year-month fixed effects, we observe a comparable and slightly stronger coefficient compared with our main model. Table C.5 shows results for the analysis of ownership changes. Also here we see a stronger effect with the new fixed effects. Table C.6 shows results of the OxyContin reformulation. Columns (3), (4), (7), and (8) present new estimates with ZIP code $\times$ year-month fixed effects added, which have the same sign as our main estimates. Compared with Table 4, the estimate in column (4) is slightly smaller (3.8%), but the estimate in column (8) is 26.7% larger. These exercises demonstrate that our results are robust to richer time-varying fixed effects.

C.3 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

Table C.2: Change in Ownership: Independent to Chain, Per Capita

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D^{PRE}	-0.005^{***}	-0.003	0.0002		-0.0002	0.0001	0.0003	
	(0.002)	(0.002)	(0.001)		(0.0004)	(0.0004)	(0.0003)	
D^{POST}	-0.009^{***}	-0.011^{***}	-0.007^{***}	-0.005^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
CHAIN	-0.010^{***}	-0.010^{***}	-0.006^{***}		-0.001^{***}	-0.001^{***}	-0.001^{***}	
	(0.0004)	(0.0004)	(0.0003)		(0.00004)	(0.00004)	(0.00003)	
Constant	0.026^{***}				0.002^{***}			
	(0.0004)				(0.00004)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Facility FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.0195	0.0195	0.0195	0.0195	0.0016	0.0016	0.0016	0.0016
Mean effect in percent	-46.86	-55.45	-34.81	-26.55	-44.86	-60.53	-44.85	-40.38
N	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318	5,042,318
R^2	0.013	0.017	0.537	0.845	0.008	0.020	0.402	0.683

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

Notes: Results of the ownership analysis considering per capita dispensing. 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. D^{PRE} displays the coefficient β_0, the effect of independent pharmacies before a change in ownership. D^{POST} displays the coefficient β_1, the effect of chain pharmacies that were independent before a change in ownership. *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. Facility fixed effects are based on the geographical location of a pharmacy. When facility fixed effects are used, 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

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

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
Independent*Post	-0.0001***	-0.0001***	-0.0001***	-0.0000	-0.0005***	-0.0005***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Independent	0.0010***	0.0010***	0.0008***		0.0014***	0.0014***	0.0011***	
	(0.0000)	(0.0000)	(0.0000)		(0.0001)	(0.0001)	(0.0000)	
Post	0.0003***				-0.0001***			
	(0.0000)				(0.0000)			
Constant	0.0011***				0.0014***			
	(0.0000)				(0.0000)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	0.0016	0.0016	0.0016	0.0016	0.0019	0.0019	0.0019	0.0019
Mean effect in percent	-5.48	-6.72	-5.59	-1.97	-25.15	-25.30	-23.68	-21.15
N	5,042,318	5,042,318	5,042,318	5,041,444	3,643,791	3,643,791	3,643,791	3,642,963
R^2	0.009	0.020	0.402	0.684	0.011	0.013	0.459	0.760

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3). One observation corresponds to a pharmacy within a month. 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 in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Independent* displays the dispensing of independent pharmacies relative to chains. *Post* takes the value 1 for all months since August 2010, when the new OxyContin entered the market and shipment of the old OxyContin ceased. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table C.4: Regression, Direct Comparison, ZIP Code × Year-Month Fixed Effects

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	50.131***	51.362***	108.790***	132.193***	8.393***	8.640***	14.690***	17.008***
	(4.908)	(4.912)	(5.726)	(5.948)	(0.577)	(0.578)	(0.679)	(0.737)
Constant	306.488***				23.671***			
	(2.109)				(0.269)			
Year-month FE	No	Yes	No	No	No	Yes	No	No
County × year-month FE	No	No	Yes	No	No	No	Yes	No
ZIP code × year-month FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	327.19	327.19	327.19	327.19	27.14	27.14	27.14	27.14
Mean effect in percent	15.32	15.7	33.25	40.4	30.93	31.84	54.13	62.67
N	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761
R^2	0.002	0.010	0.098	0.280	0.003	0.019	0.080	0.240

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

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 in MED. In models (5) to (8) we consider monthly dispensed OxyContin in MED as an outcome. *Independent* displays the coefficient β. We show the mean outcome of the outcome variable as well as the mean effect in percent, which is defined as $\frac{\beta}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

robustness we create a quarterly pharmacy-level data set and compare independent pharmacies with chain pharmacies using the same model as in the main paper:

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

where Y_{it} is the dispensed MED of opioids at pharmacy i in quarter t as well as the dispensed MED of OxyContin. $Independent_i$ 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.7 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 code and year-quarter fixed effects, independent pharmacies dispense 35.9% more opioids compared with chain pharmacies. Using monthly data, the effect size was 39.1%. Considering only OxyContin, we find an effect of 57.1% more dispensing for independent pharmacies when using quarterly data. This result also is comparable to the result of 60.5% using monthly data. Therefore, we find that the monthly analysis is robust to a quarterly analysis.

Similarly, we also conduct the analysis of ownership changes using quarterly data:

$$Y_{it} = \beta_0 D_{it}^{PRE} + \beta_1 D_{it}^{POST} + \beta_C CHAIN_i + \alpha_i + \mu_t + \varepsilon_{it}, \tag{11}$$

Table C.5: Change in Ownership: Independent to Chain, ZIP Code × Year-Month Fixed Effects

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D^{PRE}	1.516	32.777	−1.226		5.099	9.193	7.526	
	(33.915)	(33.655)	(32.747)		(6.886)	(6.832)	(7.314)	
D^{Post}	−102.890***	−130.867***	−153.215***	−127.849***	−9.303***	−13.306***	−14.604***	−17.237***
	(19.755)	(19.610)	(20.439)	(20.586)	(2.373)	(2.369)	(2.531)	(4.989)
CHAIN	−49.933***	−50.890***	−127.879***		−8.362***	−8.573***	−16.361***	
	(4.931)	(4.934)	(5.912)		(0.578)	(0.578)	(0.724)	
Constant	356.624***				32.036***			
	(4.883)				(0.554)			
Year-month FE	No	Yes	Yes	No	No	Yes	Yes	No
ZIP code × Year-month FE	No	No	Yes	Yes	No	No	Yes	Yes
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	327.19	327.19	327.19	327.19	27.14	27.14	27.14	27.14
Mean effect in percent	−31.45	−40	−46.83	−39.08	−34.28	−49.03	−53.82	−63.52
N	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761	5,055,761
R^2	0.002	0.010	0.225	0.852	0.003	0.019	0.159	0.720

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

Notes: Results of the regression analysis of ownership changes. 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. D^{PRE} displays the coefficient β_0, the effect of independent pharmacies before a change in ownership. D^{POST} displays the coefficient β_1, the effect of chain pharmacies that were independent before a change in ownership. *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. Facility fixed effects are based on the geographical location of a pharmacy. When facility fixed effects are used, 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table C.6: OxyContin Reformulation: ZIP Code × Year-Month Fixed Effects

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-6.097^{***}	-6.436^{***}	-6.691^{***}	-5.060^{***}	-10.475^{***}	-10.526^{***}	-13.716^{***}	-11.397^{***}
	(0.529)	(0.529)	(0.806)	(0.618)	(0.672)	(0.672)	(1.042)	(0.778)
Independent	10.569^{***}	10.912^{***}	19.385^{***}		14.947^{***}	15.002^{***}	26.410^{***}	
	(0.681)	(0.683)	(1.026)		(0.897)	(0.897)	(1.357)	
Post	6.095^{***}				-1.332^{***}			
	(0.154)				(0.178)			
Constant	21.495^{***}				28.923^{***}			
	(0.281)				(0.357)			
Year-month FE	No	Yes	No	No	No	Yes	No	No
ZIP code × Year-month FE	No	No	Yes	Yes	No	No	Yes	Yes
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	27.14	27.14	27.14	27.14	32.29	32.29	32.29	32.29
Mean effect in percent	−22.47	−23.72	−24.66	−18.65	−32.44	−32.60	−42.48	−35.30
N	5,055,761	5,055,761	5,055,761	4,679,983	3,653,388	3,653,388	3,653,388	3,386,832
R^2	0.004	0.019	0.240	0.709	0.006	0.008	0.240	0.772

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3). One observation corresponds to a pharmacy within a month. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table C.7: Regression, Quarterly Direct Comparison

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	121.266***	124.722***	287.205***	345.483***	22.468***	23.184***	40.028***	45.620***
	(14.313)	(14.326)	(16.039)	(16.921)	(1.683)	(1.685)	(1.900)	(2.085)
Constant	912.188***				70.451***			
	(6.283)				(0.802)			
Year-quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
County FE	No	No	Yes	No	No	No	Yes	No
ZIP code FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	963.05	963.05	963.05	963.05	79.87	79.87	79.87	79.87
Mean effect in percent	12.59	12.95	29.82	35.87	28.13	29.03	50.11	57.11
N	1,717,656	1,717,656	1,717,656	1,717,656	1,717,656	1,717,656	1,717,656	1,717,656
R^2	0.001	0.009	0.090	0.227	0.003	0.019	0.068	0.165

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

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. 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses..

where Y_{it} represents OxyContin dispensing at pharmacy i in quarter t. D_{it}^{PRE} and D_{it}^{POST} are dummies that take the value 1 for independent pharmacies before or after they become a chain pharmacy. $CHAIN_i$ is a dummy that takes the value 1 if a chain pharmacy does not change ownership. Thus the reference group are independent pharmacies without an ownership change. We use facility (α_i) and year-quarter (μ_t) fixed effects. We show results in Table C.8. Results are also slightly larger than the ones based on monthly data.

Last, we conduct the OxyContin reformulation analysis at the quarter level as follows:

$$Y_{it} = \beta Independent_i \cdot Post_t + \alpha_i + \mu_t + \varepsilon_{it}, \tag{12}$$

where Y_{it} represents OxyContin dispensing at pharmacy i in quarter t. $Post_t$ takes the value 1 for all quarters since Quarter 4 in 2010, because the new OxyContin formulation entered the market and shipment of the old OxyContin ceased in August 2010. $Independent_i$ indicates whether a pharmacy is an independent pharmacy, μ_t are year-quarter fixed effects, and α_i are pharmacy fixed effects. Table C.9 shows that our main results are robust with quarterly data, and the effect size in percent is slightly larger than that shown in Table 4.

Table C.8: Quarterly Analysis of Change in Ownership: Independent to Chain

	All				OxyContin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D^{PRE}	−14.265	76.867	−16.520		12.843	24.482	20.142	
	(97.418)	(96.647)	(93.746)		(19.654)	(19.506)	(20.824)	
D^{Post}	−336.850***	−415.206***	−474.783***	−357.646***	−30.425***	−41.875***	−44.978***	−45.365***
	(54.631)	(54.253)	(56.593)	(49.685)	(6.555)	(6.535)	(7.029)	(12.086)
CHAIN	−120.602***	−123.243***	−344.981***		−22.374***	−22.983***	−45.482***	
	(14.382)	(14.393)	(17.030)		(1.685)	(1.687)	(2.098)	
Constant	1,033.546***				92.845***			
	(14.230)				(1.612)			
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	962.94	962.94	962.94	962.94	79.86	79.86	79.86	79.86
Mean effect in percent	−34.98	−43.12	−49.31	−37.14	−38.1	−52.43	−56.32	−56.8
N	1,717,846	1,717,846	1,717,846	1,717,846	1,717,846	1,717,846	1,717,846	1,717,846
R^2	0.001	0.009	0.227	0.834	0.003	0.019	0.165	0.687

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

Notes: Results of the regression analysis of ownership changes using quarterly data. One observation corresponds to a pharmacy within a quarter. 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. D^{PRE} displays the coefficient β_0, the effect of independent pharmacies before a change in ownership. D^{POST} displays the coefficient β_1, the effect of chain pharmacies that were independent before a change in ownership. *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. Facility fixed effects are based on the geographical location of a pharmacy. When facility fixed effects are used, 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 at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

Table C.9: Quarterly Analysis, OxyContin Reformulation

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent*Post	-21.462^{***}	-22.463^{***}	-24.024^{***}	-19.305^{***}	-33.357^{***}	-33.502^{***}	-34.515^{***}	-29.526^{***}
	(1.576)	(1.574)	(1.688)	(1.477)	(1.969)	(1.968)	(2.064)	(1.807)
Independent	29.562^{***}	30.564^{***}	53.550^{***}		41.457^{***}	41.604^{***}	68.693^{***}	
	(1.980)	(1.984)	(2.407)		(2.576)	(2.577)	(3.042)	
Post	17.153^{***}				-4.339^{***}			
	(0.469)				(0.538)			
Constant	64.765^{***}				86.257^{***}			
	(0.838)				(1.054)			
Year-quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes
Mean outcome	79.88	79.88	79.88	79.88	95.18	95.18	95.18	95.18
Mean effect in percent	−26.87	−28.12	−30.08	−24.17	−35.05	−35.20	−36.26	−31.02
N	1,717,612	1,717,612	1,717,612	1,715,743	1,239,271	1,239,271	1,239,271	1,237,413
R^2	0.003	0.019	0.166	0.688	0.006	0.008	0.181	0.767

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

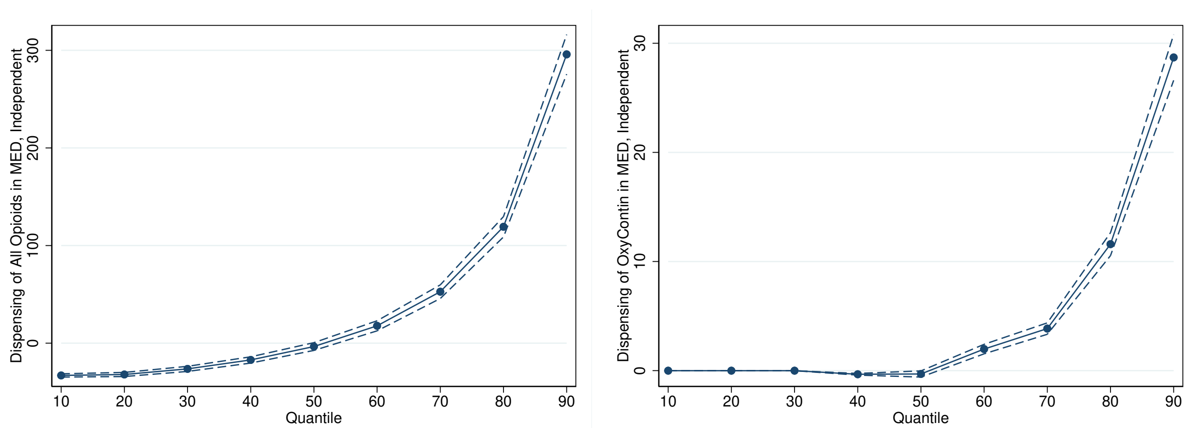
Notes: Results of the OxyContin reformulation regression analysis in equation (3). One observation corresponds to a pharmacy in a quarter. The outcome variable is quarterly OxyContin dispensing in MED at the pharmacy level. *Independent*Post* displays the coefficient $\hat{\beta}$, the change in OxyContin dispensing of independent pharmacies after the reformulation relative to chains. *Independent* displays the dispensing of independent pharmacies relative to chains. *Post* takes the value 1 if a quarter is after 2010 Q3, after the new OxyContin entered the market and shipment of the old OxyContin ceased in August 2010. 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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

D Quantile Regression for Direct Comparison

In addition to looking at how pharmacy ownership affects the average level of prescription opioid dispensing, as 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 following the method developed by Firpo et al. (2009). 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, 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 dispensing of all prescription opioids and OxyContin (in MED) at different quantiles from unconditional quantile regressions. Year-month and ZIP code fixed effects are included. The dashed lines are the 95% confidence interval based on standard errors clustered at the ZIP code level to control for within-cluster correlation.

E Event Studies

E.1 Pharmacy Ownership Change: Independent to Chain Pharmacy

In Section 4, we show the average treatment effects due to the change in ownership. In the following we add fixed effects within an event study. Consider the following regression model for pharmacy i dispensing Y_{it} MED of opioids or OxyContin in month t:

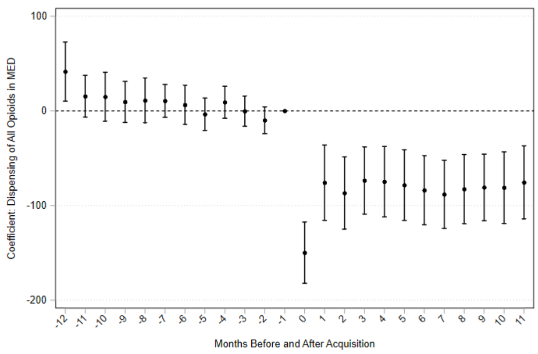
$$Y_{it} = \sum_{k=-12}^{k=11} \beta_1^k T_{ik} + \mu_t + \alpha_i + \varepsilon_{it}, \tag{13}$$

where $T_{ik} = 1$ if a pharmacy i changes ownership from independent to chain k months ago (or if k is negative, k months in the future). We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The reference month is $k = -1$, the last month before the ownership change. The event study includes year-month (μ_t) and facility (α_i) fixed effects. As a robustness check, we also replace year-month fixed effects μ_t with ZIP code $\times$ year-month fixed effects μ_{zt}.

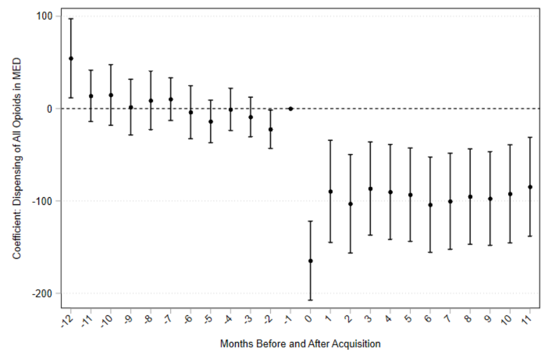
We start with estimating the model using an two-way fixed effects using OLS. Recent literature shows that linear regressions with period and group fixed effects could be biased in case of a staggered treatment design and heterogeneous treatment effects across cohorts (Sun and Abraham, 2020). We therefore also estimate a robust estimator based on Sun and Abraham (2020). However, the large sample size makes an estimation on the entire sample infeasible. To reduce the sample size we use all treatment groups (facilities that change the ownership) and 900 (almost three times) random control groups. This sample builds the basis for the robustness check. Figures E.1 and E.2 show the result for the ownership change for all opioids and OxyContin only. We observe a decrease in dispensing following the ownership change. We observe a slight decrease in months before the ownership change, for all opioids as well as for OxyContin. Results are stable independent of the fixed effects.

In Figures E.3 and E.4 we use a sample to evaluate robustness to heterogeneous treatment effects across cohorts. Subfigures E.3a and E.4a show results of the two-way fixed effect estimation for the outcome of dispensing of all opioids and OxyContin. As those estimates are closely aligned to the results of the general population in Figures E.1 and E.2 we believe that the sample is representative. Subfigures E.3b and E.4b corrrespond to the estimation based on Sun and Abraham (2020). The general effect size before and after an ownership is comparable to the effect we observe when using a two-way fixed effect estimator.

Figure E.1: Event Study: Ownership Change, All Opioids



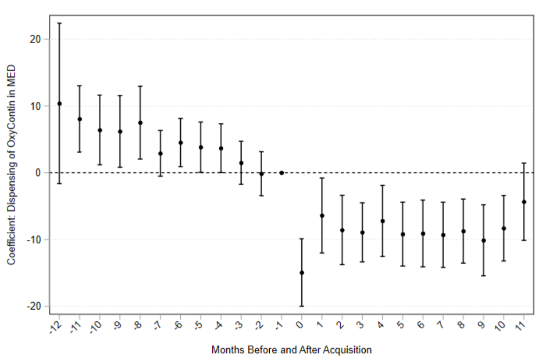
(a) Dispensing of all opioids in MED, facility and year-month fixed effects



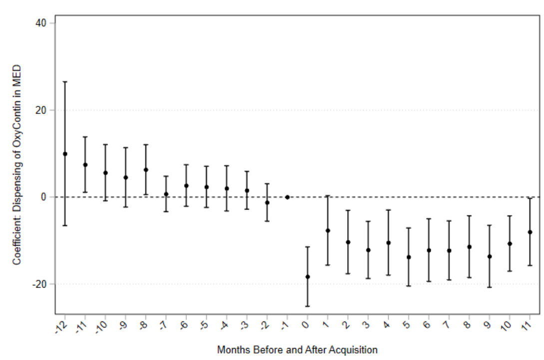
(b) Dispensing of all opioids in MED, facility and ZIP code $\times$ year-month fixed effects

Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcomes are dispensing of opioids and OxyContin in MED. The plotted coefficients from $k = -12$ to $k = 11$ correspond to months before or after the ownership change. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The coefficient $k = -1$ is the default. Each subfigure includes facility fixed effects. Additionally, the left figure includes month fixed effects, and the right figure includes ZIP code-year-month fixed effects. The error bars represent 95% confidence intervals. Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

Figure E.2: Event Study: Ownership Change, OxyContin



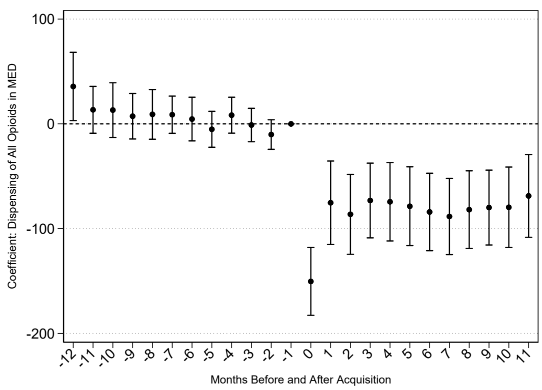
(a) Dispensing of OxyContin in MED, facility and year-month fixed effects



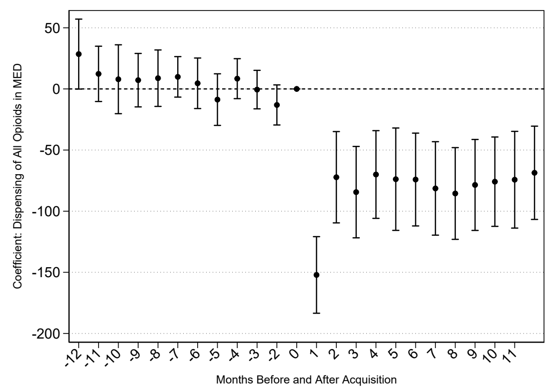
(b) Dispensing of OxyContin in MED, facility and ZIP code $\times$ year-month fixed effects

Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcome dispensing of OxyContin in MED. The plotted coefficients from $k = -12$ to $k = 11$ correspond to months before or after the ownership change. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The coefficient $k = -1$ is the default. Each subfigure includes facility fixed effects. Additionally, the left figure includes month fixed effects, and the right figure includes ZIP code-year-month fixed effects. The error bars represent 95% confidence intervals. Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

Figure E.3: Event Study: Ownership Change, All Opioids, Robustness



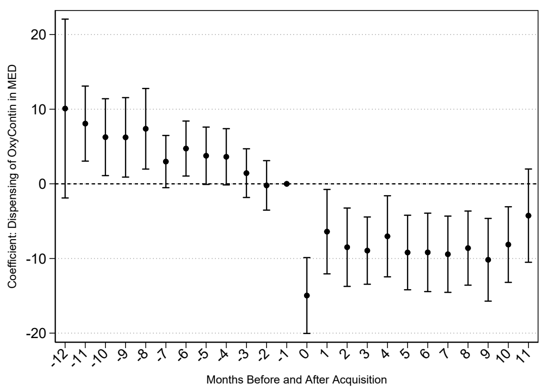
(a) Dispensing of all opioids in MED, two-way Fixed Effects



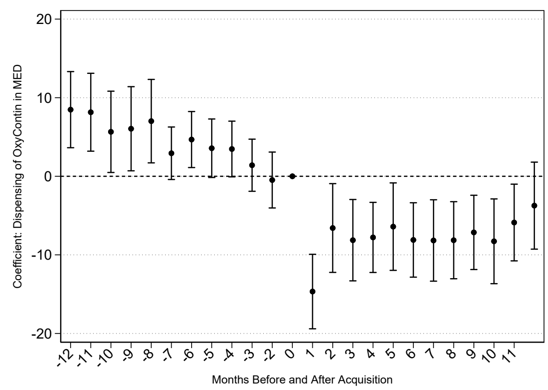
(b) Dispensing of all opioids in MED, Sun and Abraham (2020)

Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. The sample is based on the 304 treatment groups and 900 random control groups. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcomes are dispensing of opioids in MED. The plotted coefficients from $k = -12$ to $k = 11$ correspond to months before or after the ownership change. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The coefficient $k = -1$ is the default. The first subfigure shows a two-way fixed effects estimation with facility and year-month fixed effects. The error bars represent 95% confidence intervals. The second subfigure shows results from the method based on Sun and Abraham (2020). Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

Figure E.4: Event Study: Ownership Change, OxyContin, Robustness



(a) Dispensing of OxyContin in MED, two-way Fixed Effects



(b) Dispensing of OxyContin in MED, Sun and Abraham (2020)

Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. The sample is based on the 304 treatment groups and 900 random control groups. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcomes are dispensing of OxyContin in MED. The plotted coefficients from $k = -12$ to $k = 11$ correspond to months before or after the ownership change. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The coefficient $k = -1$ is the default. The first subfigure shows a two-way fixed effects estimation with facility and year-month fixed effects. The error bars represent 95% confidence intervals. The second subfigure shows results from the method based on Sun and Abraham (2020). Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

E.2 OxyContin Reformulation

In Section 5, we show the average treatment effects due to the OxyContin reformulation. In the following, we do the event study analysis to assess the pre-trend and the dynamic effects of the OxyContin reformulation on dispensing by independent pharmacies relative to chains:

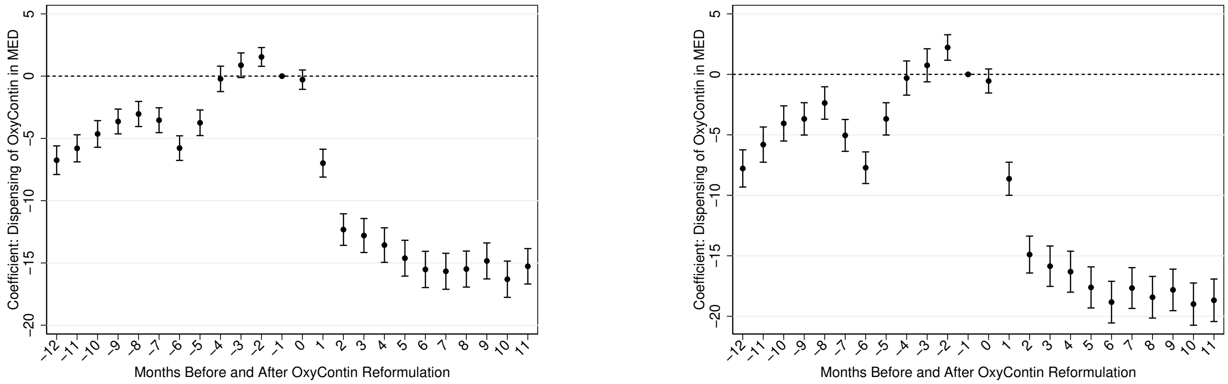
$$Y_{it} = \sum_{k=-12}^{k=11} \beta_1^k Independent_i * T_k + \mu_t + \alpha_i + \varepsilon_{it}, \tag{14}$$

where $T_k = 1$ if a month is k months from the OxyContin reformulation (negative k means a month is $|k|$ months before the reformulation). We denote the first post-period (August 2010) after the OxyContin reformulation with $k = 0$. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The reference month is $k = -1$, the last month before the shipment of abuse-deterrent OxyContin into the market, i.e., July 2010. $Independent_i$ indicates if a pharmacy is an independent pharmacy. μ_t and α_i are year-month and pharmacy fixed effects. As a robustness check, we also replace year-month fixed effects μ_t with ZIP code $\times$ year-month fixed effects μ_{zt}.

In addition, since the new OxyContin formula was approved by the FDA in April 2010, even though the first shipment did not occur until August 2010, we suspect there might have been some anticipatory stockpiling behavior by drug abusers and drug dealers. Therefore, we also do the event study analysis using March 2010 (relative month -5) as the reference month.

Figure E.5 and Figure E.6 show the event study results with July 2010 and March 2010 as the omitted reference month, respectively. Each of these figures has two subfigures: (1) with ZIP code fixed effects and year-month fixed effects, and (2) with ZIP code $\times$ year-month fixed effects. The standard errors are clustered at the ZIP code level. The time period is restricted to 2008–2012 to avoid the divergence in trends between independent and chain pharmacies that occurred in 2007. Both Figure E.5 and Figure E.6 show an upward pre-trend, indicating that before the reformulation, the gap between independent pharmacies and chain pharmacies in OxyContin dispensing increased over time. Therefore, if we believe that this upward trend would be the counterfactual if there were no reformulation, our $Independent * Post$ estimate tends to be the lower bound of the actual effect, i.e., understating the real effect. Comparing the estimates with ZIP code and year-month fixed effects and ZIP code $\times$ year-month fixed effects, we find that effect sizes from the latter are slightly larger in size. In addition, Figure E.6 demonstrates the existence of the anticipatory effect, which is plausibly due to stockpiling. Overall, our event study shows that the OxyContin reformulation reduced the gap between independent and chain pharmacies by more than 10 MED per month on average since the third post-reformulation month, slightly larger than our average treatment effect in column (8) of Table 4.

Figure E.5: Event Study: OxyContin Reformulation – July 2010 as Base

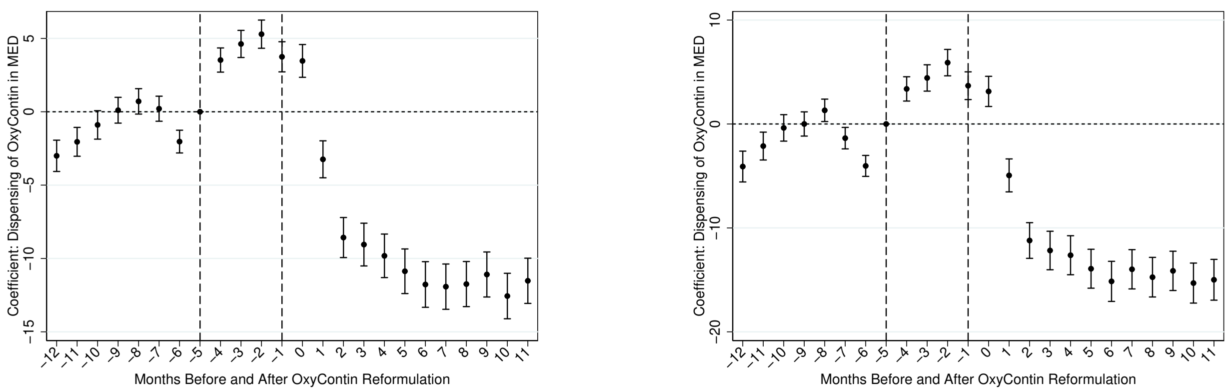


(a) Dispensing of OxyContin in MED, pharmacy and year-month fixed effects

(b) Dispensing of OxyContin in MED, pharmacy and ZIP code × year-month fixed effects

Notes: Data from 2008 to 2012 are included. July 2010 is the reference period, the month before the new abuse-deterrent OxyContin entered the market. Both graphs include pharmacy fixed effects. Additionally, the left figure includes year-month fixed effects, and the right figure includes ZIP code × year-month fixed effects. Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

Figure E.6: Event Study: OxyContin Reformulation – March 2010 as Base



(a) Dispensing of OxyContin in MED, pharmacy and year-month fixed effects

(b) Dispensing of OxyContin in MED, pharmacy and ZIP code × year-month fixed effects

Notes: Data from 2008 to 2012 are included. The reference time period is March 2010 (relative month -5), right before the FDA approval of the reformulated OxyContin in April 2010. Relative month -1 is July 2010, the last month before the shipment of new OxyContin. Both graphs include pharmacy fixed effects. Additionally, the left figure includes year-month fixed effects, and the right figure includes ZIP code × year-month fixed effects. Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

F Difference in Firm Size

Independent and chain pharmacies have different firm sizes. The larger a firm, the more flexibility it has in raising funds, cutting costs, and forming partnerships with third parties, such as various health insurance providers. On the other hand, however, large firms are also under closer monitoring from regulatory agencies, the media, and the public.[24] If firm size matters for the likelihood of committing a crime, we should find that compared with large chains, smaller chains would 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 that of Rite Aid in 2012): Walmart, Costco, Kroger, Target, Ahold, Sears, Albertsons, and Publix; and (3) the remaining smaller chains.

Figure F.1 shows the comparison between smaller chains, independent pharmacies, and major pharmacy chains.[25] 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 F.1, smaller chains reduced their dispensing by about 4.6 more MED than major chains after the reformulation, while independent pharmacies reduced their dispensing by 9.6 more MED than the major chains. Although the reduction by smaller chains was smaller than that of independent pharmacies, this evidence supports our hypothesis that smaller firms are more likely to dispense prescription opioids for non-medical demand than large chains.

G Robustness Checks of the OxyContin Reformulation

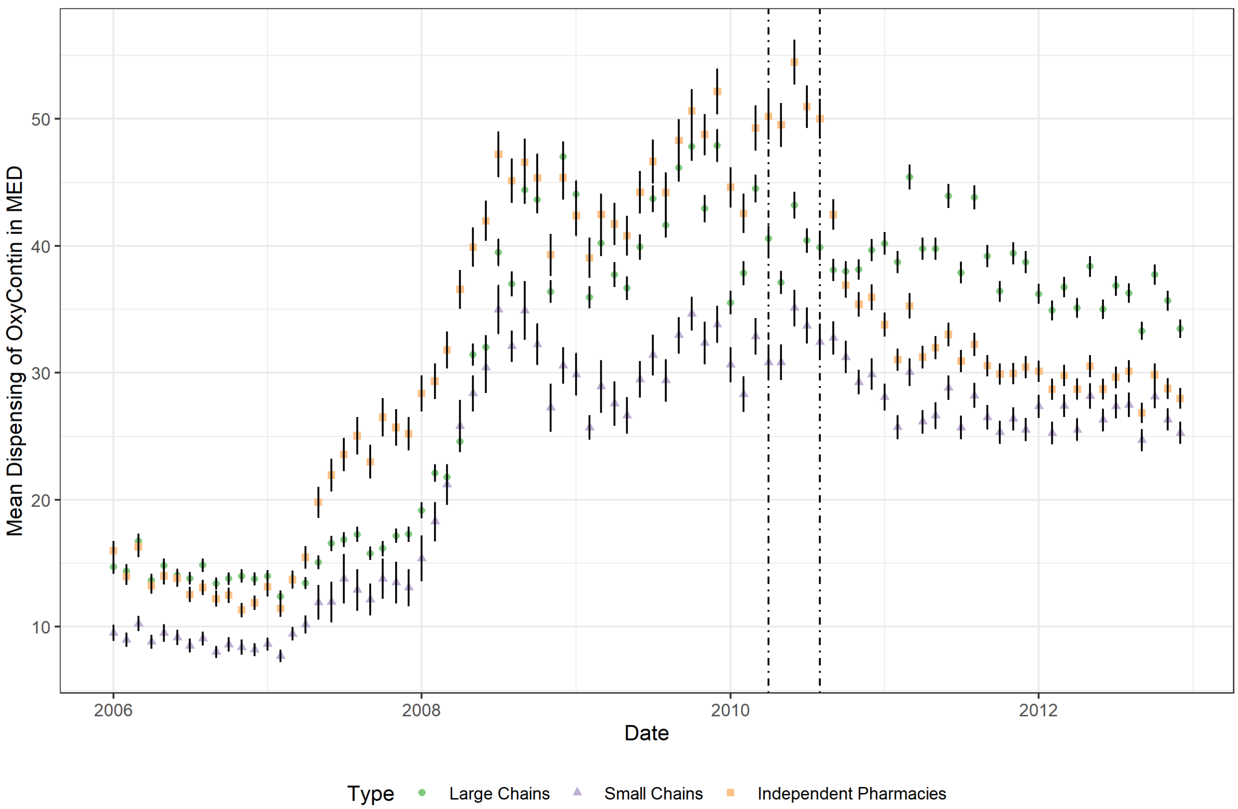
G.1 Excluding Florida

According to federal officials, by the clinics' peak in 2010, 90 of the nation's top 100 opioid prescribers were Florida doctors, and 85% of the nation's oxycodone was prescribed in the state (Spencer 2019). 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

[24] Given that most lawsuits involving pharmacies' role in the opioid epidemic are against major chain pharmacies (Hoffman 2020), it is likely that large pharmacy chains are more closely watched by both regulators and the media.

[25] 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.

Figure F.1: OxyContin Dispensing: Smaller Chains, Independent Pharmacies, and Large Chains



Notes: The figure presents average OxyContin dispensing in MED by three types 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. The error bars correspond to the 95% confidence interval.

Table F.1: OxyContin Reformulation: Smaller Chains, Independent Pharmacies, and Large Chains

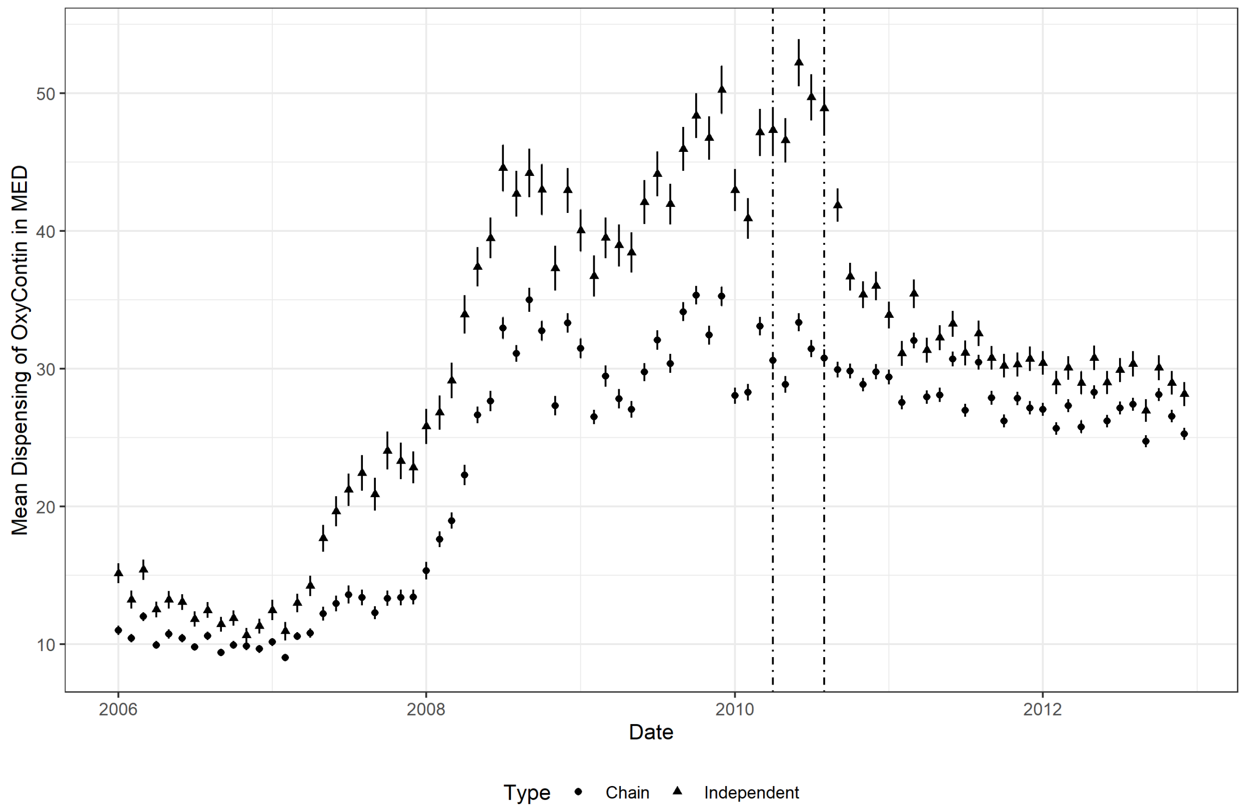
	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	Small chains	Small chains	Independent	Independent	Small chains	Small chains	Independent	Independent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Small chain*Post	-3.081^{***}	-4.584^{***}			-1.883^{***}	-2.589^{***}		
	(0.392)	(0.391)			(0.479)	(0.484)		
Small chain	-7.546^{***}				-8.744^{***}			
	(0.674)				(0.860)			
Independent*Post			-9.488^{***}	-9.613^{***}			-11.641^{***}	-10.735^{***}
			(0.508)	(0.461)			(0.634)	(0.548)
Independent			3.404^{***}				5.557^{***}	
			(0.651)				(0.868)	
Post	9.486^{***}		9.486^{***}		-0.167		-0.167	
	(0.218)		(0.218)		(0.232)		(0.232)	
Constant	28.660^{***}				38.313^{***}			
	(0.328)				(0.426)			
Year-month FE	No	Yes	No	Yes	No	Yes	No	Yes
Pharmacy FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean Outcome	27.14	27.14	27.14	27.14	32.29	32.29	32.29	32.29
Mean Effect in Percent	−11.35	−16.89	−34.96	−35.43	−5.83	−8.02	−36.05	−33.25
N	2,015,790	2,015,643	3,302,039	3,301,265	1,468,799	1,468,660	2,392,776	2,392,069
R^2	0.011	0.672	0.001	0.643	0.006	0.722	0.003	0.723

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

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. One observation corresponds to a pharmacy within a month. 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.

in 2010, a fourfold increase from 2000, with 2,710 of the deaths deemed overdoses, according to a state medical examiner's report (Spencer 2019). Figure G.1 shows the average OxyContin dispensing excluding Florida, and we find that 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 G.1 also demonstrates that the estimated effect (−3.7, −14.0%) is similar to our baseline estimate (−5.3, −19.7%).

Figure G.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.

G.2 Excluding Top Dispensing Pharmacies and Quantile Regression

Since drug diversion is misconduct, it is possible that only 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 in Table G.1. Although we find shrinkage of the estimated effect when excluding more pharmacies in the top percentiles, the estimated effect is still robust.

Moreover, we also estimate the unconditional quantile treatment effects of the OxyContin reformulation, as shown by Figure G.2. We find that, compared with chain counterparts whose OxyContin dispensing was at or below the median, independent pharmacies in the similar quantiles do not significantly reduce OxyContin dispensing. However, among pharmacies that dispense more than the median level of OxyContin, independent pharmacies reduce OxyContin dispensing significantly after the reformulation, compared with chains.

Table G.1: Robustness Checks, OxyContin Reformulation

	OxyContin				
	Baseline (1)	Exclude Florida (2)	Exclude top 1% (3)	Exclude top 5% (4)	Exclude top 10% (5)
Independent*Post	-5.339^{***} (0.484)	-3.741^{***} (0.417)	-2.491^{***} (0.293)	-1.057^{***} (0.223)	-0.890^{***} (0.200)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Pharmacy FE	Yes	Yes	Yes	Yes	Yes
Mean outcome	27.14	26.82	24.54	20.26	17.04
Mean effect in percent	−19.67	−13.95	−10.15	−5.22	−5.22
N	5,054,885	4,712,791	4,895,984	4,678,297	4,402,628
R^2	0.650	0.658	0.625	0.591	0.555

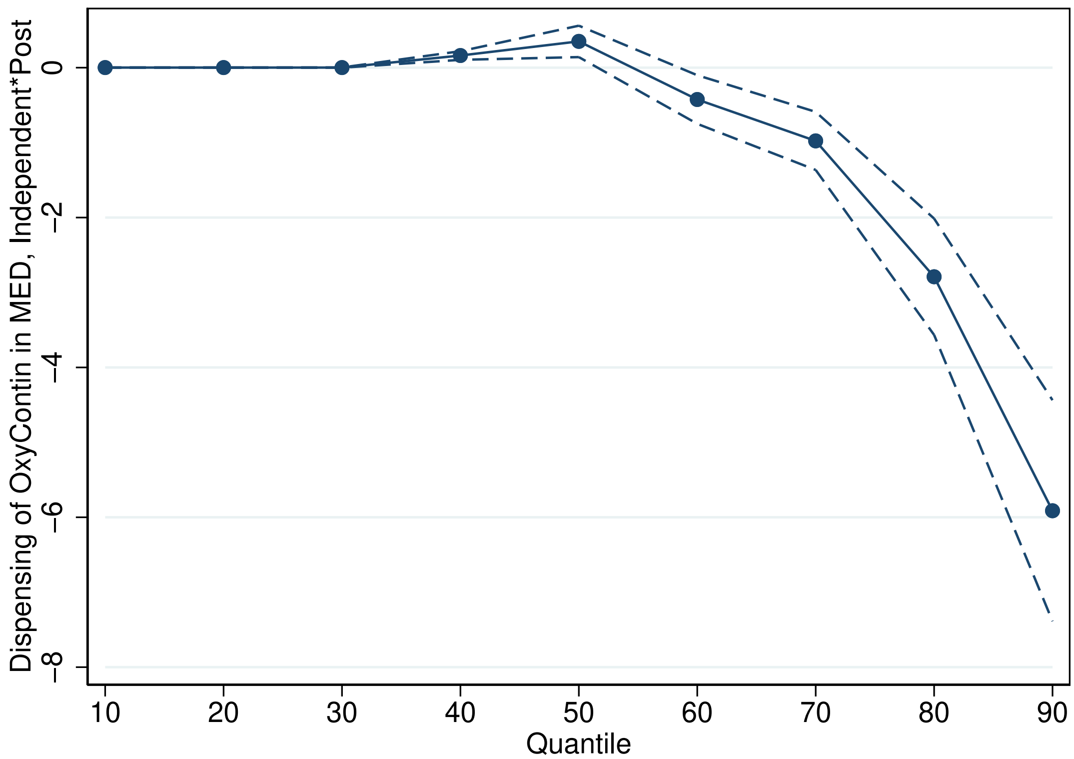
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results of the OxyContin reformulation regression analysis in equation (3) with different samples. One observation corresponds to a pharmacy within a month. Column (1) includes the full sample. Pharmacies in Florida are excluded in column (2). The 6,816 pharmacies with only post-reformulation records and 229 pharmacies located in ZIP codes with small population size (< 1st percentile, 725 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 population at the ZIP code level) in the top 1%, 5%, and 10% are excluded in columns (3), (4), and (5), respectively. *Independent*Post* displays the coefficient $\hat{\beta}$, the change of independent pharmacies relative to chains after the reformulation. We show the mean of the outcome variable as well as the mean effect in percent across each subsample, which is defined as $\frac{\hat{\beta}}{\bar{y}}$ where $\bar{y}$ is the mean of outcome y. Standard errors are clustered at the ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

G.3 80 mg OxyContin vs. Non–80 mg OxyContin

Within this subsection we evaluate whether the results of the OxyContin reformulation for dispensing behavior differ across the potency of OxyContin. The rationale for a difference is that the high-dosage OxyContin has been especially subject to abuse. Indeed, in a settlement agreement between the US Department of Justice and Purdue Pharma, the manufacturer admits that the majority

Figure G.2: Effect of the OxyContin Reformulation at Different Quantiles: Chain vs. Independent



Notes. The figure reports regression coefficients of $Independent * Post$ on the OxyContin dispensing at different quantiles from unconditional quantile regressions. Year-month and pharmacy fixed effects are included. The dashed lines are the 95% confidence interval based on standard errors clustered at the ZIP code level to control for within-cluster correlation.

of high-dosage 80 mg OxyContin pills were misused (Department of Justice 2020). We therefore expect to observe a stronger decrease of OxyContin dispensing for independent pharmacies compared with chain pharmacies in the 80 mg segment. In contrast, we expect that OxyContin tablets with a lower dosage should result in a smaller decline in dispensing by independent pharmacies.

We start by showing OxyContin dispensing in the 80 mg dose and the remaining OxyContin dosages in G.3. In Figure G.3a, we observe a large decline of dispensing in 80 mg pills for independent pharmacies after the OxyContin reformulation, while dispensing by chain pharmacies remains almost constant. In Figure G.3b, on the contrary, we only find a slight decline in dispensing of non–80 mg OxyContin by independent pharmacies after the reformulation.

For each of the two segments, we also show regression evidence based on equation (3). Panel A of Table G.2 shows that independent pharmacies reduced their dispensing of 80 mg OxyContin by 33.1% in the post-reformulation period, whereas Panel B of Table G.2 shows that they only reduced non–80 mg OxyContin dispensing by 7.5%. This demonstrates that the 19.7% reduction in

OxyContin dispensing on average by independent pharmacies as shown in column (4) of Table 4 is primarily driven by the reduction in dispensing of high-dosage OxyContin, which further supports our claim that independent pharmacies are more likely to be involved in opioid dispensing for non-medical demand.

H Other Potential Mechanisms

In Section 6, we show evidence of two mechanisms that can explain the difference between independent and chain pharmacies in dispensing for non-medical demand. In this section, we show evidence of three other potential mechanisms, but the evidence is weaker than what we show in Section 6.

H.1 Difference in Internal Database

Compared with chain pharmacies, independent pharmacies may have lower levels of non-human capital, such as insufficient internal tracking systems.[26] Independent pharmacies have up to three stores, and thus their internal databases naturally have less complete information on patients' prescription 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. In addition, small-scale interviews reveal that the data network of chain pharmacies may deter some drug abusers and dealers from going there (Rigg et al. 2010). To test this hypothesis, we exploit the implementation of must-access Prescription Drug Monitoring Programs (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.[27]

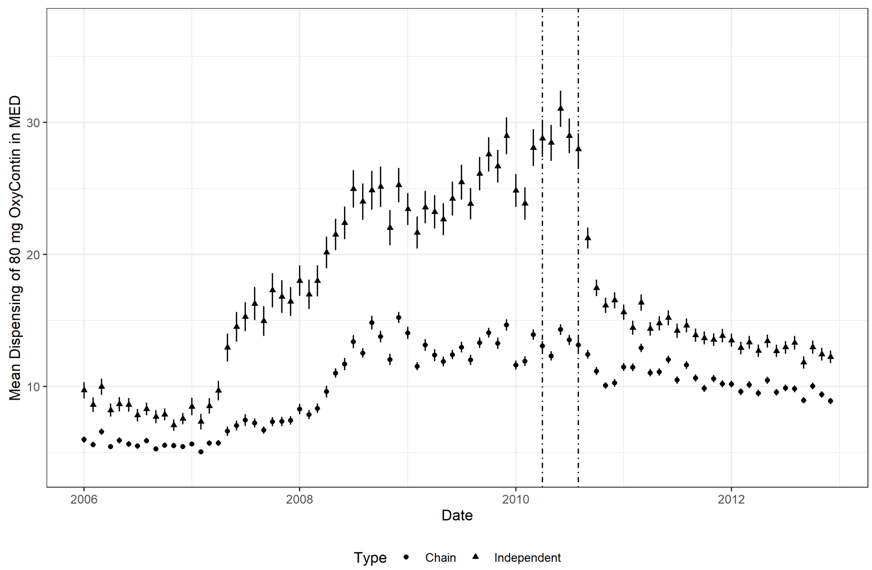
Multiple tools have been implemented to reduce diversion: quantitative prescription limits, patient identification requirements, doctor-shopping restrictions, pain clinic shutdowns, and state-run PDMPs (Doleac et al. 2018). Meara et al. (2016) show that the majority of these tools did not have an effect between 2006 and 2012. However, research shows that recently implemented PDMPs decreased diversion. PDMPs suggest or require that prescribers and pharmacists access a within-

[26] Another difference is the security level. However, as pharmacy theft and robberies account for only 1.5% of drug diversion (Inciardi et al. 2007), 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).

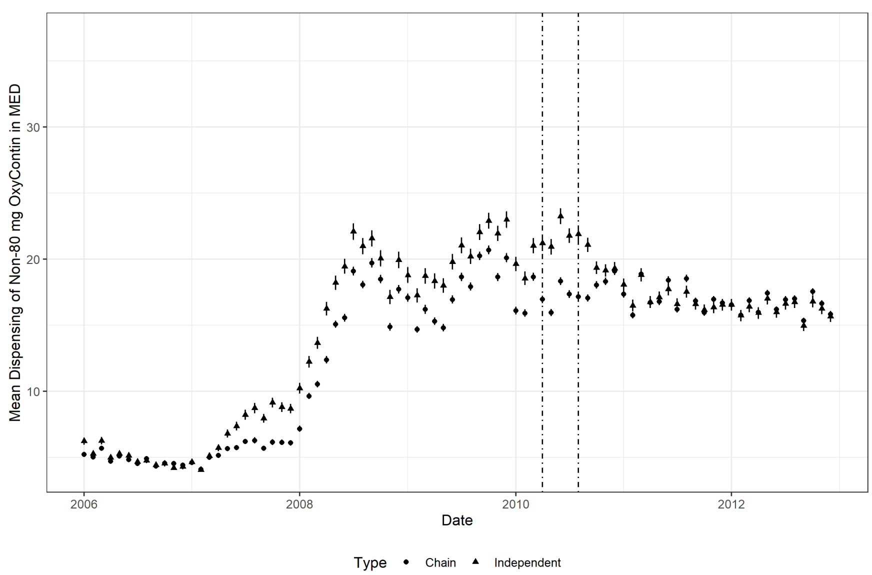
[27] Four states required dispensers to access the PDMP database before dispensing controlled substances between 2006 and 2012: Ohio in August 2011, West Virginia in June 2012, Kentucky in July 2012, and New Mexico in August 2012 (PDMP Training and Technical Assistance Center 2021; Prescription Drug Abuse Policy System 2016).

Figure G.3: OxyContin Dispensing, Chain vs. Independent Pharmacies, 80 mg and Non–80 mg

(a) 80 mg OxyContin



(b) Non–80 mg OxyContin



Notes: The figures show average dispensing of OxyContin in MED for chain and independent pharmacies between 2006 and 2012. Figure (a) shows mean dispensing of 80 mg OxyContin, while Figure (b) considers all but 80 mg OxyContin. 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 G.2: OxyContin Reformulation: 80 mg vs. Non–80 mg OxyContin

	OxyContin							
	Full sample: 2006–2012				Subsample: 2008–2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 80 mg OxyContin								
Independent*Post	−4.468***	−4.619***	−5.191***	−4.295***	−7.746***	−7.770***	−8.198***	−6.925***
	(0.406)	(0.406)	(0.439)	(0.377)	(0.536)	(0.536)	(0.563)	(0.474)
independent	8.635***	8.788***	13.036***		11.913***	11.938***	16.700***	
	(0.514)	(0.515)	(0.617)		(0.668)	(0.668)	(0.779)	
Post	0.803***				−1.858***			
	(0.096)				(0.118)			
Constant	9.779***				12.440***			
	(0.178)				(0.217)			
Mean outcome	12.98	12.98	12.98	12.98	14.85	14.85	14.85	14.85
Mean effect in percent	−34.41	−35.58	−39.98	−33.08	−52.16	−52.32	−55.21	−46.63
N	5,055,761	5,055,761	5,055,761	5,054,885	3,653,388	3,653,388	3,653,388	3,652,557
R^2	0.004	0.010	0.122	0.592	0.008	0.009	0.137	0.664
Panel B: Non–80 mg OxyContin								
Independent*Post	−1.612***	−1.799***	−1.780***	−1.052***	−2.673***	−2.700***	−2.631***	−2.104***
	(0.190)	(0.188)	(0.198)	(0.177)	(0.210)	(0.210)	(0.218)	(0.193)
Independent	1.856***	2.045***	5.749***		2.916***	2.945***	7.517***	
	(0.233)	(0.233)	(0.287)		(0.323)	(0.323)	(0.382)	
Post	5.310***				0.545***			
	(0.078)				(0.079)			
Constant	11.688***				16.453***			
	(0.120)				(0.163)			
Mean outcome	14.10	14.10	14.10	14.10	17.38	17.38	17.38	17.38
Mean effect in percent	−11.43	−12.76	−12.63	−7.46	−15.38	−15.53	−15.14	−12.11
N	5,055,761	5,055,761	5,055,761	5,054,885	3,653,388	3,653,388	3,653,388	3,652,557
R^2	0.006	0.035	0.205	0.651	0.001	0.006	0.217	0.740
Year-month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ZIP code FE	No	No	Yes	No	No	No	Yes	No
Pharmacy FE	No	No	No	Yes	No	No	No	Yes

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3). One observation corresponds to a pharmacy within a month. The outcome variable is OxyContin dispensing in MED per month at the pharmacy level. Panel A examines the dispensing of 80 mg OxyContin, the most likely abused OxyContin type. Panel B examines non–80 mg OxyContin dispensing. *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 ZIP code level, adjusted for within-cluster correlation, and reported in parentheses.

state electronic database that tracks patients' prescription histories. There are two types of PDMPs: voluntary and must-access PDMPs. The difference is whether 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; Grecu et al. 2019; Meinhofer 2018). Four states had implemented must-access laws for dispensers (including pharmacists) during 2006–2012: Ohio in August 2011, West Virginia in June 2012, Kentucky in July 2012, and New Mexico in August 2012 (PDMP Training and Technical Assistance Center 2021; Prescription Drug Abuse Policy System 2016).

We estimate the following event study model to examine if must-access PDMPs for dispensers help independent pharmacies to reduce their dispensing compared with chains:

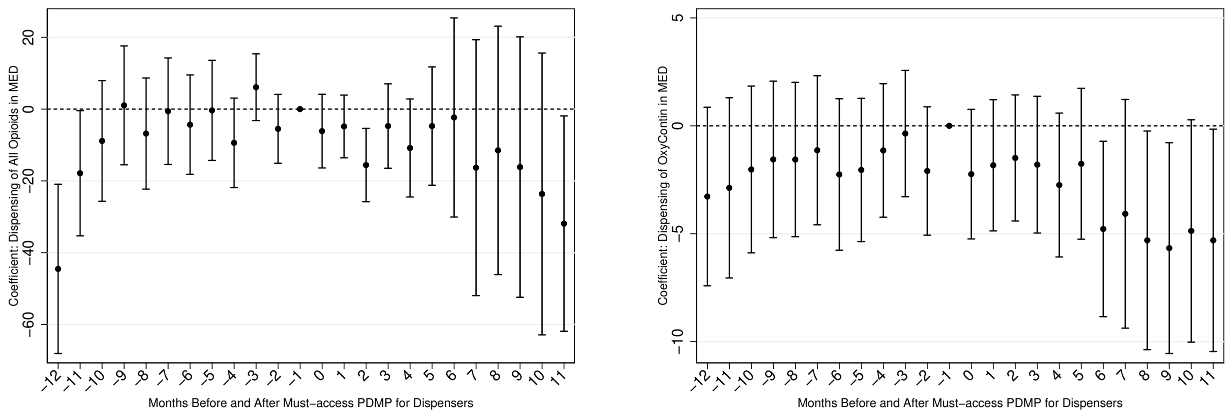
$$Y_{it} = \sum_{k=-12}^{k=11} \beta_1^k Independent_i * T_{isk} + \sum_{k=-12}^{k=11} \beta_2^k T_{isk} + \beta_3 Independent_i \cdot \mu_t + \mu_t + \alpha_i + \varepsilon_{it}, \qquad (15)$$

where T_{isk} = 1 if a pharmacy i in state s implemented a must-access PDMP for dispensers k months ago (or if k is negative, will implement a PDMP k months in the future). We denote the first post-period after the implementation with $k = 0$. We combine all post-periods after 12 months ($k > 11$) into $k = 11$, and all pre-periods more than one year prior into $k = -12$. The reference month is $k = -1$, the last month before the implementation of PDMP in state s. $Independent_i \cdot \mu_t$ captures the differences between independent and chain pharmacies over time across all US states.

Figure H.1 shows the results of the must-access PDMP for dispensers on prescription opioid dispensing by independent pharmacies relative to chains, i.e., β_1^k in equation (15). The left figure shows the impact on all prescription opioids dispensed, and the right figure shows the impact on OxyContin dispensed. In general, the must-access PDMP had limited impact on the total opioids and OxyContin dispensed by independent pharmacies relative to chain pharmacies. As the must-access PDMP implementation timing is staggered, the event study coefficients from the two-way fixed effects model might be biased if there are heterogeneous effects across treatment cohorts (Sun and Abraham 2020). Therefore, we also show results by adopting the estimation method from Sun and Abraham (2020) in Figure H.2. The point estimates are moderately different from the estimates we get from the two-way fixed effects model, but the main takeaways remain the same, i.e., must-access PDMP had limited impact on the total opioids and OxyContin dispensed by independent pharmacies relative to chain pharmacies.

Therefore, even though a must-access PDMP might help reduce the gap between independent and chain pharmacies slightly, it is less likely that the difference in internal tracking systems can be a main explanatory factor for the difference in dispensing for non-medical demand by independent and chain pharmacies.

Figure H.1: Must-access PDMP for Dispensers and Prescription Opioid Dispensing



(a) All prescription opioids (b) OxyContin

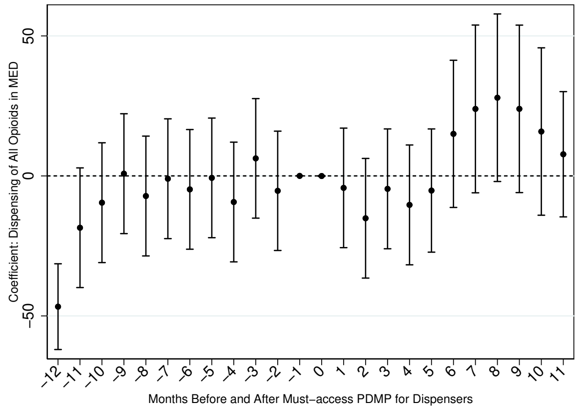
Notes: The figures show the effect of the must-access PDMP for dispensers on prescription opioid dispensing or OxyContin dispensing by independent pharmacies relative to chain pharmacies before and after the implementation of a must-access PDMP, i.e., β_1^k in equation (15). Relative month -1 is the reference point, the month right before the implementation of a PDMP. To analyze the impact of PDMPs, we use four states that required dispensers to access the PDMP database before dispensing controlled substances between 2006 and 2012: Ohio in August 2011, West Virginia in June 2012, Kentucky in July 2012, and New Mexico in August 2012. The error bars correspond to the 95% confidence interval of the estimates. Standard errors are clustered at the ZIP code level and adjusted for within-cluster correlation and heteroskedasticity.

H.2 Difference in Price

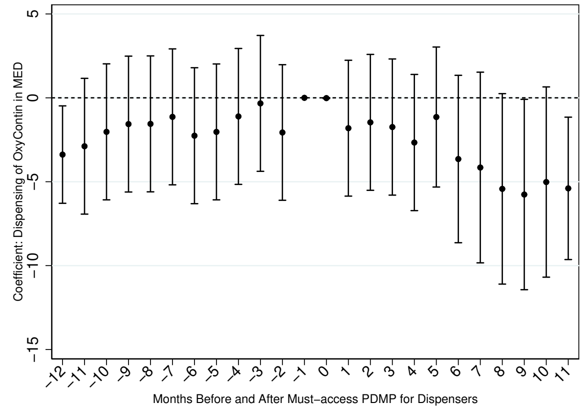
Another difference between independent and chain pharmacies that may lead to different dispensing for non-medical demand is the difference in price. However, we find mixed evidence on whether independent or chain pharmacies offer lower prices. For example, Luo et al. (2019) find that independent pharmacies on average charge higher cash prices than chains across the US.[28] In addition, Gellad et al. (2009) use data from Florida and find that independent pharmacies in poor areas charge the highest prices. However, Arora et al. (2017) find that independent pharmacies offer lower prices when checking prices by phone calls in Los Angeles County. Moreover, Luo et al. (2019) documents that for brand-name drugs, the variation in price is much smaller, even though independent pharmacies still offer more expensive prices than chains on average. Therefore, it

[28] Cash price is the price available at any retail pharmacy for consumers without prescription drug coverage or do not want to use their prescription insurance to fill their prescriptions.

Figure H.2: Must-access PDMP for Dispensers and Prescription Opioid Dispensing, Robustness



(a) All opioids, Sun and Abraham (2020)



(b) OxyContin, Sun and Abraham (2020)

Notes: The figures show the effect of the must-access PDMP for dispensers on prescription opioid dispensing or OxyContin dispensing by independent pharmacies relative to chain pharmacies before and after the implementation of a PDMP, i.e., β_1^k in equation (15), using the estimation method from Sun and Abraham (2020). Relative month -1 is the reference point, the month right before the implementation of a PDMP. To analyze the impact of PDMPs, we use four states that required dispensers to access the PDMP database before dispensing controlled substances between 2006 and 2012: Ohio in August 2011, West Virginia in June 2012, Kentucky in July 2012, and New Mexico in August 2012. The error bars correspond to the 95% confidence interval of the estimates. Standard errors are clustered at the ZIP code level and adjusted for within-cluster correlation and heteroskedasticity.

is not very likely that independent pharmacies dispense more opioids (especially OxyContin, the brand-name drug) because they offer lower prices.

H.3 Difference in Human Capital

In addition, 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 and have lax rules. 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 (Centers for Disease Control and Prevention 2016; Dowell et al. 2016).[29] Therefore, neither the older nor the younger pharmacists would have had this information prior to 2016. As for the on-the-job training, both the

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

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). However, evidence from small-scale interviews does reveal that pharmacists in chain pharmacies have more rules and regulations and tend to ask more questions about opioid prescriptions (Rigg et al. 2010). Therefore, evidence on human capital is also mixed and inconclusive.