Online Appendix for Retail Pharmacies and Drug Diversion during the Opioid Epidemic

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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.[1] 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.

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[1] 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

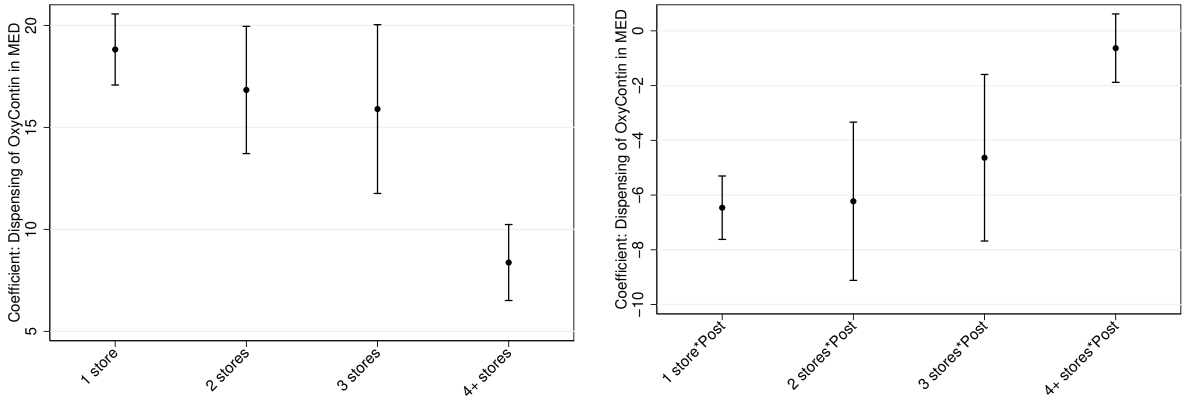
Notes: We identify number of stores using the pharmacy name-state-month combinations. The reference group is chain pharmacies in the ARCOS data. *No. of stores* measures the number of stores an independent pharmacy (as defined by the ARCOS data) has in a month. Standard errors are clustered at the ZIP 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

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.

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.

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

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.

from a basic regression framework in the lower two subfigures:

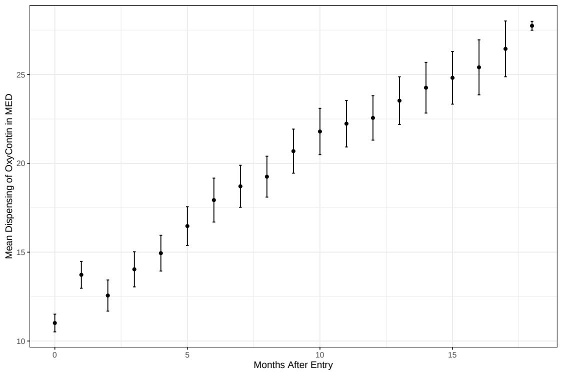
$$Y_{it} = \sum_{k=0}^{k=18} \beta_1^k Entry_{ik} + \mu_t + \alpha_i + \varepsilon_{it} \tag{1}$$

$$Y_{it} = \sum_{k=-18}^{k=0} \beta_1^k Exit_{ik} + \mu_t + \alpha_i + \varepsilon_{it}, \tag{2}$$

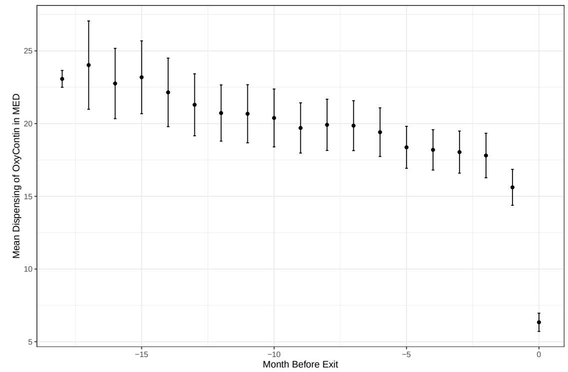
where Y_{it} are the dispensing of OxyContin. Additionally, $Entry_{ik} = 1$ if a pharmacy i enters k months ago. $Exit_{ik}$ takes the value 1 if a pharmacy exits in k months. The event study includes year-month and pharmacy fixed effects. We normalize the coefficients to periods after 18 months in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

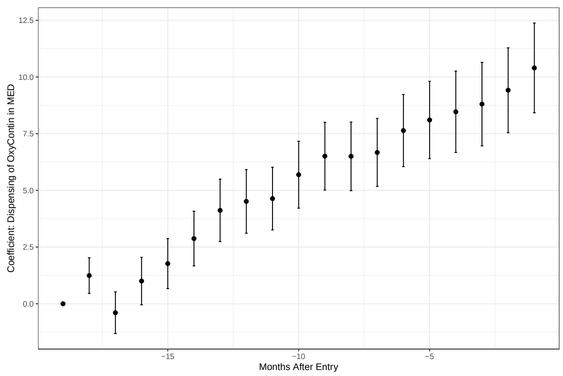
Figure B.1: Dispensing of OxyContin After Entry and Before Exits



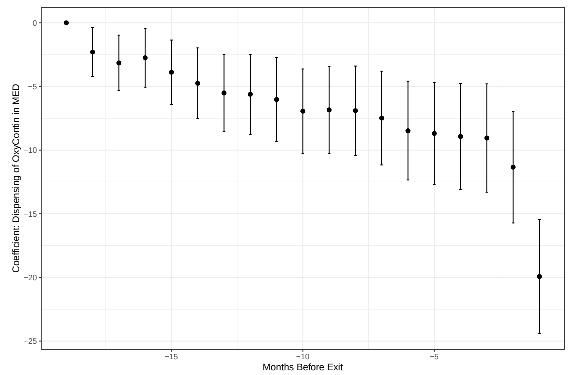
(a) Raw Trend of Dispensing After Entry



(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.

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

$$Y_{it} = \beta_1 Entry_i(Exit_i) \cdot Independent_i + \alpha_i + \mu_t + \varepsilon_{it} \tag{3}$$

$$Y_{it} = \beta_2 MonthAfterEntry_{it}(MonthBeforeExit_{it}) \cdot Independent_i + \alpha_i + \mu_t + \varepsilon_{it}, \tag{4}$$

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 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 (3), 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 (4) 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.

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 to our OxyContin reformulation in the main paper:

$$\begin{aligned} Y_{it} = & \beta Indep_i \cdot PostReform_t + \alpha_i + \mu_t + \sum_{k=1}^{K} \rho^k_{chain} CompChain_{itk}(\cdot County_i) + \\ & \sum_{k=1}^{K} \rho^k_{indep} CompIndep_{itk}(\cdot County_i) + \varepsilon_{it}. \end{aligned} \tag{5}$$

In comparison to the main analysis, we add individual regressors for the number of competing

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

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.

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

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

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.

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).[2] 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.

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

Notes: Results of the OxyContin reformulation regression analysis in equation (5) 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.

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

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

Notes: Results of the OxyContin reformulation regression analysis in equation (5) 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.

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.

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

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.

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 geographic × 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 × year-month fixed effects.

Table C.4 shows the result of the direct comparison. With ZIP code × 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 × year-month fixed effects added, which have the same sign as our main estimates. Compared with Table 4 of the main paper, 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.

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

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3) in the main article. 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

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.

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 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:

$$Y_{it} = \beta Independent_i + \mu_t + \gamma_{FE} + \varepsilon_{it}, \tag{6}$$

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.

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

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3) in the main article. 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.

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.

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

Notes: Results of a direct comparison between independent and chain pharmacies in equation (1) in the main article. 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..

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

$$Y_{it} = \beta_0 D_{it}^{PRE} + \beta_1 D_{it}^{POST} + \beta_C CHAIN_i + \alpha_i + \mu_t + \varepsilon_{it}, \tag{7}$$

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.

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

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.

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

$$Y_{it} = \beta Independent_i \cdot Post_t + \alpha_i + \mu_t + \varepsilon_{it}, \tag{8}$$

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 of the main article.

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3) in the main article. 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, Fortin and Lemieux (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.

E Event Studies

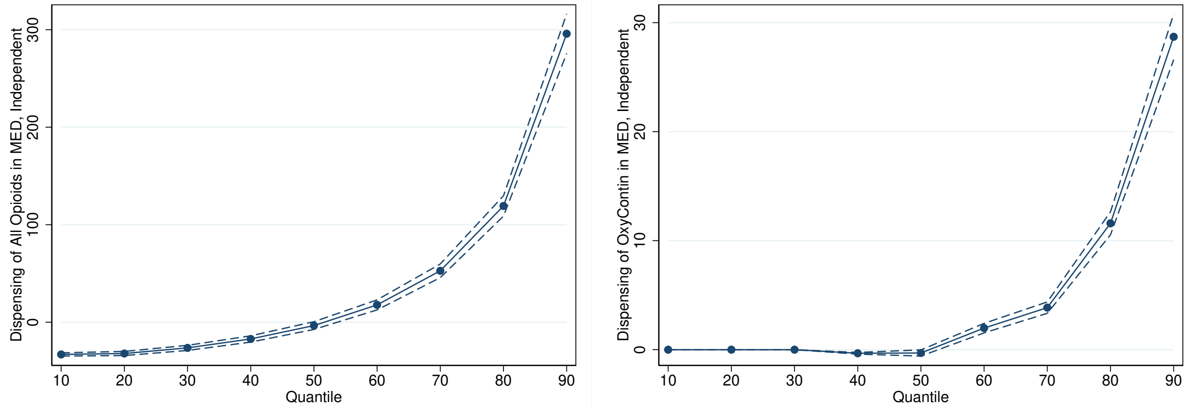
E.1 Pharmacy Ownership Change: Independent to Chain Pharmacy

In Section III, 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:

$$Y_{it} = \sum_{k=-12}^{k=11} \beta_1^k T_{ik} + \mu_t + \alpha_i + \varepsilon_{it}, \tag{9}$$

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

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



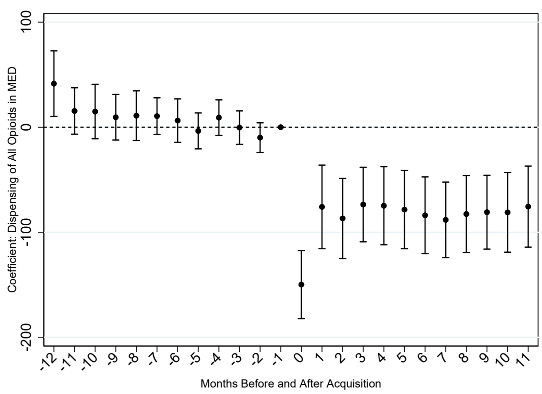
Notes: The figure reports regression coefficients of the effects of independent ownership on dispensing of all prescription opioids and OxyContin (in MED) at different quantiles from unconditional quantile regressions. Year-month and ZIP code fixed effects are included. The dashed lines are the 95% confidence interval based on standard errors clustered at the ZIP code level to control for within-cluster correlation.

$k = 11$, 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}.

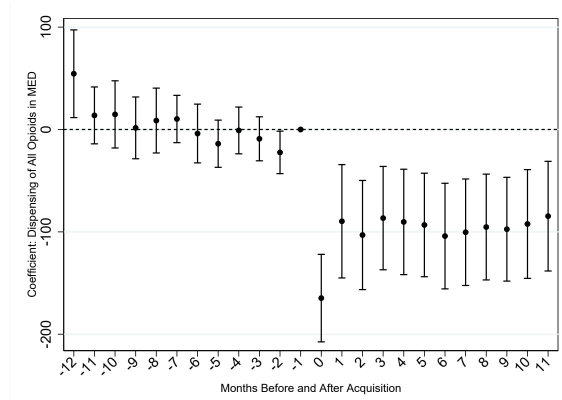
We start with estimating the model using an two-way fixed effects using OLS. Recent literature shows that linear regressions with period and group fixed effects could be biased in case of a staggered treatment design and heterogeneous treatment effects across cohorts (Sun and Abraham, 2021). We therefore also estimate a robust estimator based on Sun and Abraham (2021). 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 (2021). 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

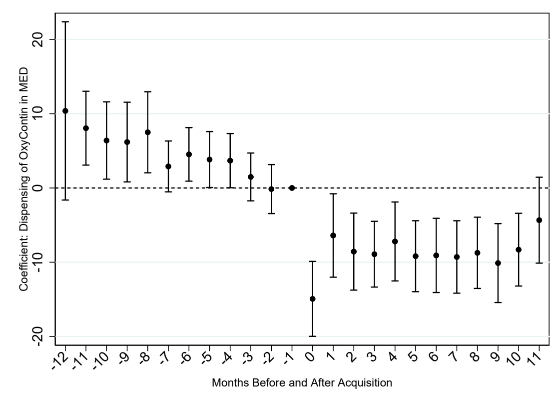
Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcomes are dispensing of opioids and OxyContin in MED. The plotted coefficients 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.

E.2 OxyContin Reformulation

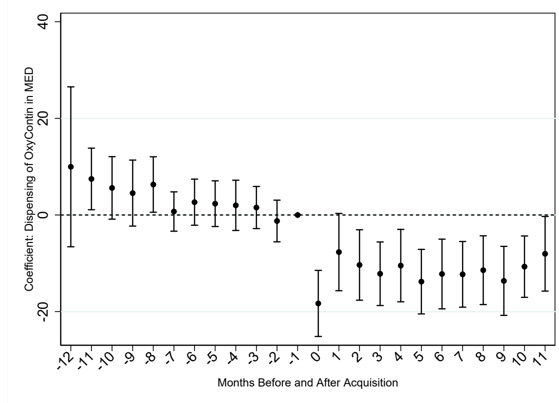
In Section IV, we show the average treatment effects due to the OxyContin reformulation. In the following, we do the event study analysis to assess the pre-trend and the dynamic effects of the OxyContin reformulation on dispensing by independent pharmacies relative to chains:

$$Y_{it} = \sum_{k=-12}^{k=11} \beta_1^k Independent_i * T_k + \mu_t + \alpha_i + \varepsilon_{it}, \tag{10}$$

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

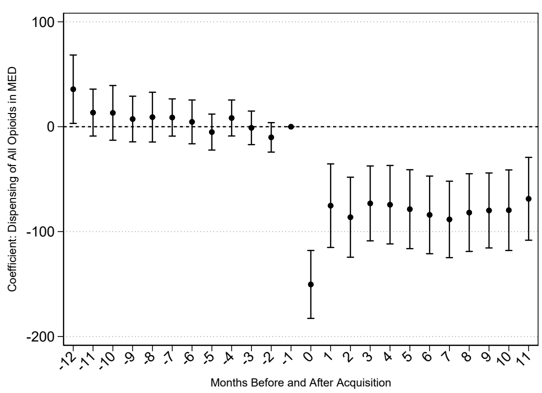
Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. The outcome dispensing of OxyContin in MED. The plotted coefficients from $k = -12$ 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.

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}.

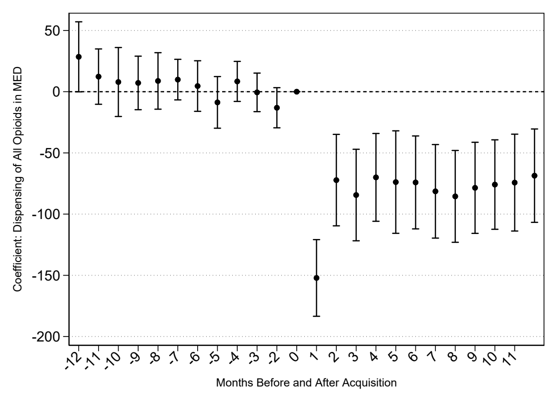
In addition, since the new OxyContin formula was approved by the FDA in April 2010, even though the first shipment did not occur until August 2010, we suspect there might have been some anticipatory stockpiling behavior by drug abusers and drug dealers. Therefore, we also do the event study analysis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

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



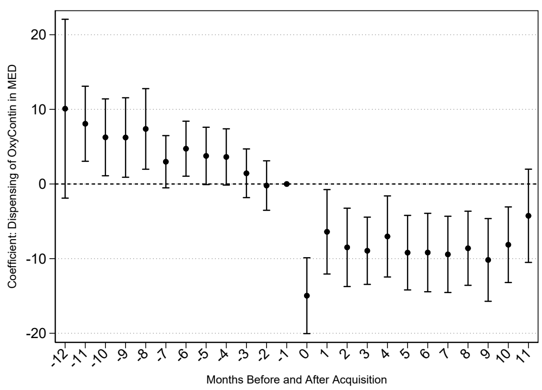
(a) Dispensing of all opioids in MED, two-way Fixed Effects



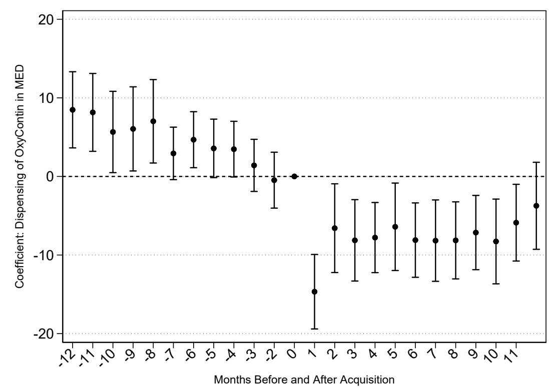
(b) Dispensing of all opioids in MED, Sun and Abraham (2021)

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 (2021). 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

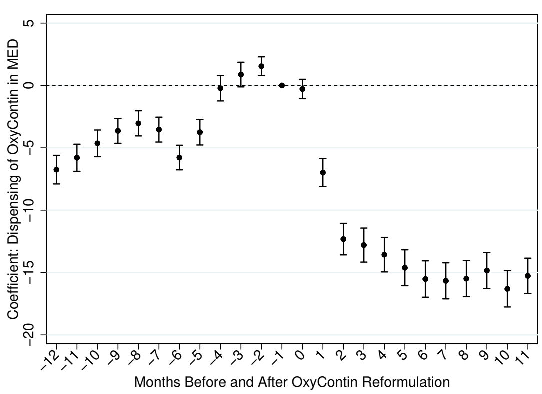


(b) Dispensing of OxyContin in MED, Sun and Abraham (2021)

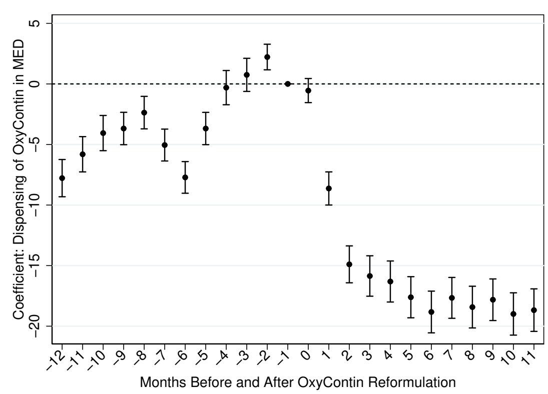
Notes: The figure presents coefficients from the event study of pharmacies with an ownership change. The sample is based on the 304 treatment groups and 900 random control groups. One observation corresponds to a pharmacy within a month that changes ownership from an independent to a chain pharmacy. 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 (2021). Standard errors are clustered at the ZIP code level to control for within-cluster correlation.

fixed effects and year-month fixed effects, and (2) with ZIP code × 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 × 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 of the main article.

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



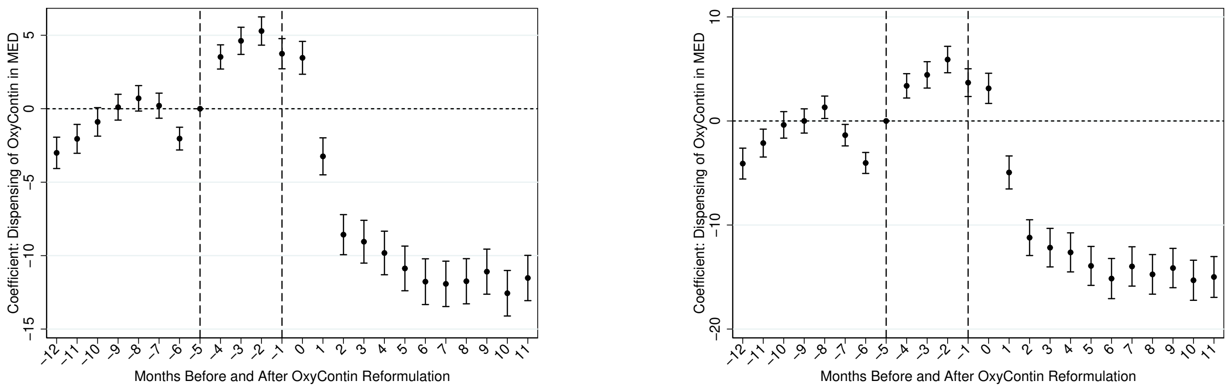
(a) Dispensing of OxyContin in MED, pharmacy and year-month fixed effects



(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.[3] 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.[4] Compared with the three major pharmacy chains, independent pharmacies still

[3]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.

[4]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

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.

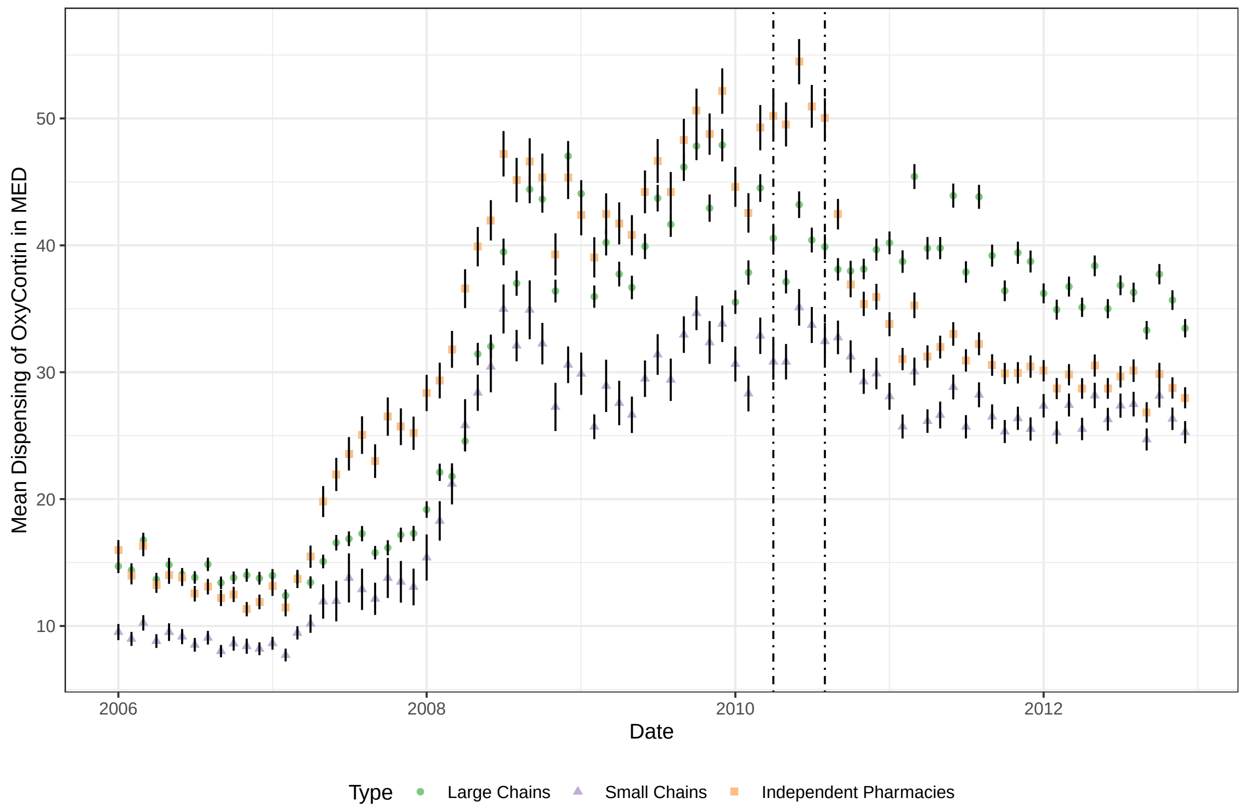
Table F.1: OxyContin Reformulation: Smaller Chains, Independent Pharmacies, and Large Chains

	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

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.

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.

G Robustness Checks of the OxyContin Reformulation

G.1 Excluding Florida

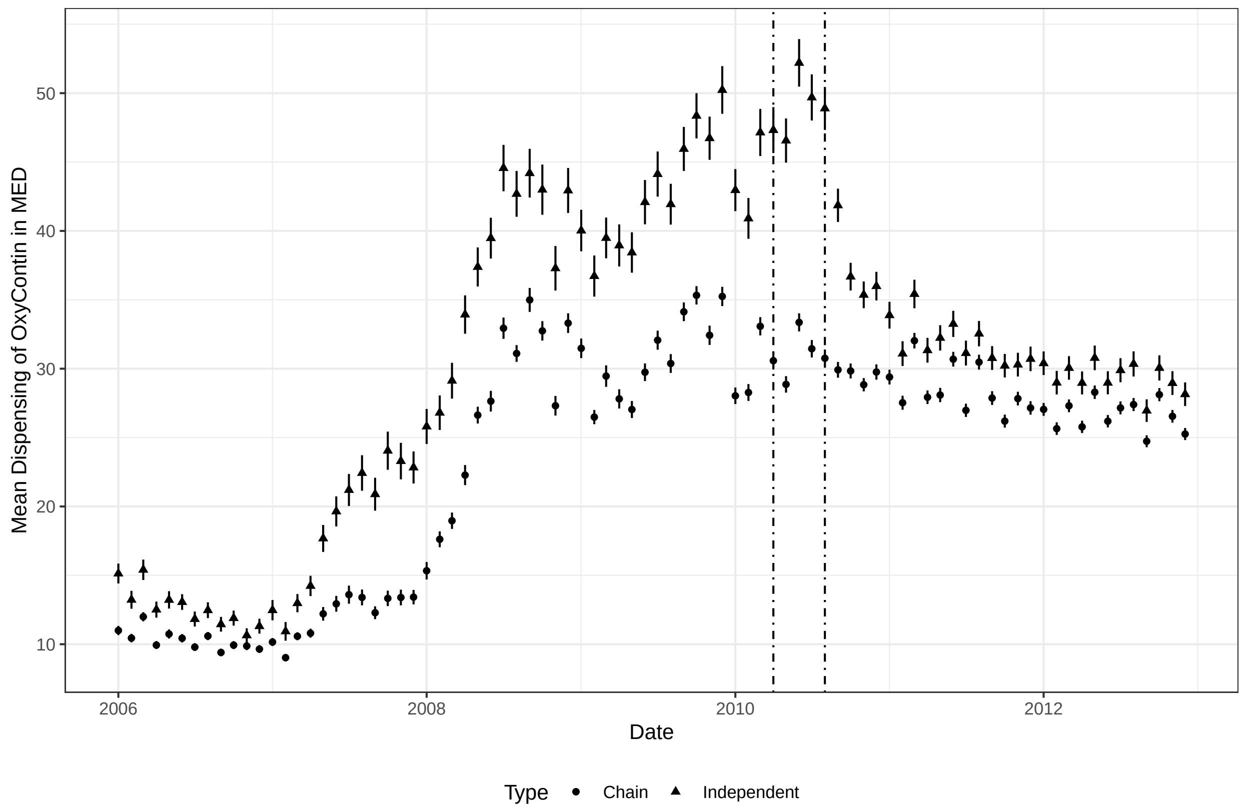
According to federal officials, by the clinics' peak in 2010, 90 of the nation's top 100 opioid prescribers were Florida doctors, and 85% of the nation's oxycodone was prescribed in the state (Spencer 2019). That year alone, about 500 million pills were sold in Florida. The number of people who died in Florida with oxycodone or another prescription opioid in their system hit 4,282 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%).

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.

Figure G.1: OxyContin Reformulation, Excluding Florida



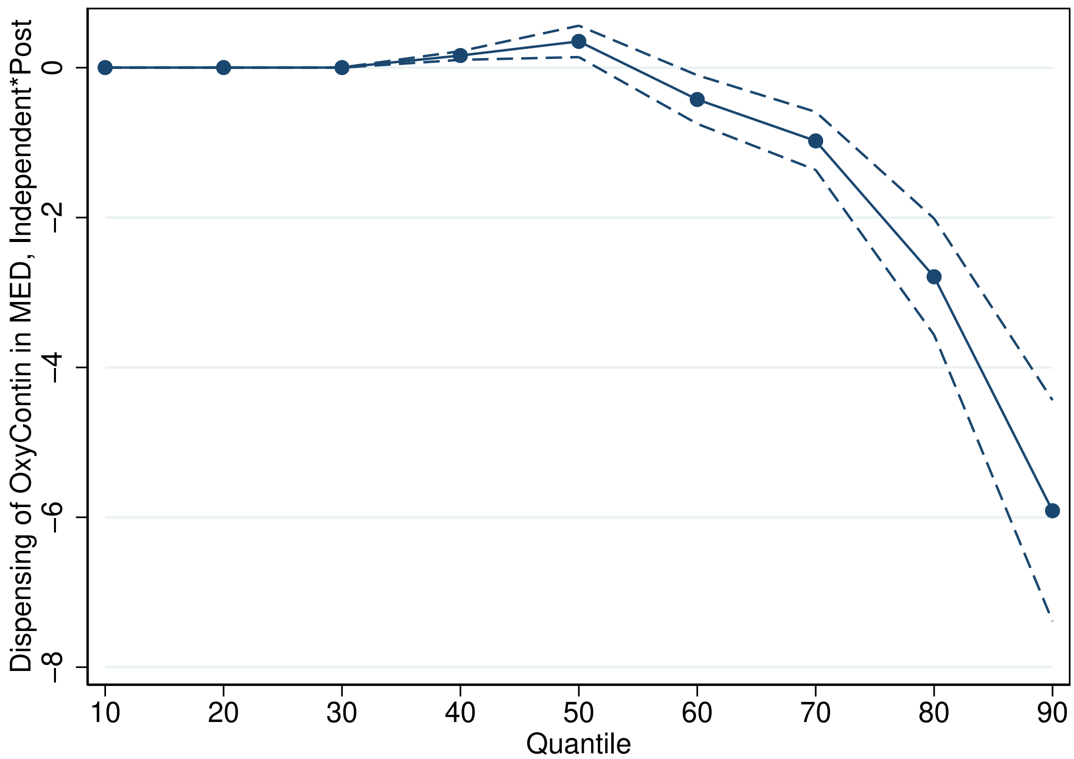
Notes: The figure shows the average dispensing of OxyContin in MED for chain and independent pharmacies between 2006 and 2012 without Florida. The first vertical line is April 2010, when the new OxyContin was approved by the FDA. The second vertical line corresponds to August 2010, when the new formula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

Table G.1: Robustness Checks, OxyContin Reformulation

	OxyContin				
	Baseline	Exclude Florida	Exclude top 1%	Exclude top 5%	Exclude top 10%
	(1)	(2)	(3)	(4)	(5)
Independent*Post	−5.339	−3.741	−2.491	−1.057	−0.890
	(0.484)	(0.417)	(0.293)	(0.223)	(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

Notes: Results of the OxyContin reformulation regression analysis in equation (3) in the main article 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.

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.

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 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) of the main article. 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 in the main article 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 V, 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 V.

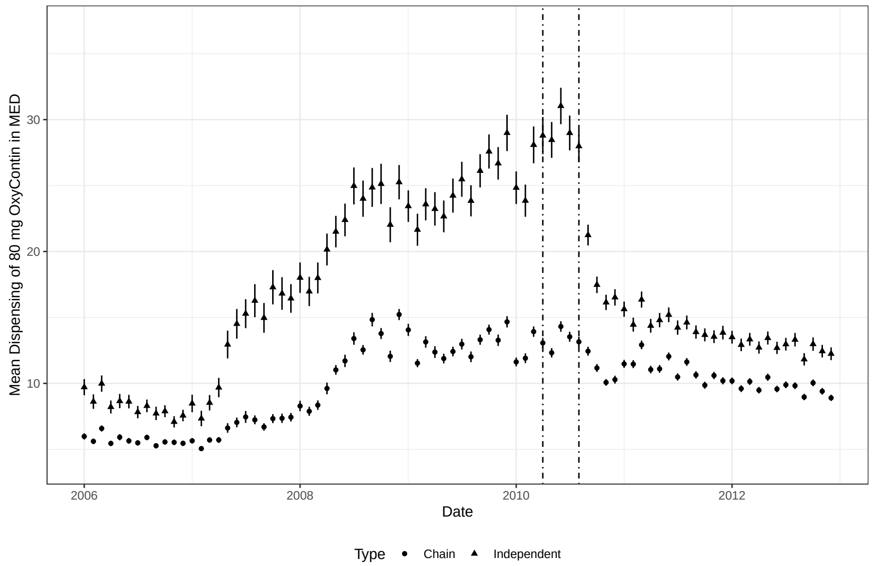
H.1 Difference in Internal Database

Compared with chain pharmacies, independent pharmacies may have lower levels of non-human capital, such as insufficient internal tracking systems.[5] 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

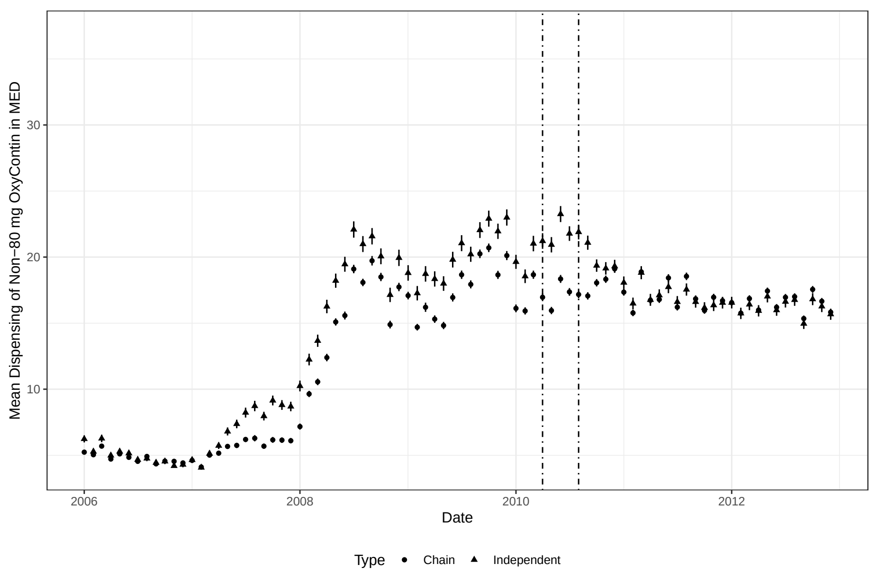
[5] Another difference is the security level. However, as pharmacy theft and robberies account for only 1.5% of drug diversion (Inciardi et al. 2007), we think security has only a limited impact. In fact, regarding security, existing studies do not find an average difference between independent and chain pharmacies. If anything, chain pharmacies have more cases of theft and robbery of controlled substances (Pharmacists Mutual 2016).

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

Notes: Results of the OxyContin reformulation regression analysis in equation (3) in the main article. 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.

the data network of chain pharmacies may deter some drug abusers and dealers from going there (Rigg, March and Inciardi 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.[6]

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, Mukherjee and Schnell 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-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, Dave and Saffer 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:

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

where $T_{isk} = 1$ if a pharmacy i in state s implemented a must-access PDMP for dispensers k months

[6] 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).

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 (11). 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 2021). Therefore, we also show results by adopting the estimation method from Sun and Abraham (2021) 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.

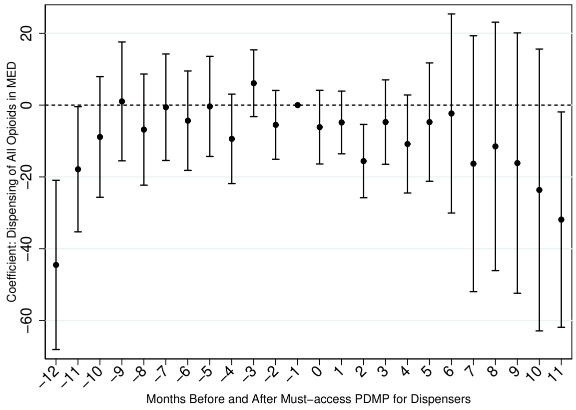
Therefore, even though a must-access PDMP might help reduce the gap between independent and chain pharmacies slightly, it is less likely that the difference in internal tracking systems can be a main explanatory factor for the difference in dispensing for non-medical demand by independent and chain pharmacies.

H.2 Difference in Price

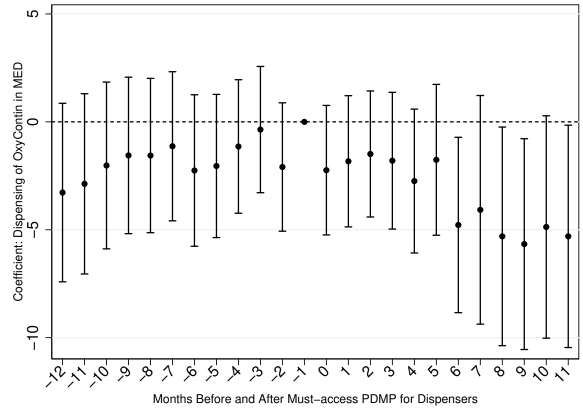
Another difference between independent and chain pharmacies that may lead to different dispensing for non-medical demand is the difference in price. However, we find mixed evidence on whether independent or chain pharmacies offer lower prices. For example, Luo et al. (2019) find that independent pharmacies on average charge higher cash prices than chains across the US.[7] In addition, Gellad et al. (2009) use data from Florida and find that independent pharmacies in poor

[7] 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.1: Must-access PDMP for Dispensers and Prescription Opioid Dispensing



(a) All prescription opioids



(b) OxyContin

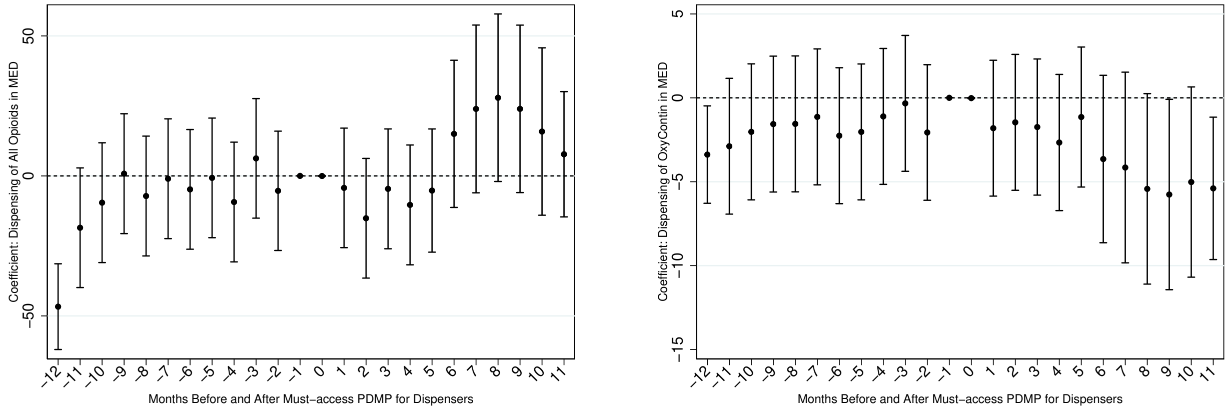
Notes: The figures show the effect of the must-access PDMP for dispensers on prescription opioid dispensing or OxyContin dispensing by independent pharmacies relative to chain pharmacies before and after the implementation of a must-access PDMP, i.e., β_1^k in equation (11). Relative month -1 is the 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.

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 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, Brown and Sogol 2007). However, medical and pharmacy schools only added opioid

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



(a) All opioids, Sun and Abraham (2021)

(b) OxyContin, Sun and Abraham (2021)

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 (11), using the estimation method from Sun and Abraham (2021). 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.

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, Haegerich and Chou 2016).[8] 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 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, Brown and Sogol 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, March and Inciardi 2010). Therefore, evidence on human capital is also mixed and inconclusive.

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

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