This is the Online Appendix (not for publication) for "Disrupting Drug Markets: The Effects of Crackdowns on Rogue Opioid Suppliers" by Adam Soliman.

Additional Figures

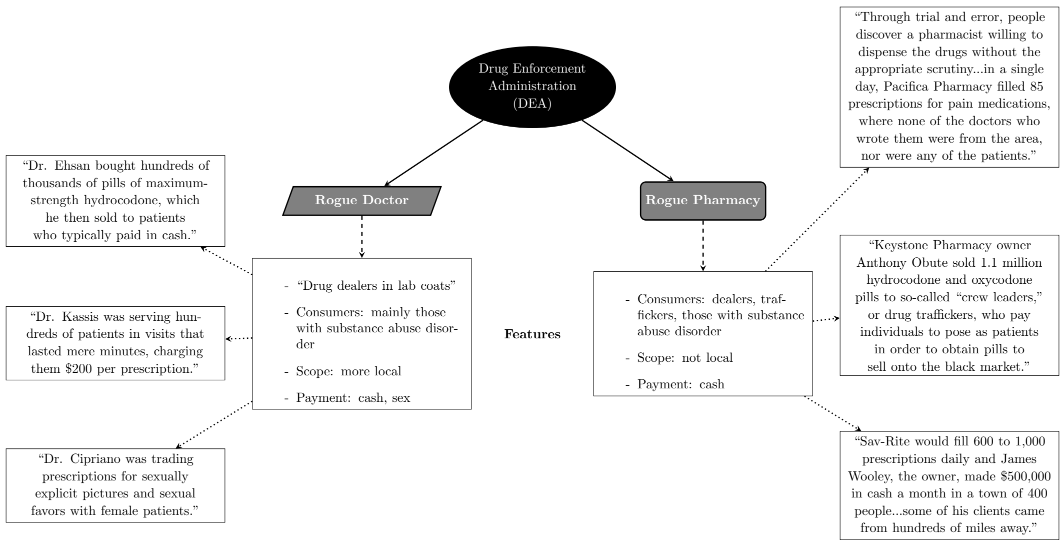


Figure A.1. : Descriptions of Rogue Doctors and Pharmacies

Notes: This flow chart captures excerpts from interviews with a DEA agent and a DEA litigation and compliance attorneys, news media articles, and DEA Diversion Control Division reports.

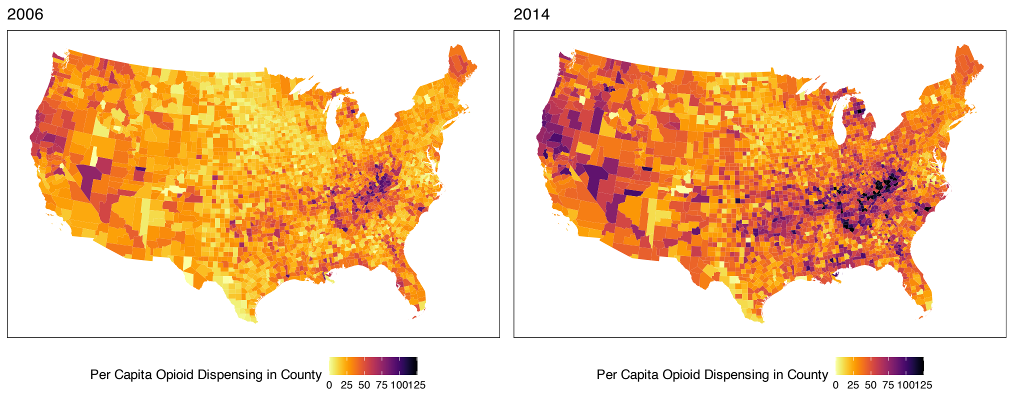


Figure A.2. : Opioid Dispensing Changes by County

Notes: These figures capture the cross sectional variation in annual per capita opioid pill volume dispensed in a county at the beginning (2006) and end (2014) of my sample period. The same scale is used in each figure to highlight the growth in dispensing, where 2912 of the 3108 contiguous counties experienced an increase from 2006 to 2014.

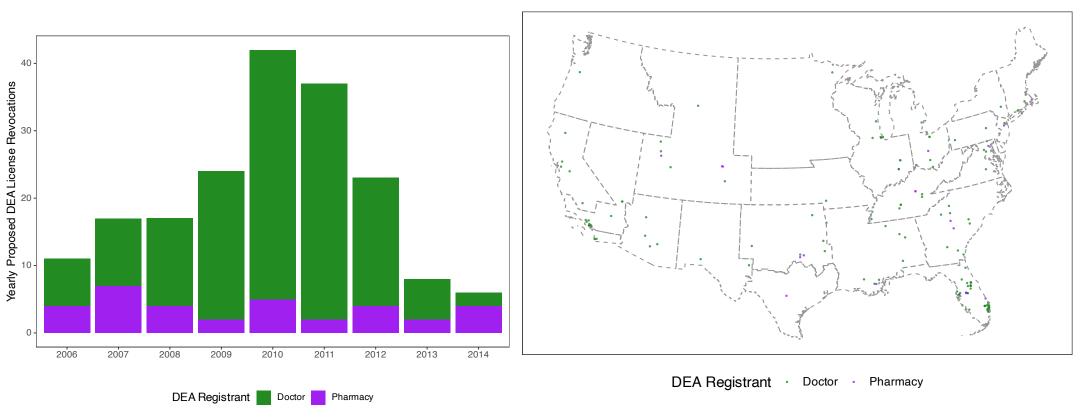


Figure A.3. : Yearly DEA Crackdowns from 2006 to 2014

Notes: The left panel shows the annual number of Orders to Show Cause related to a proposed revocation of a license with a final decision issued due to a Controlled Substance Act violation stemming from a DEA audit by registrant type. This is my primary treatment measure. The right panel shows where these administrative actions are issued and the dashed gray lines are DEA jurisdiction boundaries.

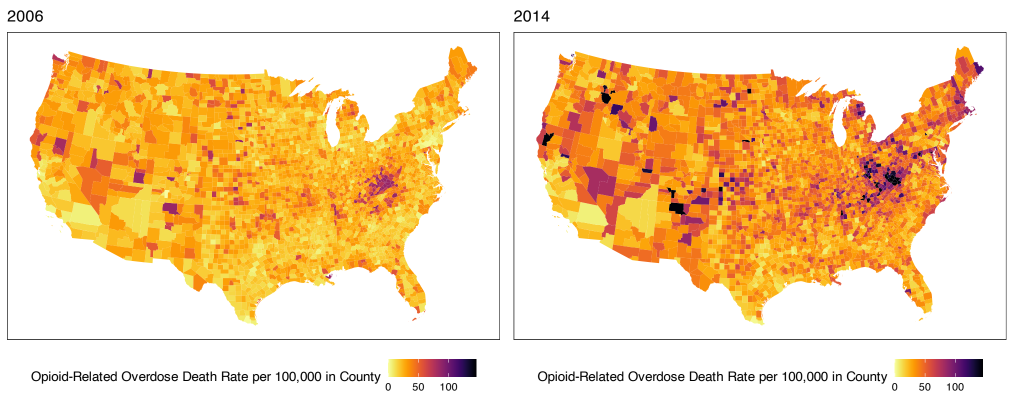


Figure A.4. : Opioid-Related Overdose Death Changes by County

Notes: These figures capture the cross sectional variation in opioid-related overdose death rates in a county at the beginning (2006) and end (2014) of my sample period. County rates are calculated by dividing opioid-related overdose deaths from the CDC by population of that year. 2628 of the 3108 contiguous counties experience increases in their overdose rate from 2006 to 2014. Similar to Griffith et al. (2021), opioid-related deaths were determined using the following ICD-10 codes: T40.0 (Opium), T40.1 (Heroin), T40.2 (Other opioids), T40.3 (Methadone), T40.4 (Other synthetic narcotics), T40.6 (Other and unspecified narcotics), X40-X44 (Accidental poisoning), X60-64 (Intentional self-poisoning), Y10-Y14 (Poisoning) by non-opioid analgesics, antipyretics and antirheumatics; antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified; narcotics and psychodysleptics [hallucinogens], not elsewhere classified; other drugs acting on the autonomic nervous system; other and unspecified drugs, medicaments and biological substances. I also include ICD-10 code X85 (Assault by drugs, medicaments and biological substances).

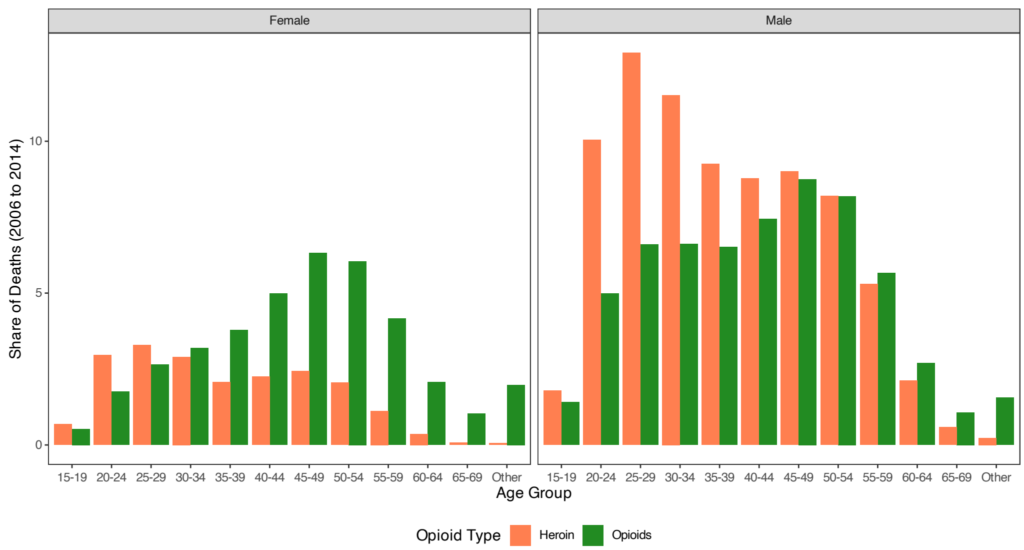


Figure A.5. : Differences in Age Profiles of Overdose Deaths by Opioid Type and Gender

Notes: This figure break down the shares of heroin and opioid overdose deaths separately by gender and age from 2006 to 2014. To make this more concrete, approximately 10% of all heroin overdose deaths during my sample period were suffered by males in the 20-24 age group. The same ICD-10 codes are used as in Figure A.4 and the rest of the paper.

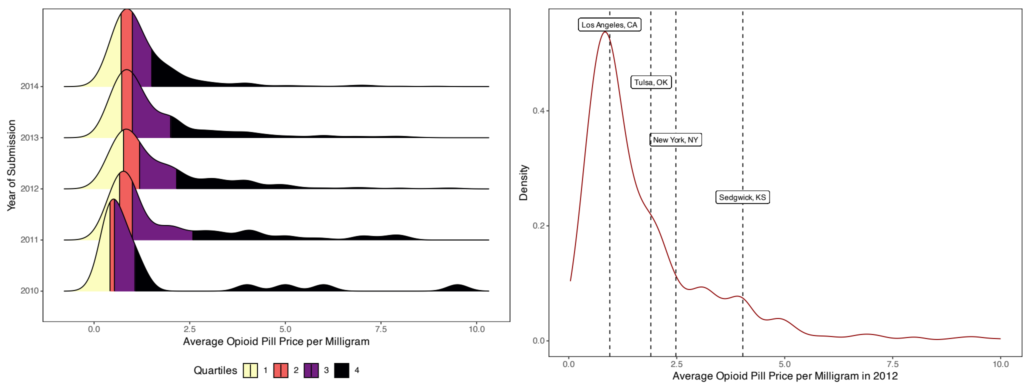


Figure A.6. : Distribution of the Average County Street Opioid Pill Price

Notes: The left panel shows how the distribution of the county-level average street opioid pill price per milligram varies during the second half of my sample period, while the right panel focuses in on 2012, where four counties are highlighted to show the significant variation in cross-sectional prices. I only consider prices for Oxycodone, Hydrocodone, and OxyContin both to match the prescription opioid data and because Dasgupta et al. (2013) validates them. I then take the average price per milligram in a given county and year to use here and in the analysis. The source of these data is StreetRx.

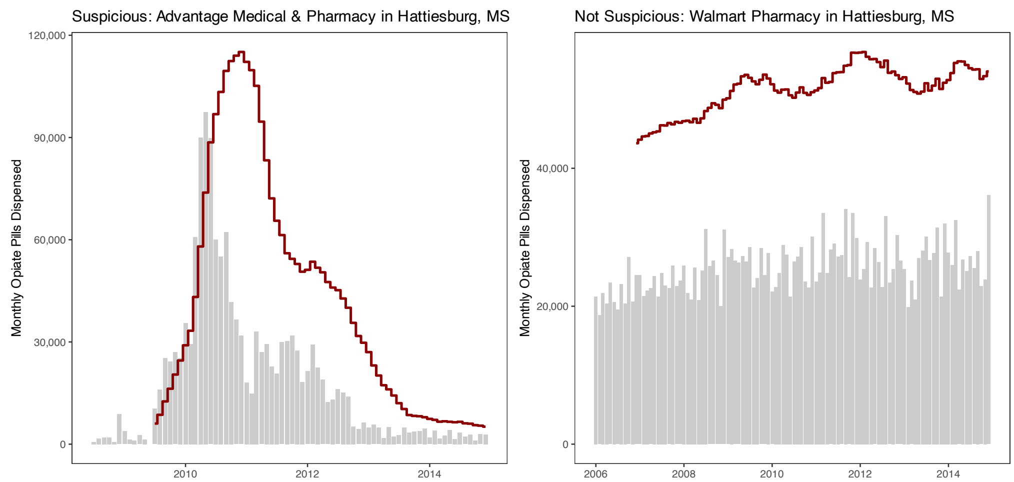


Figure A.7. : Examples of Implementing Criteria for Flagging Suspicious Orders

Notes: Gray bars show total monthly opioid pills dispensed and the red line captures the "twice the trailing 12-month average pharmacy dosage units" outlier detection threshold for each pharmacy. This recommended criteria is referenced in court documents from a lawsuit filed against opioid distributors (Ohio MDL 2804) and implicitly flags large deviations in normal dispensing behavior. Therefore, the left pharmacy would be flagged as suspicious, as monthly orders during 2009 and 2010 exceed the red line, while the right pharmacy would not be flagged.

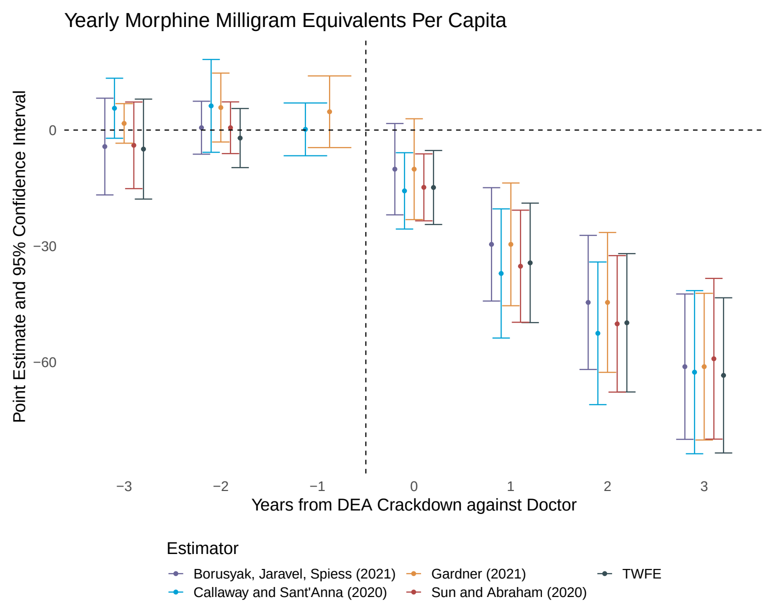


Figure A.8. : Dynamic Impact of Doctor Crackdowns on Opioid Dispensing

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with various DID estimators. The outcome is yearly morphine milligram equivalents (MME) dispensed in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor and the orange line captures the aggregated post-treatment effect, β, from estimating Equation (2). The control mean is 395 MME.

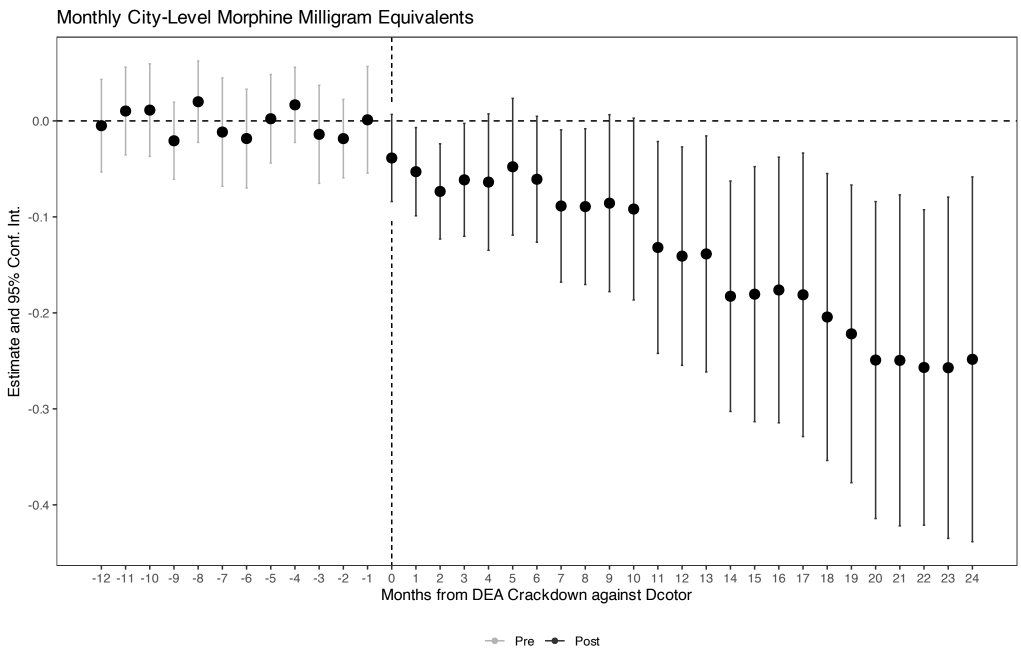


Figure A.9. : Monthly Impact of Doctor Crackdowns on Opioid Dispensing

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with city and state-by-year fixed effects. The outcome is the logarithm of monthly city-level opioids. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. The sample is limited to cities that had a doctor crackdown and thus the control group are the not yet treated cities. Standard errors are clustered at the city-level and computed using a multiplier bootstrap, and the estimation method is doubly robust from Callaway and Sant'Anna (2021). Note I cannot do this analysis for non-opioid outcomes as they are at the county-year level.

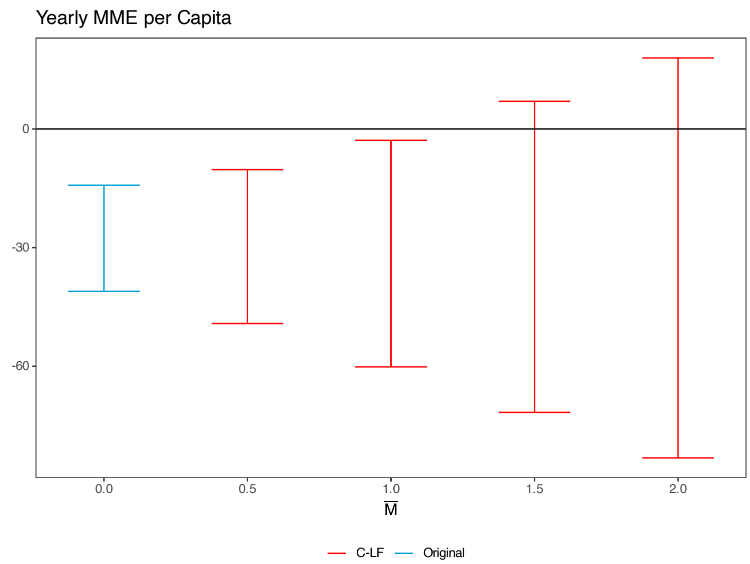


Figure A.10. : HonestDID's Sensitivity Analysis using Relative Magnitudes Restrictions

Notes: This figure shows robust confidence intervals for the treatment effect for all post-treatment periods using different values of $\bar{M}$ for morphine milligram equivalents per capita (opioid dispensing). If I impose $\bar{M} = 1$, meaning that I restrict the post-treatment violations of parallel trends to be no larger than the maximal pre-treatment violation of parallel trends, then the robust confidence set is [-60.2, -2.88]. This is wider than the original confidence interval, which is only valid if parallel trends holds exactly, but nevertheless rules out a null effect. The "breakdown value" is about $\bar{M} \approx 1.5$, thus the conclusion of a significant effect depends on whether we are willing to restrict that the post-treatment violations of parallel trends can be no more than one and a half times as large as the maximal pre-treatment violation.

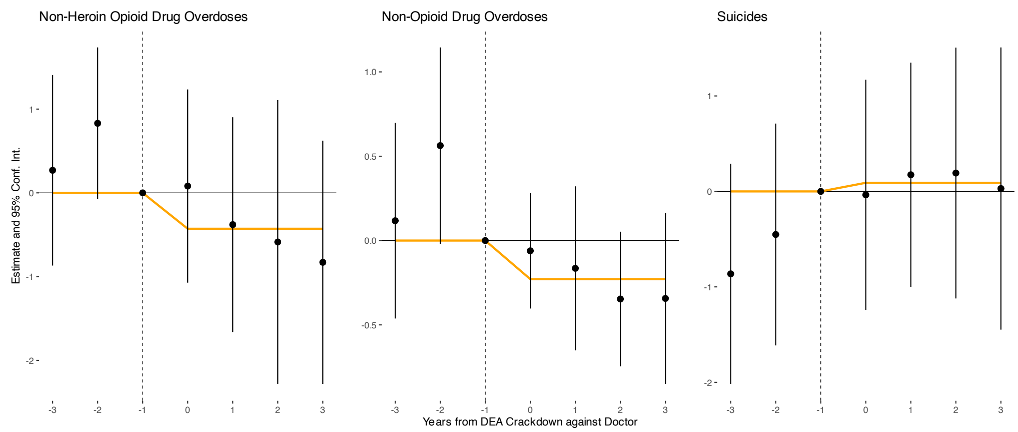


Figure A.11. : Impact of Doctor Crackdowns on Other Mortality Outcomes

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange lines capture the aggregated post-treatment effect, β, from estimating Equation (2). The outcome are various mortality rates per 100,000 residents in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor.

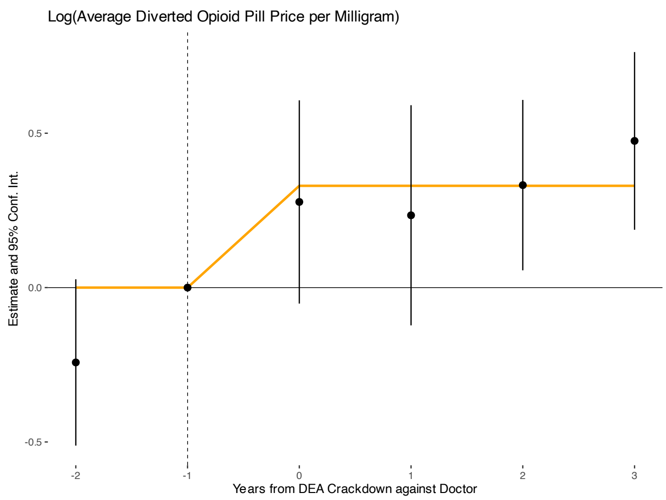
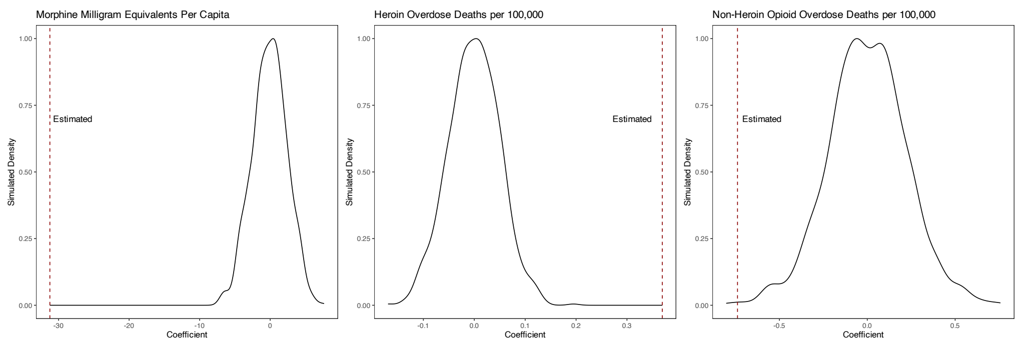


Figure A.12. : Impact of Doctor Crackdowns on Street Opioid Pill Prices

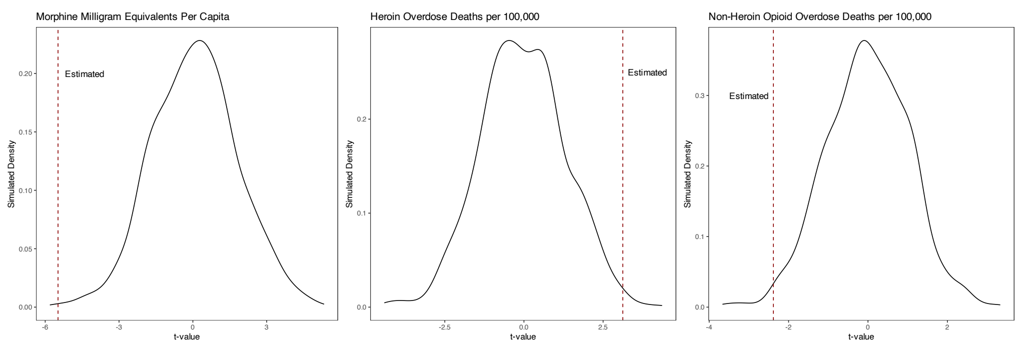
Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange line captures the aggregated post-treatment effect, β, from estimating Equation (2). The outcome is the logarithm of the average yearly county diverted pill price per milligram. I was suggested to not use data prior to 2008, which is what prevents the additional pre-period of -3 from being estimated. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor.

Figure A.13. : Permutation Test for the Impacts of Doctor Crackdowns

Panel A: Coefficients



Panel B: t-statistics



Notes: I first randomize which county gets treated by state and then conditional on receiving treatment, I randomize the year of treatment within that subset. I run Equation (2) 1000 times using this new sample, where the figures present the distribution of coefficients (Panel A) and t-statistics (Panel B) obtained from these regressions. The dotted vertical red line is the estimated coefficient or t-statistic.

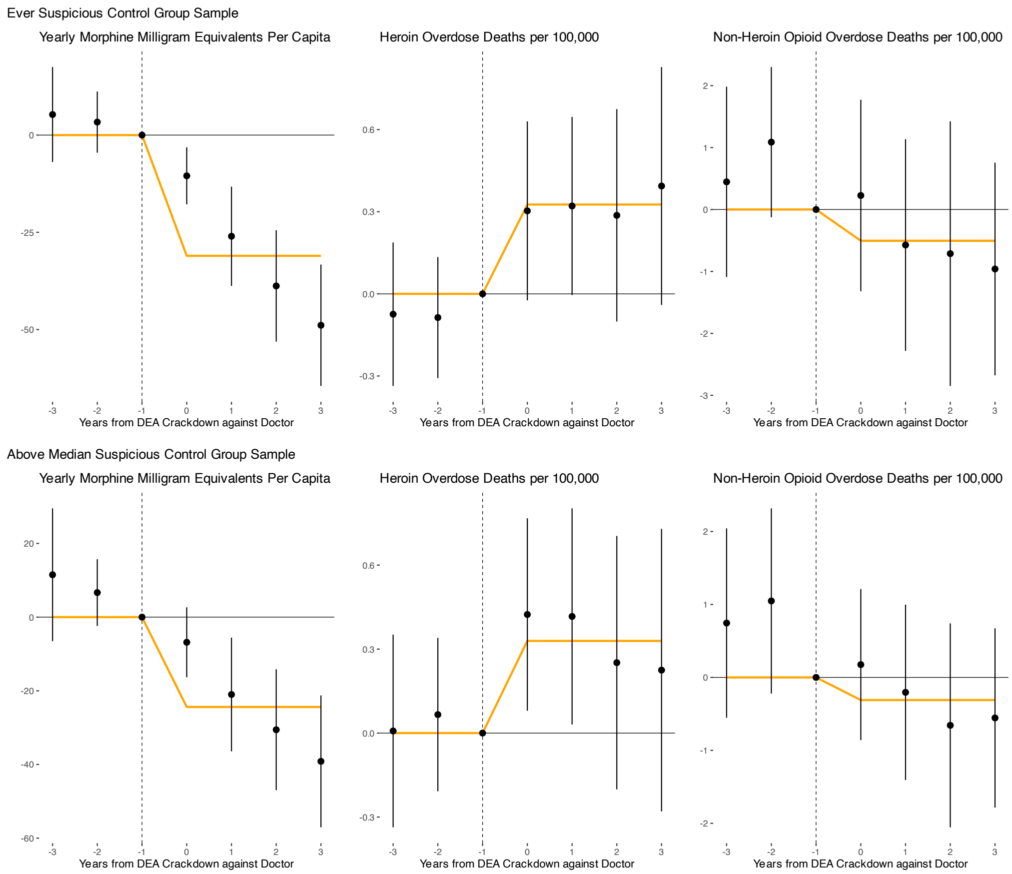
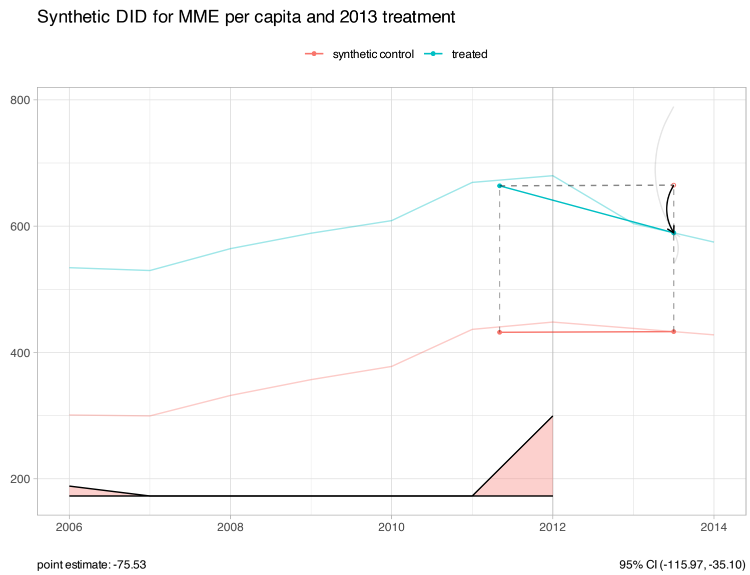


Figure A.14. : Dynamic Impact of Doctor Crackdowns on Opioid Dispensing

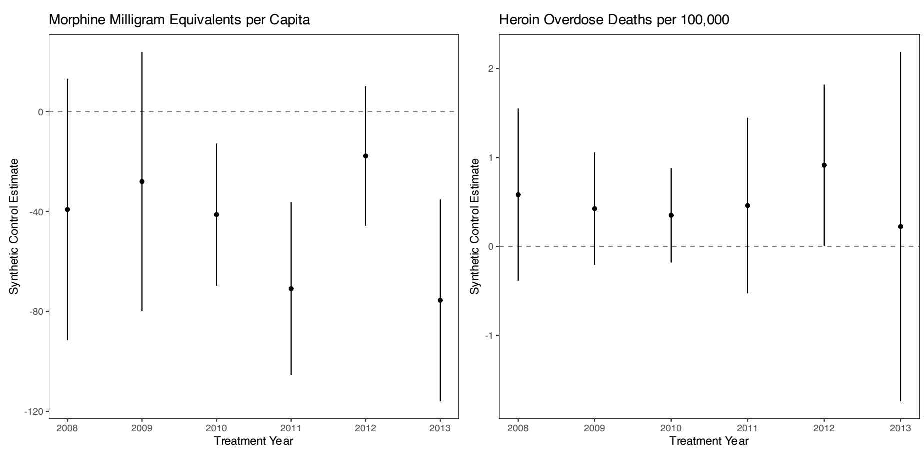
Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange line captures the aggregated post-treatment effect, β, from estimating Equation (2). The control groups are generated using the outlier detection methods from Section II.A. The top panel includes counties that were ever flagged as having a suspicious pharmacy, while the bottom panel includes counties that were flagged as having an above median share of suspicious pharmacies. The outcome is yearly morphine milligram equivalents (MME) dispensed in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor.

Figure A.15. : Synthetic DID Method for Impacts of Doctor Crackdowns

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



Panel B: Dispensing and Heroin Overdose Treatment Effects by Year of Crackdown



Notes: Panel A shows an example of the parallel trends and the impact of crackdowns in 2013, as I estimate the synthetic control DID method of Arkhangelsky et al. (2021) separately for each treatment year. I do this because their method is for a single treatment date and there is no consensus on how to weight the coefficients from different treatment years. Standard errors are calculated using the placebo method. Panel B shows the impacts of crackdowns for each treatment year for per capita dispensing and heroin overdose deaths.

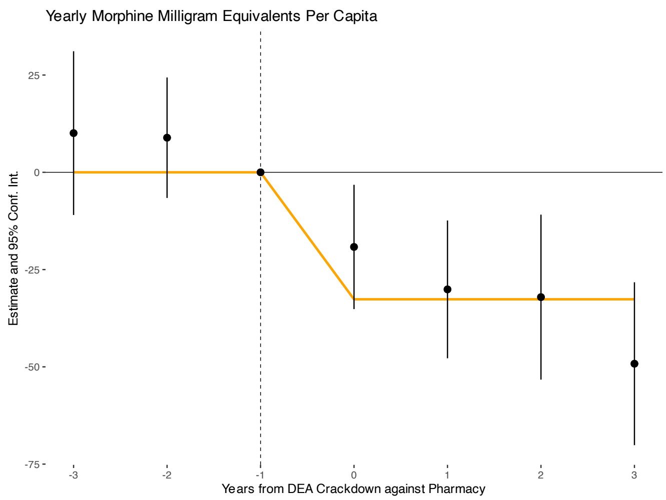


Figure A.16. : Impact of Pharmacy Crackdowns on Opioid Dispensing

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange line captures the aggregated post-treatment effect, β, from estimating Equation (2). The outcome is yearly morphine milligram equivalents (MME) dispensed in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a pharmacy.

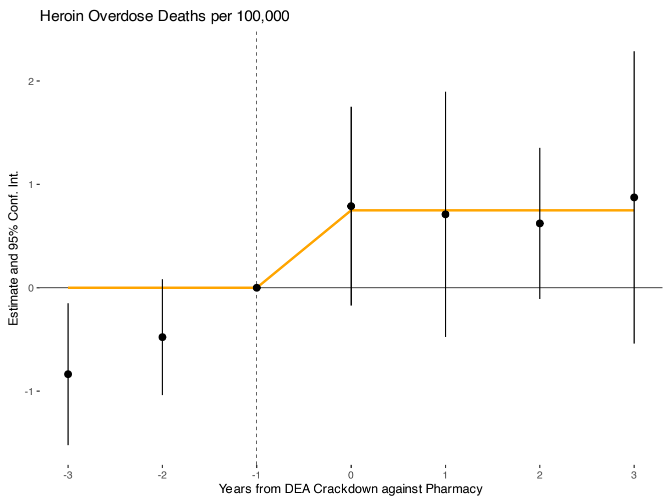


Figure A.17. : Impact of Pharmacy Crackdowns on Heroin Overdose Deaths

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange line captures the aggregated post-treatment effect, β, from estimating Equation (2). The outcome is yearly heroin overdose deaths per 100,000 residents in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a pharmacy.

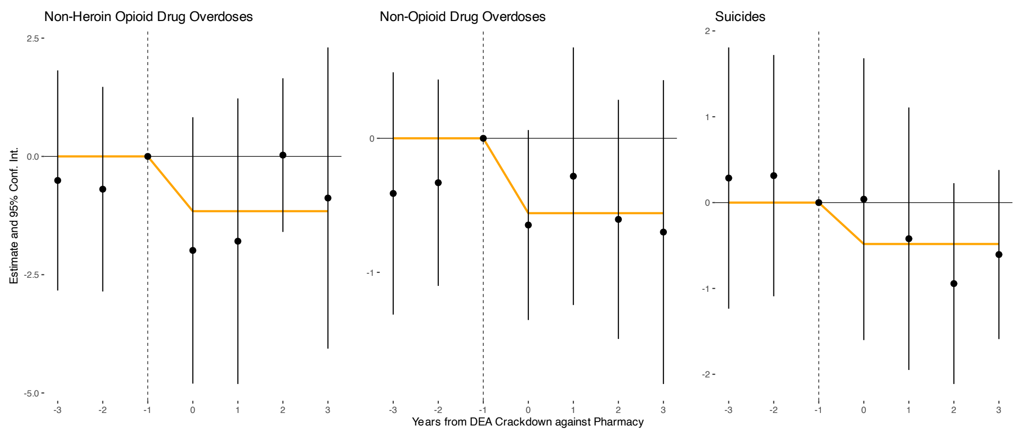


Figure A.18. : Impact of Pharmacy Crackdowns on Other Mortality Outcomes

Notes: This figure presents the DID coefficients, ρ_t, from estimating Equation (1) with county and state-by-year fixed effects, and the orange lines capture the aggregated post-treatment effect, β, from estimating Equation (2). The outcome are various mortality rates per 100,000 residents in a county. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a pharmacy.

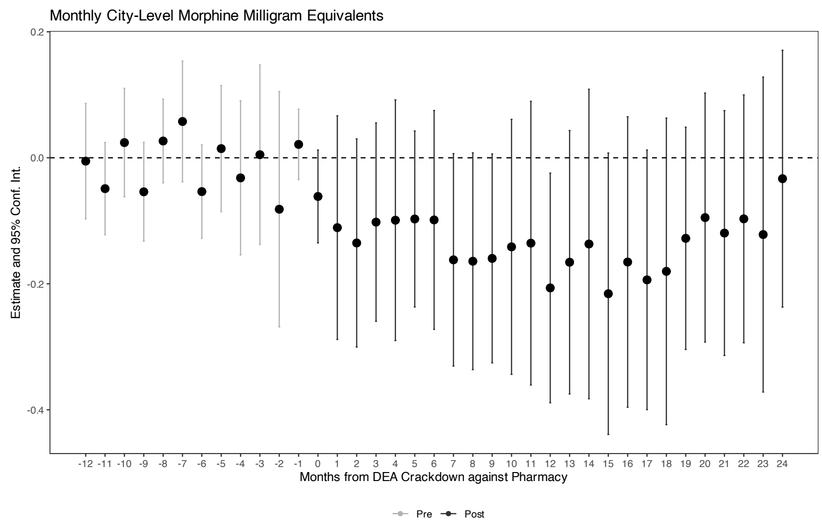


Figure A.19. : City-Level Impacts of DEA Action against a Pharmacy

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

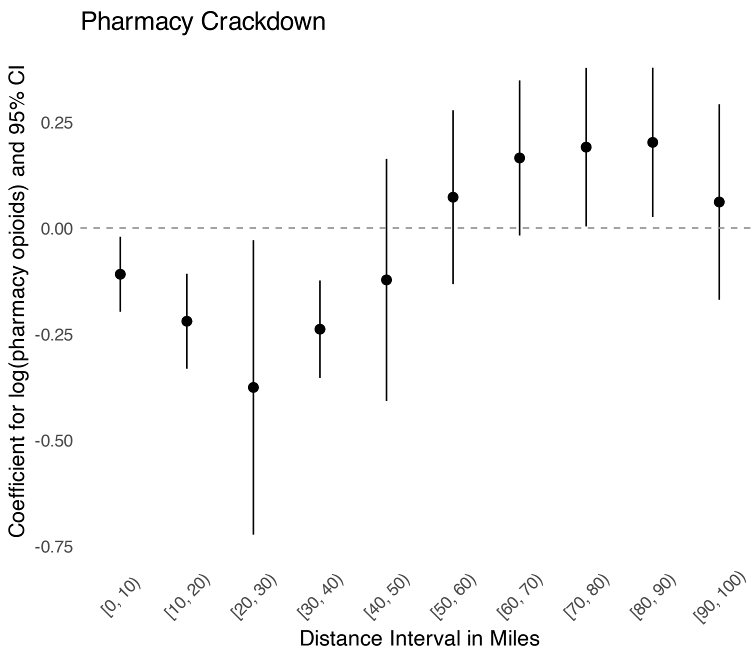


Figure A.20. : Pharmacy-Level Opioid Dispensing Impacts of Pharmacy Crackdowns

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

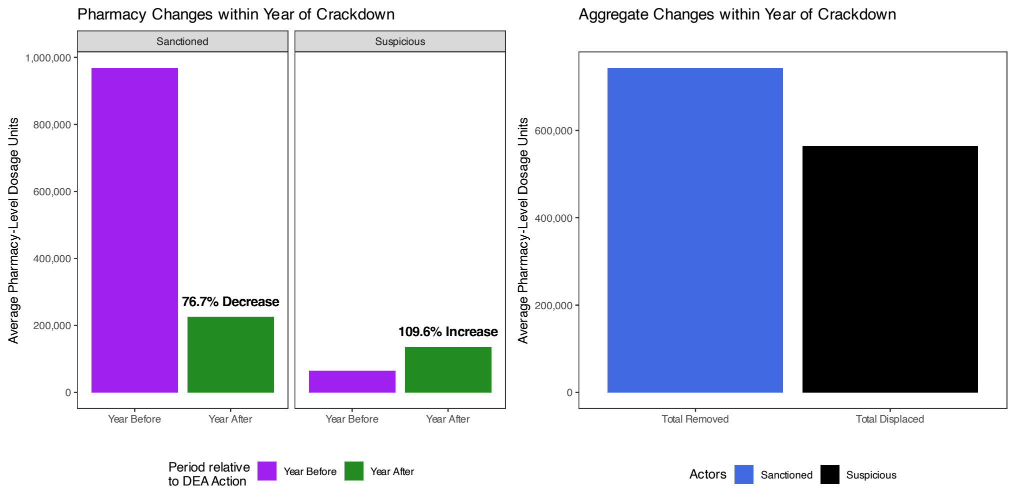


Figure A.21. : Displacement following a Pharmacy Crackdown

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

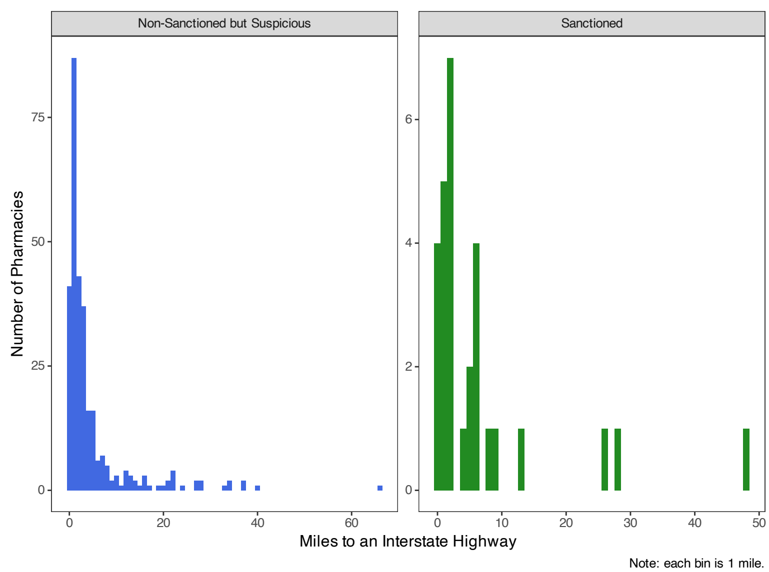


Figure A.22. : Distance to the Nearest Interstate Highway

Additional Tables

Table B.1—: Testing Implication of Identifying Assumption at County-Level

	Early DEA Action (Dummy Variable)	
	Doctors	Pharmacies
	(1)	(2)
log(Opioids in Previous Year)	−0.089	−0.133
	(0.128)	(0.243)
log(Overdoses in Previous Year)	0.173	−0.103
	(0.131)	(0.209)
Rural	−0.006	0.039
	(0.055)	(0.132)
Doctors per 100,000	0.067	0.102
	(0.068)	(0.206)
Population Density	0.043	−0.016
	(0.058)	(0.198)
Percent Manufacturing	0.068	−0.155
	(0.059)	(0.131)
Mental Health Clinics per 100,000	−0.008	0.075
	(0.057)	(0.127)
log(Median Income)	0.025	−0.038
	(0.061)	(0.116)
Joint F-stat	1.191	1.266
Observations	97	29
R^2	0.098	0.336

Table B.2—: Impacts of Doctor Crackdowns on Opioid Dispensing and Mortality Rates (County and Year Fixed Effects)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-36.85***	-1.034*	0.3553**	-0.9255**	-0.4637***	0.5881**
	(6.720)	(0.5440)	(0.1642)	(0.4271)	(0.1291)	(0.2389)
Dependent variable mean	396.36	12.990	0.64490	11.397	0.94842	5.8315
R^2	0.93977	0.52989	0.45776	0.51542	0.35899	0.51748
Observations	26,505	26,505	26,505	26,505	26,505	26,505

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and year fixed effects. The outcome MME in Column (1) is a measure of opioid dispensing, namely Morphine Milligram Equivalents per capita, and Columns (2) to (6) are mortality rates per 100,000. Columns (2) to (5) are overdose deaths for each particular drug grouping, where All Drugs (2) combines Heroin (3), Non-Heroin Opioid (4), and Non-Opioid (5). Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.3—: Impacts of Doctor Crackdowns on Opioid Dispensing and Mortality Rates

Panel A: Short Run (Within First Year of Crackdown)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-21.10***	-0.4022	0.3775**	-0.4404	-0.3393**	0.4283
	(5.653)	(0.4999)	(0.1576)	(0.4308)	(0.1319)	(0.2743)
Dependent variable mean	396.09	12.958	0.63770	11.376	0.94431	5.7911
R^2	0.94935	0.55148	0.52886	0.53476	0.38066	0.52721
Observations	26,340	26,340	26,340	26,340	26,340	26,340

Panel B: Long Run (Years 2 and 3)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-30.29***	-0.9484*	0.3862**	-0.8115*	-0.5231***	0.4317
	(6.149)	(0.5267)	(0.1689)	(0.4445)	(0.1264)	(0.2857)
Dependent variable mean	396.15	12.992	0.64176	11.397	0.95294	5.8302
R^2	0.94904	0.55184	0.52888	0.53492	0.38337	0.52976
Observations	26,539	26,539	26,539	26,539	26,539	26,539

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects for two samples. The short run estimates limit the sample from event years -3 to 1, while the long run sample is limited to -3 to 0 and 2 to 3. The outcome MME in Column (1) is a measure of opioid dispensing, namely Morphine Milligram Equivalents per capita, and Columns (2) to (6) are mortality rates per 100,000. Columns (2) to (5) are overdose deaths for each particular drug grouping, where All Drugs (2) combines Heroin (3), Non-Heroin Opioids (4), and Non-Opioids (5). Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.4—: Impacts of Doctor Crackdowns on Mortality Rates by Age and Gender

	Overall (1)	Males (15-29) (2)	Males (30-49) (3)	Females (15-29) (4)	Females (30-49) (5)	Elderly (85+) (6)
Post-DEA Crackdown	-8.581	-0.6613**	-2.500***	-0.1830	-0.7836*	2.077
	(7.989)	(0.2992)	(0.6370)	(0.1569)	(0.4135)	(2.589)
Dependent variable mean	304.59	5.0545	14.299	1.8999	8.8130	87.877
R^2	0.89904	0.58999	0.76003	0.44504	0.71083	0.88433
Observations	26,505	26,505	26,505	26,505	26,505	26,505

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. All outcomes are mortality rates per 100,000 and other than Column (1), they capture different subgroups by age and gender. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.5—: Impacts of Doctor Crackdowns on Mortality Rates by Gender and Race

	Overall (1)	Men (2)	Women (3)	White (4)	Black (5)
Post-DEA Crackdown	-8.581	-4.643	-3.938	-9.382	0.4831
	(7.989)	(4.278)	(3.932)	(7.186)	(1.516)
Dependent variable mean	304.59	153.16	151.43	274.98	25.052
R^2	0.89904	0.89431	0.89468	0.89592	0.92652
Observations	26,505	26,505	26,505	26,505	26,505

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. All outcomes are mortality rates per 100,000 and other than Column (1), they capture different subgroups by race and gender. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.6—: Impacts of Doctor Crackdowns on Opioid Dispensing and Mortality Rates (Matched Control Groups)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-19.54***	-1.236**	0.3028	-1.057**	-0.4823***	0.1913
	(7.158)	(0.5869)	(0.1827)	(0.5124)	(0.1465)	(0.2894)
Dependent variable mean	371.28	14.641	1.2017	11.885	1.5543	8.8820
R^2	0.92723	0.69517	0.69367	0.67049	0.55609	0.71447
Observations	6,146	6,146	6,146	6,146	6,146	6,146

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. Control groups are generated using nearest neighbor propensity score matching without replacement and regression weights are included in all specifications. The outcome MME in Column (1) is a measure of opioid dispensing, namely Morphine Milligram Equivalents per capita, and Columns (2) to (6) are mortality rates per 100,000. Columns (2) to (5) are overdose deaths for each particular drug grouping, where All Drugs (2) combines Heroin (3), Non-Heroin Opioid (4), and Non-Opioid (5). Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the match group level.

Table B.7—: Impacts of Doctor Crackdowns on Opioid Dispensing and Mortality Rates (Florida Removed)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-29.44***	-1.005*	0.4487**	-1.004**	-0.4505***	0.4710
	(6.049)	(0.5904)	(0.1780)	(0.5018)	(0.1346)	(0.3023)
Dependent variable mean	396.02	12.900	0.65319	11.322	0.92467	5.7170
R^2	0.94965	0.55163	0.53141	0.53415	0.37970	0.52020
Observations	25,941	25,941	25,941	25,941	25,941	25,941

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. This is similar to Table 1 but removes Florida. All outcomes are mortality rates per 100,000 and other than Column (1), they capture different subgroups by race and gender. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.8—: Impacts of Doctor Crackdowns on Opioid Dispensing and Mortality Rates (Neighboring Counties Removed)

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-31.38***	-0.8206	0.3737**	-0.7761*	-0.4182***	0.5130*
	(5.919)	(0.5466)	(0.1576)	(0.4681)	(0.1235)	(0.2831)
Dependent variable mean	396.97	12.983	0.64105	11.401	0.94057	5.8291
R^2	0.94926	0.55156	0.52511	0.53438	0.38315	0.53093
Observations	25,670	25,670	25,670	25,670	25,670	25,670

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. This is similar to Table 1 but removes all neighboring counties. All outcomes are mortality rates per 100,000 and other than Column (1), they capture different subgroups by race and gender. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a doctor. Standard errors are clustered at the county.

Table B.9—: Impacts of Pharmacy Crackdowns on Opioid Dispensing and Mortality Rates

	MME Per Capita (1)	All Drugs (2)	Heroin (3)	Non-Heroin Opioids (4)	Non-Opioids (5)	Suicides (6)
Post-DEA Crackdown	-35.73***	-0.1580	1.107**	-0.9398	-0.3251	-0.6021
	(8.795)	(1.108)	(0.5215)	(0.7597)	(0.3290)	(0.4625)
Dependent variable mean	396.67	13.020	0.64778	11.417	0.95456	5.8619
R^2	0.94900	0.55273	0.53145	0.53544	0.38450	0.53280
Observations	26,650	26,650	26,650	26,650	26,650	26,650

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. The outcome MME in Column (1) is a measure of opioid dispensing, namely Morphine Milligram Equivalents per capita, and Columns (2) to (6) are mortality rates per 100,000. Columns (2) to (5) are overdose deaths for each particular drug grouping, where All Drugs (2) combines Heroin (3), Non-Heroin Opioid (4), and Non-Opioid (5). Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a pharmacy. Standard errors are clustered at the county.

Table B.10—: Impacts of Pharmacy Crackdowns on Mortality Rates by Age and Gender

	Overall (1)	Males (15-29) (2)	Males (30-49) (3)	Females (15-29) (4)	Females (30-49) (5)	Elderly (85+) (6)
Post-DEA Crackdown	-26.47	-1.368**	-3.207**	-0.0040	-1.416**	-0.9378
	(17.18)	(0.5533)	(1.276)	(0.2281)	(0.5715)	(6.118)
Dependent variable mean	306.66	5.0801	14.381	1.9114	8.8591	88.510
R^2	0.89982	0.59041	0.76095	0.44540	0.71228	0.88552
Observations	26,650	26,650	26,650	26,650	26,650	26,650

Notes: This table presents the DID coefficients, β, from estimating Equation (2) with county and state-by-year fixed effects. All outcomes are mortality rates per 100,000 and other than Column (1), they capture different subgroups by age and gender. Treatment is the issuance of an order to show cause for a proposed license revocation due to a Controlled Substance Act violation stemming from a DEA audit of a pharmacy. Standard errors are clustered at the county.

Additional Validation Exercises

C1. Placebo test using an alternative "treatment"

I provide a placebo test to examine the opioid dispensing impacts of the two different categories of OTSCs: proposed revocations (my main treatment measure) and denials of applications (what I exclude from the sample). Figure C.1 compares these two "treatments," where the impact of proposed revocation OTSCs on per capita opioid dispensing (orange triangles) are identical to what is found in Figure 3, while application denial OTSCs are the other set of coefficients (teal circles), which are not related to unlawful prescribing and have no effect on prescription opioid dispensing.

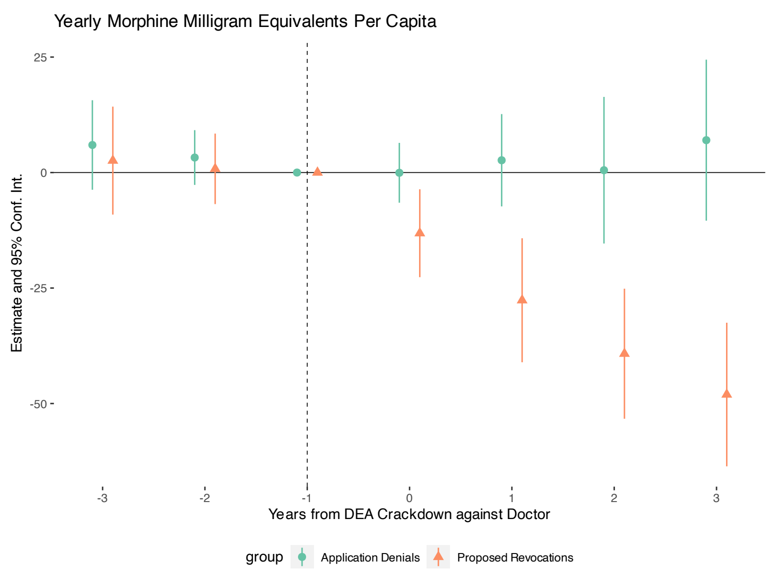


Figure C.1. : Impact of Each Category of OTSCs on Local Opioid Dispensing

Notes: This figure presents the DID coefficients, ρ_t, from estimating Manuscript Equation (1) with county and state-by-year fixed effects. The outcome is yearly morphine milligram equivalents (MME) dispensed in a county. Treatment is the issuance of an order to show cause (OTSC) for either an application denial (what I exclude) or a proposed revocation (my treatment measure).

C2. Validation exercise using data from Florida

DEA registration data has proven difficult to obtain, and any other source I attempted to use, such as licensing bodies and internet searches, was missing key information that made it difficult to define a crackdown (e.g., investigation, disciplinary action, etc.) and a relevant date, while OTSCs are consistently defined and reported over time and space. That said, I was able to find both reliable historical and individual information on doctors for Florida. Figure C.2 shows the most relevant measure I found, whether a doctor faced a criminal charge for prescribing (orange bar chart, left). The blue (middle) bar chart captures my treatment measure in Florida, i.e., the number of OTSCs for proposed revocations for unlawful prescribing. The levels and trends between the two sources are similar; note the unit of observation is the same. The grey bar chart captures whether a license is revoked for *any* reason in Florida and is to give a sense of scale of disciplinary actions (that there are very few in general); the reason for this revocation is not given but could include anything from an ethics violation to Medicare fraud.

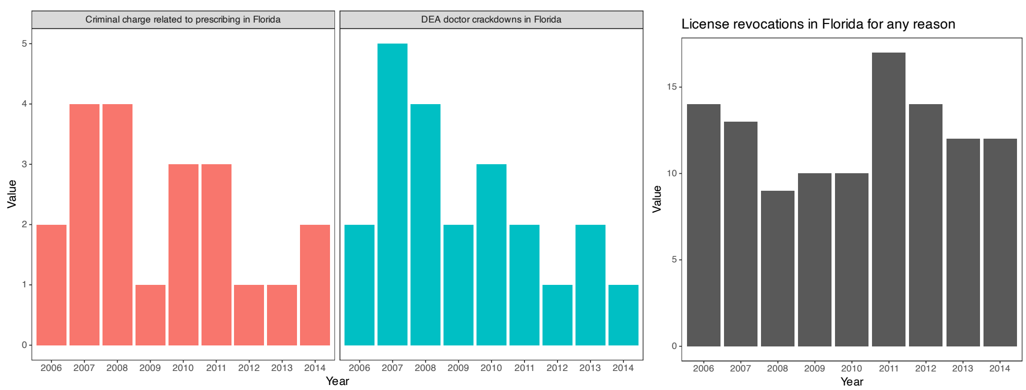


Figure C.2. : Comparing information from Florida and the DEA

Notes: Data used in the first and third panels comes from Florida's Department of Health, while the center panel comes from the DEA and captures my primary treatment measure in Florida. The orange bar chart captures the number of criminal charges against doctors for prescribing, while the grey bar chart captures all license revocations in Florida for any reason, which can include anything from an ethics violation to Medicare fraud.

The Professional Licensing Division of Pennsylvania's Department of State provides something similar, namely monthly PDFs for disciplinary actions since 2006 for Business Licenses, Health Licenses, and Real Estate/Vehicle Licenses. I searched each PDF for the term controlled substances under actions taken by the Board of Medicine, then read each outcome to determine whether it was related to prescribing. Figure C.3 presents the result of this exercise, where yearly totals from the state are captured by the red bars. The treatment measure I use in the analysis are the blue bars, which capture OTSCs for proposed license revocations related to unlawful prescribing. These two sources have similar levels and trends.

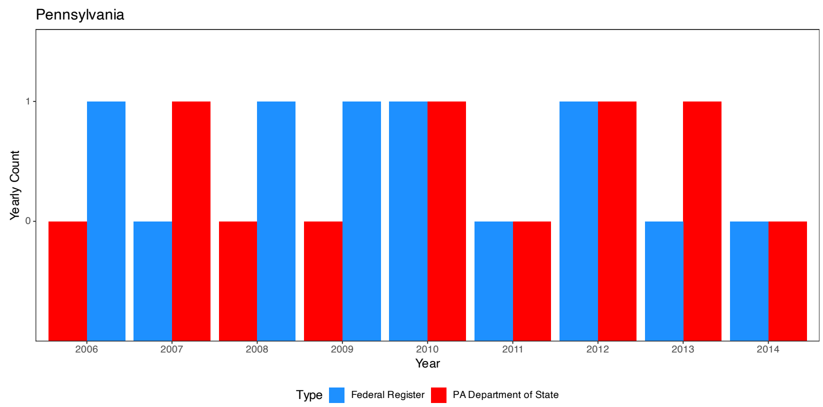


Figure C.3. : Comparing information from Pennsylvania and the DEA

Notes: The Professional Licensing Division of Pennsylvania's Department of State provides monthly PDFs for disciplinary actions since 2006 for Business Licenses, Health Licenses, and Real Estate/Vehicle Licenses. I searched each PDF for the term controlled substances under the Board of Medicine heading, then read each case to determine whether it was related to prescribing. These yearly totals are captured by the blue bars. The treatment measure I use in the analysis are the orange bars, which capture OTSCs for proposed license revocations related to unlawful prescribing.

C3. Validation exercise using claims data

Given the opioid data are at the pharmacy-level, I cannot examine individual prescribing behavior for doctors, and so I have added a validation exercise using claims data (Medicare Part D). Note the match rate suggests doctors I study were rarely seeing Medicare patients or billing insurance. That said, while imperfect, for the rogue doctor I was able to match to the claims data, as well as two other cities that also experienced a crackdown (but the sanctioned doctor could not be matched), I plot the yearly number of standardized 30-day fills for prescription opioids in Figure C.4. I stratify by those operating in the same city as the one cracked down upon and the doctor who experienced the crackdown. The figure shows that the number of 30-day fills for opioids drops dramatically after the crackdown for other doctors in the same city, suggesting a potential chilling effect.

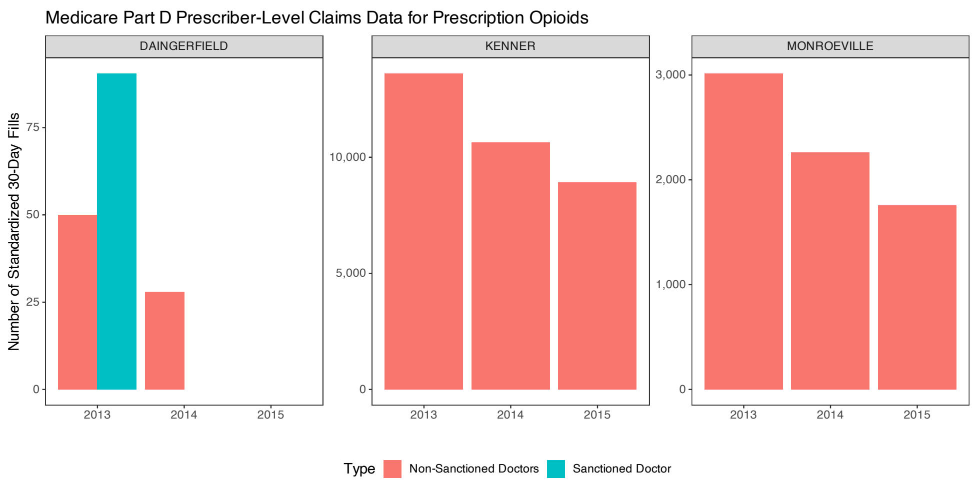


Figure C.4. : Direct and Indirect Impact of Doctor Crackdowns in a City

Notes: These plots examine the yearly number of standardized 30-day fills for prescription opioids using Medicare Part D claims data for cities where there was a doctor crackdown. These yearly data are available starting in 2013. I first limit the sample to claims where the drug ingredient is either Oxycodone or Hydrocodone to match my prescription opioid sample and then aggregate the total number of fills stratifying by the direct and indirect impacts in a given city. The OTSC issue dates were January 2013 for Monroeville, Alabama, June 2013 for Daingerfield, Texas, and November 2013 for Kenner, Louisiana.