Internet Appendix to:

"Spillover Effects of Opioid Abuse on Skilled Human Capital and Innovation Activity,"

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A. Definitions and Additional Results

Table A1: Data Sources and Coverage

This table reports the sources for the data and variables that we use in the paper, in addition to the sample years for which we collect information from each data source.

#	Data	Coverage	Source
1	Individual Opioid prescriptions to Medicare beneficiaries	2007	CMS Part D Event files (obtained via DUA)
2	Restricted-use micro mortality data	1990–2019	National Vital Statistics System, division of NCHS (obtained via DUA)
3	Oxycodone distribution by three-digit zip code	1997–2000	DEA's Archived Reports
4	OxyContin misuse rates in the state	2004–2009	NSDUH, from Alpert et al. (2018)
5	County- and state-level migration information	2005–2019	IRS Statistics of Income
6	State-level migration information by educational attainment	2007–2019	American Community Survey (ACS)
7	State-level job-to-job worker migration by educational attainment	2002–2019	Public-use Longitudinal Employer-Household Dynamics (LEHD)
8	Inventor and research lab migration, patent rates, and patent values	2002–2023	Mike Woeppel's USPTO data repository and Kogan et al. (2017)'s github
9	State and county employment, wages, and GDP statistics	2002–2019	BEA
10	State and county population and population shares	2002–2019	SEER
11	State and county college graduation rates	2000	2000 Decennial Census
12	State and county unemployment rates	2007–2009	Bureau of Labor Statistics (BLS)
13	County gini coefficients	2000	2000 Decennial Census
14	School quality measures	2002–2019	Common Core Data from NCES
15	Local Government Expenditures	2002–2017	State and Local Government Finances
16	Crime Statistics	2002–2019	Uniform Crime Reporting (UCR) via Jordan Kaplan
17	Inventor home sales	1900–2019	CoreLogic Sales and Transfer Database

Table A2: Variable Definitions

Variable Name	Variable Definition
Explanatory Variables	
Employment	The natural log of the number of employees working in the county, from BEA files, during the year 1999.
Personal Income	The natural log of the average per capita personal income in the county, from BEA files, during the year 1999.
College Education	The percent of the population age 25 years or older that have at least some college education, from the 2000 Decennial Census.
Financial Crisis Exposure	The change in the county's unemployment rate between 2007 and 2009.
Inequality	The county's gini coefficient, estimating the dispersion of household income inequality in the county, from the 2000 Decennial Census.
Opioid Abuse Exposure	The total morphine milligram equivalent (MME) of morphine, oxycodone, oxymorphone, hydromorphone, and fentanyl prescribed during the year 2007 to Medicare Part D beneficiaries residing in county i that year. This total is then scaled by the number of residents age 65 years or older in the county that year. The individual prescription outcomes for Medicare beneficiaries come from restricted-use Medicare Part D Event files obtained through a DUA.
Population Density	The natural log of the number of county residents (from SEER Cancer Statistics), scaled by the square mileage of the county, as of the year 2000.
Population Share 20–64	The fraction of the population between 20 and 64 years old during the year 2000.
Population Share 65+	The fraction of the population greater than 64 years old during the year 2000.
Population Share - Female	The fraction of the population that is female during the year 2000.
Population Share - Hispanic	The fraction of the population that identifies as Hispanic during te year 2000.
Population Share - White	The fraction of the population that identifies as Caucasian during the year 2000.
Post-2010	An indicator variable equal to one during the period after 2010.
Prescription Opioid Mortality Rate	The county's annual death rate from all opioids, averaged across the years 1999–2000. Opioid-related deaths are identified from the following ICD-10 codes: X40, X41, X42, X43, X44, X60, X61, X62, X63, X64, X85, Y10, Y11,Y12, Y13, Y14. Accidental deaths due to prescription opioids are further marked as condition (i.e., contributing cause) T40.2 or T40.3.
Pre-Sample Oxycodone	The total volume of MME of oxycodone shipped to the county during the year 2002, scaled by the county's population that year. We hand collect all oxycodone pills shipped to each three-digit zip code each year from archived DEA reports and then map the shipment of oxycodone in three-digit zip codes to counties each year.
Pre-Sample Oxycodone Growth	The growth rate of per capita MME of oxycodone shipped to county i during the period 1997–2002. We hand collect all oxycodone pills shipped to each three-digit zip code each year from archived DEA reports and then map the shipment of oxycodone in three-digit zip codes to counties each year.
Real Wages	The natural log of average annual wages and salary for workers in the county (from BEA) as of the year 2000. We CPI-adjust the wages to 2019 dollars.
Dependent Variables	
Bachelors and Above Out-of-State Moves	The number of residents with at least a bachelor's degree migrating out of the state that year, per 100,000 of age 20–64 state residents that year. *Some College Out-of-State Moves*, *No College Out-of-State Moves*, and *Some High School Out-of-State Moves* are defined similarly, but reflect the scaled number of residents migrating out of the state that have some college education, no college education, and no high school degree, respectively.
Inventor Out-Migration (home sales-based)	The number of inventors who sell their home in county i during year t and do not buy or sell a separate home in the same county during the subsequent ten years.
Inventor Out-Migration (Patents-based)	The number of highly-productive inventors who file for a patent in county i during year t and move to a different county between year t and year $t+4$. Highly productive inventors are those who are in the 75^{th} percentile of patents filed over the previous ten years.
Net Outflows Exemptions	The number of personal tax exemptions associated with filers who migrate out of county i during year t, minus the number of personal tax exemptions associated with filers who migrate into county i during year t, per 1,000 residents in the county.
Net Outflows Filers	The number of filers who migrate out of county i during year t, minus the number of tax filers who migrate into county i during year t, per 1,000 residents in the county.
Net Outflows Job-to-Job	The number of job-to-job worker movements out of the state, minus the number of job-to-job worker movements into the state, scaled by state's population in thousands.

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Table A2 – continued from previous page

Variable Name	Variable Definition
Net Outflows Job-to-Job Stable	The number of job-to-job worker movements out of the state conditional on the workers maintaining constant employment, minus the number of job-to-job worker movements into the state conditional on the workers maintaining constant employment, scaled by state's population in thousands.
# Patents per capita	The number of patents filed by inventors in county *i* during year *t*, per 100,000 residents in the county that year.
Patent Value per capita	The aggregate stock market value (in 2019 dollars) of patents filed by inventors working for publicly-traded firms in county *i* during year *t*, per 1,000 residents in the county. Patent stock market values are provided by Kogan et al. (2017).
Real GDP	The natural log of the real gross domestic product (in the BEA's chained 2012 dollars) for county *i* during year *t*. The BEA's use of chain-type annual-weighted indexes allow for the effects of changes in relative prices and in the composition of output over time.
Real GDP per capita	The real gross domestic product (in the BEA's chained 2012 dollars) for county *i* during year *t*, per 100,000 residents in the county that year.
Research Lab Out-Migration	The number of research labs in county *i* during year *t* that stop filing for patents in that county after year *t*. We identify research labs using the patent-CRSP PERMCO matches from Stoffman et al. (2022) and treat each unique firm-county with at least three inventors as a separate lab.

Table A3: Cross-State Aggregate Worker Migration

This table reports results from state-year level difference-in-differences regressions estimated using Equation 2, examining the relation between local opioid abuse and worker migration. Panel A uses state-level aggregate migration flows from the IRS's Statement of Income. Panel B uses state-level aggregate job-to-job movements from public-use LEHD files. The dependent variable in Columns (1) and (2) of Panel A, *Net Outflows Filers*, is the number of tax filers moving out of state i during year t, minus the number of tax filers that moving into state i during year t, scaled by the state's population in thousands. The dependent variable in Columns (3) and (4) of Panel A, *Net Outflows Exemptions*, is measured similarly to Columns (1) and (2) of Panel A, but using the number of tax exemptions moving out of and into state i during year t. The dependent variable in Columns (1) and (2) of Panel B, *Net Outflows Job-to-Job*, is the number of job-to-job worker movements out of the state, minus the number of job-to-job worker movements into the state, scaled by state's population in thousands. The dependent variable in Columns (3) and (4) of Panel B, *Net Outflows Job-to-Job Stable*, is measured similarly to Columns (1) and (2) of Panel B, but specific to workers that move from one job to another with constant employment. The dependent variable Columns (1) and (2) of Panel C is the number of tax filers migrating out of the county in year t, minus the number of tax filers migrating into the county in year t, scaled by population of the county (in thousands), conditional on those movers staying within the same state. The dependent variable Columns (3) and (4) of Panel C is the number of tax filers migrating out of the county during year t, minus the number of tax filers migrating into the county during year t, scaled by population of the county (in thousands), conditional on those movers migrating across state lines. *NSDUH OxyContin Misuse Rate* is state i's average rate of non-medical use of OxyContin during the period 2004–2009 collected from biennial NSDUH surveys (made available by Alpert et al. (2018)). This rate measures the number of people per 100 surveyed that report misusing OxyContin during the past year. *Post-2010* is an indicator variable equal to one for the years 2011–2019. In Columns (2) and (4) of each panel, we control for the following variables as of the year 2000 interacted with the *Post-2010* indicator variable: the state's pre-reformulation misuse of non-OxyContin pain reliever drugs; percent college educated; poverty rate; financial crisis exposure; population density; and population shares of female, ages 20–64, ages 65 and older, White, and Hispanic. The regression sample period is from 2002 to 2019. Variables are defined in Table A2 in the Internet Appendix. t-statistics are reported in parentheses. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: IRS Migration

	(1) Net Outflows Filers	(2) Net Outflows Filers	(3) Net Outflows Exemptions	(4) Net Outflows Exemptions
NSDUH OxyContin	2.351**	2.365**	4.604**	3.536*
Misuse Rate x Post-2010	(2.25)	(2.65)	(2.05)	(1.92)
Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.545	0.549	0.552	0.561
Observations	912	912	912	912

Panel B: LEHD Job-to-Job Moves

	(1) Net Outflows Job-to-Job	(2) Net Outflows Job-to-Job	(3) Net Outflows Job-to-Job Stable	(4) Net Outflows Job-to-Job Stable
NSDUH OxyContin	4.362**	4.924***	3.058**	3.650***
Misuse Rate x Post-2010	(2.07)	(2.68)	(2.12)	(2.85)
Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.453	0.455	0.440	0.443
Observations	898	898	898	898

Panel C: County-level Migration, Within vs. Outside the State

	Within-state		Out-of-state	
	(1) Net Outflows Filers	(2) Net Outflows Filers	(3) Net Outflows Filers	(4) Net Outflows Filers
Opioid Abuse Exposure x Post-2010	0.114***	0.156***	0.129***	0.160***
	(2.77)	(3.74)	(3.63)	(4.39)
Controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.542	0.548	0.665	0.665
Observations	39,269	39,149	39,148	39,028

Table A4: State-Level Inventor and Research Lab Migration

This table reports results from state-year level Poisson difference-in-differences regressions estimated using Equation 2, examining the relation between local opioid abuse and patent inventor and research lab out-migration. The dependent variable in Columns (1) and (2), *Inventor Out-Migration*, is the number of star patent inventors that file for a patent in state i during year t and filing a patent in a different state between year t and year $t+3$, conditional on the star inventor not patenting in state i over that period. Star inventors are those in the 75^{th} or higher in patent filings over the previous ten years. The dependent variable in Columns (3) and (4), *Research Lab Out-Migration*, is the number of research labs in state i during year t that stop filing for patents in that state after year t. We identify research labs using the patent-CRSP PERMCO matches from Stoffman et al. (2022) and treat each unique firm-city with at least three distinct inventors as a separate lab. *NSDUH OxyContin Misuse Rate* is state i's average rate of non-medical use of OxyContin during the period 2004–2009 collected from biennial NSDUH surveys (made available by Alpert et al. (2018)). This rate measures the number of people per 100 surveyed that report misusing OxyContin during the past year. *Post-2010* is an indicator variable equal to one for the years 2011–2019. In Columns (2) and (4), we control for the following variables as of the year 2000 interacted with the *Post-2010* indicator variable: the state's pre-reformulation misuse of non-OxyContin pain reliever drugs; percent college educated; poverty rate; financial crisis exposure; population density; and population shares of female, ages 20–64, ages 65 and older, White, and Hispanic. The regression sample period is from 2002 to 2019. Variables are defined in Table A2 in the Internet Appendix. t-statistics are reported in parentheses. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Inventor Out-Migration	(2) Inventor Out-Migration	(3) Research Lab Out-Migration	(4) Research Lab Out-Migration
NSDUH OxyContin	0.355*	0.362*	0.558**	0.467**
Misuse Rate x Post-2010	(1.72)	(1.65)	(2.47)	(2.01)
Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Observations	900	900	914	914

Table A5: Robustness of Main Results — All Counties

This table reports results from county-year difference-in-differences regressions estimated using Equation 1, examining the relation between local opioid abuse and inventor and research lab out-migration. The dependent variable in Columns (1) and (2) of Panel A, *Inventor Out-Migration*, is the number of highly-productive patent inventors who file for a patent in county i during year t and move to a different county between year t and year $t+2$. Highly-productive patent inventors are those in the 75^{th} percentile of patent filings over the previous ten years. These regressions are estimated using Poisson pseudo maximum likelihood (PPML) with the lagged number of inventors in the county as the exposure. The dependent variable in Columns (3) and (4) of Panel A is the number inventors who sell their home in county i during year t and do not buy or sell a different home in the same county during the subsequent ten years. These regressions are estimated using PPML with the lagged number of matched inventors with past home purchases in the county as the exposure. The dependent variable in Columns (5) and (6) of Panel A, *Inventor Fraction*, is the number of highly-productive patent inventors in the county, scaled by the county's population. The dependent variable in Columns (1) and (2) of Panel B, *# Patents per capita*, is the number of patents filed by inventors in county i during year t, per 100,000 residents in the county that year. The dependent variable in Columns (3) and (4) of Panel B, *Patent Value per capita*, is the aggregate stock market value (in 2019 dollars) of patents filed by inventors working for publicly traded firms in county i during year t, per 1,000 residents in the county that year. Estimates of the stock market value of patent filings are provided by Kogan et al. (2017). *Opioid Abuse Exposure* is the total MME of morphine, oxycodone, oxymorphone, hydromorphone, and fentanyl prescribed to Medicare Part D beneficiaries in the county during the year 2007, scaled by the number of residents age 65 years or older in the county that year. *Post-2010* is an indicator variable equal to one for the years 2011–2019. The regression sample period is from 2002 to 2019. Variables are defined in Table A2 in the Internet Appendix. t-statistics are reported in parentheses. Standard errors are clustered at the state-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Inventor Out-migration

	Patent Locations		Home Sales		Patent Locations	
	(1) Inventor Out-Migration	(2) Inventor Out-Migration	(3) Inventor Out-Migration	(4) Inventor Out-Migration	(5) Inventor Fraction	(6) Inventor Fraction
Opioid Abuse Exposure x Post-2010	0.178***	0.286***	0.358***	0.265***	−1.738***	−1.554***
	(3.84)	(5.00)	(6.68)	(4.78)	(−4.05)	(−3.55)
Method	Poisson	Poisson	Poisson	Poisson	OLS	OLS
Controls	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,754	16,637	18,575	18,452	55,888	55,119

Panel B: Innovation

	(1) # Patents per capita	(2) # Patents per capita	(3) Patent Value per capita	(4) Patent Value per capita
Opioid Abuse Exposure x Post-2010	−2.559***	−2.837***	−64.789**	−72.927**
	(−7.33)	(−7.80)	(−2.01)	(−2.28)
Controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.852	0.860	0.679	0.680
Observations	55,890	55,116	55,890	55,116

Table A6: County-Level Corporate Innovation and State-Level Aggregate Innovation

This table reports results from county-year level difference-in-differences regressions estimated using Equation 2, examining the relation between local opioid abuse and patent innovation. The dependent variable in Panel A, *Corporate Patent Rate*, is the number of patents filed by inventors affiliated with publicly-traded firms in county i during year t, per 100,000 residents in the county that year. *Opioid Abuse Exposure* is the total MME of morphine, oxycodone, oxymorphone, hydromorphone, and fentanyl prescribed to Medicare Part D beneficiaries in the county during the year 2007, scaled by the number of residents age 65 years or older in the county that year. *Post-2010* is an indicator variable equal to one for the years 2011–2019. The regression sample period is from 2002 to 2019. In Column (2) of Panel A, we include the same control variables that we include in Tables 2–5. The dependent variable in Columns (1) and (2) of Panel B, *# Patents per capita*, is the number of patents filed by inventors in state i during year t, per 100,000 residents in the state that year. The dependent variable in Columns (3) and (4) of Panel B, *# Patent Value per capita*, is the natural log of one plus the aggregate stock market value (in 2019 dollars) of patents filed by inventors working for publicly traded firms in state i during year t. Patent stock market values are provided by Kogan et al. (2017). *NSDUH OxyContin Misuse Rate* is state i's average rate of non-medical use of OxyContin during the period 2004–2009 collected from biennial NSDUH surveys (made available by Alpert et al. (2018)). This rate measures the number of people per 100 surveyed that report misusing OxyContin during the past year. Variables are defined in Table A2 in the Internet Appendix. t-statistics are reported in parentheses. Standard errors are clustered at the state-year level in Panel A and the state level in Panel B. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Corporate Innovation

	(1) Corporate Patent Rate	(2) Corporate Patent Rate
Opioid Abuse Exposure x Post-2010	−2.284***	−1.992***
	(−7.20)	(−7.17)
Controls	No	Yes
County FE	Yes	Yes
State-Year FE	Yes	Yes
Adj. R-squared	0.835	0.837
Observations	47,124	46,980

Panel B: State-level Aggregate Innovation

	(1) # Patents per capita	(2) # Patents per capita	(3) Patent Value per capita	(4) Patent Value per capita
NSDUH OxyContin Misuse Rate x Post-2010	−14.493**	−10.264*	−76.498	−140.895*
	(−2.35)	(−1.74)	(−0.94)	(−1.95)
Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.930	0.943	0.855	0.876
Observations	918	918	918	918

Figure A1: Map of 2004–2009 OxyContin Misuse from NSDUH

This figure plots OxyContin misuse rates across U.S. states. Specifically, the figure plots *NSDUH OxyContin Misuse Rate*, which is the state's average rate of non-medical use of OxyContin during the period 2004–2009 collected from biennial NSDUH surveys (made available by Alpert et al. (2018)). The rate measures the number of people per 100 surveyed that report misusing OxyContin during the past year. Color-shading bins contain (approximately) equal fractions of the 50 states plus the District of Columbia.

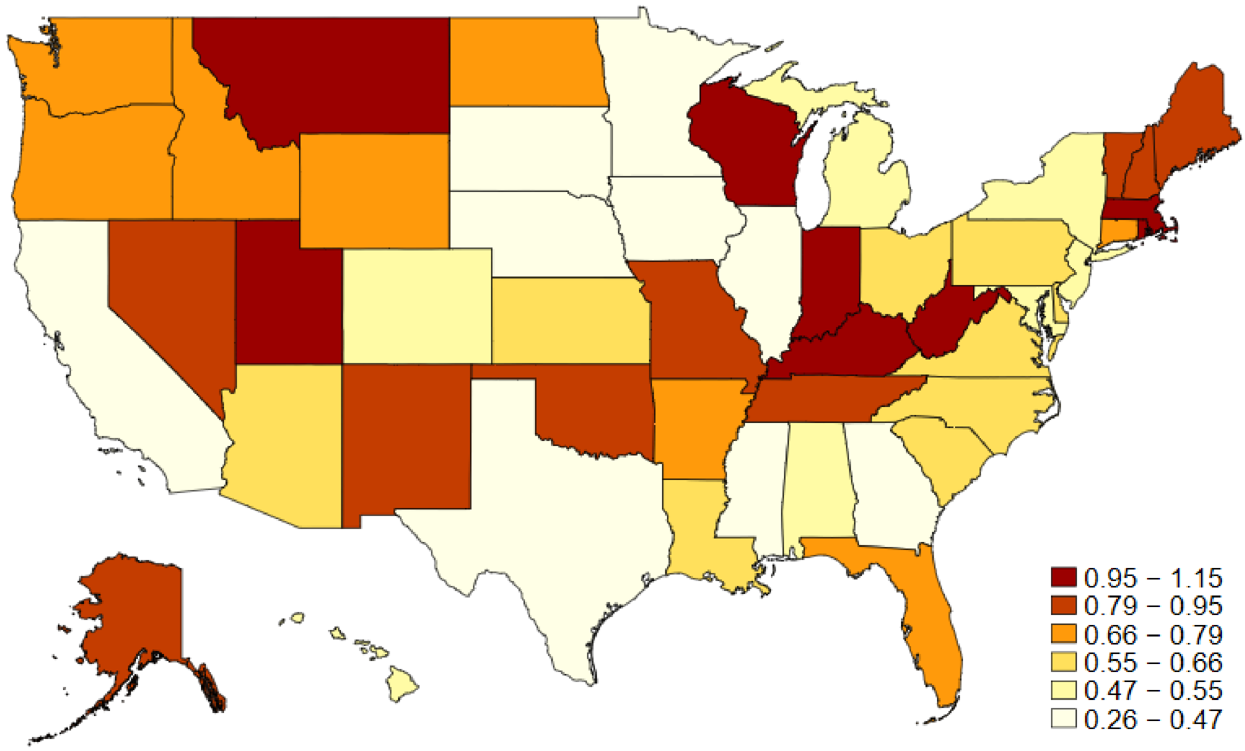


Figure A2: Maps of Opioid Abuse Exposure and Opioid-related Death Rates

This figure plots opioid-related death rates across U.S. counties during the year 2019. Opioid-related death rates are the number of opioid-related deaths in each county per 100,000 residents. We identify opioid-related deaths through one of the following sixteen ICD-10 codes provided by the CDC in their uncensored micro mortality data: X40, X41, X42, X43, X44, X60, X61, X62, X63, X64, X85, Y10, Y11, Y12, Y13, Y14. Accidental deaths due to prescription opioids are marked as condition T40.2 or T40.3, and accidental deaths due to illicit opioids are marked as condition T40.0, T40.1, T40.4, or T40.6. Color-shading bins contain equal fractions of the 2,619 counties in our sample.

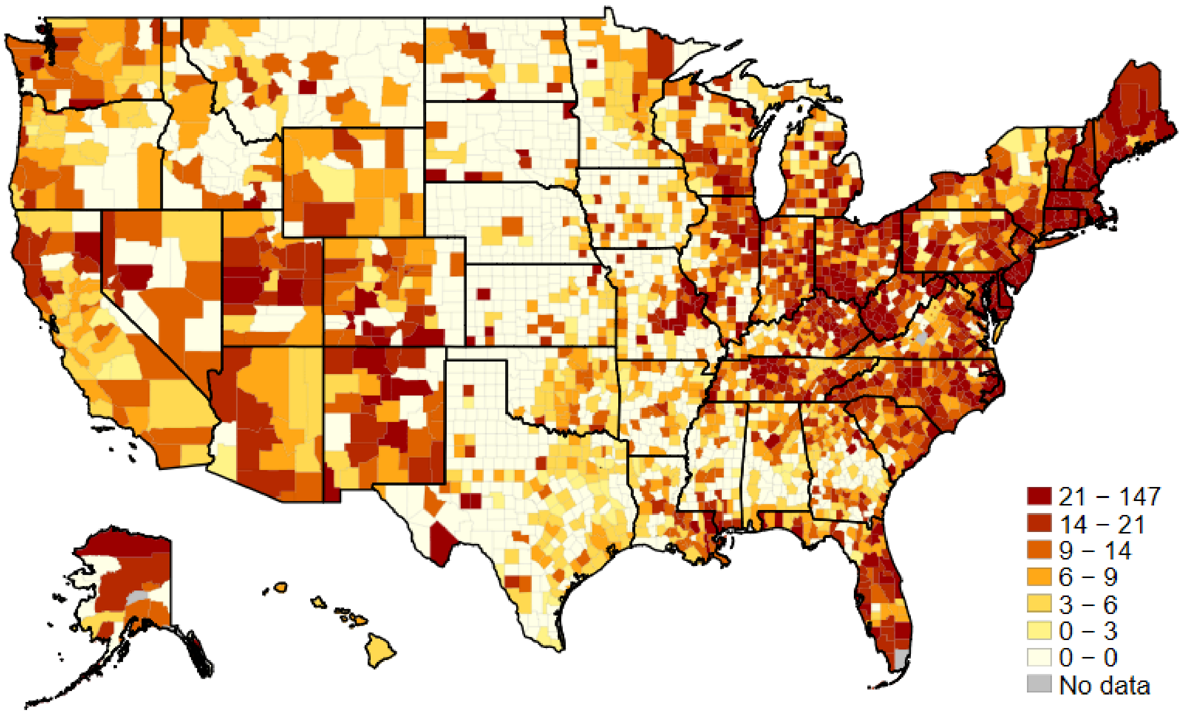


Figure A3: Total MME Distributed for Various Oxycodone-based Opioid Prescription Drugs
This figure plots the total annual distribution of morphine milligram equivalent (MME) of three different prescription opioid products containing oxycodone. The solid line plots the annual MME of extended release (ER) oxycodone products (the most common of which includes OxyContin). The dotted line plots the annual MME of immediate release oxycodone. The dashed line plots the annual MME of all oxycodone combination products (the most common of which includes Percocet). Distribution information on the various oxycodone formulations comes from the DEA's ARCOS database.

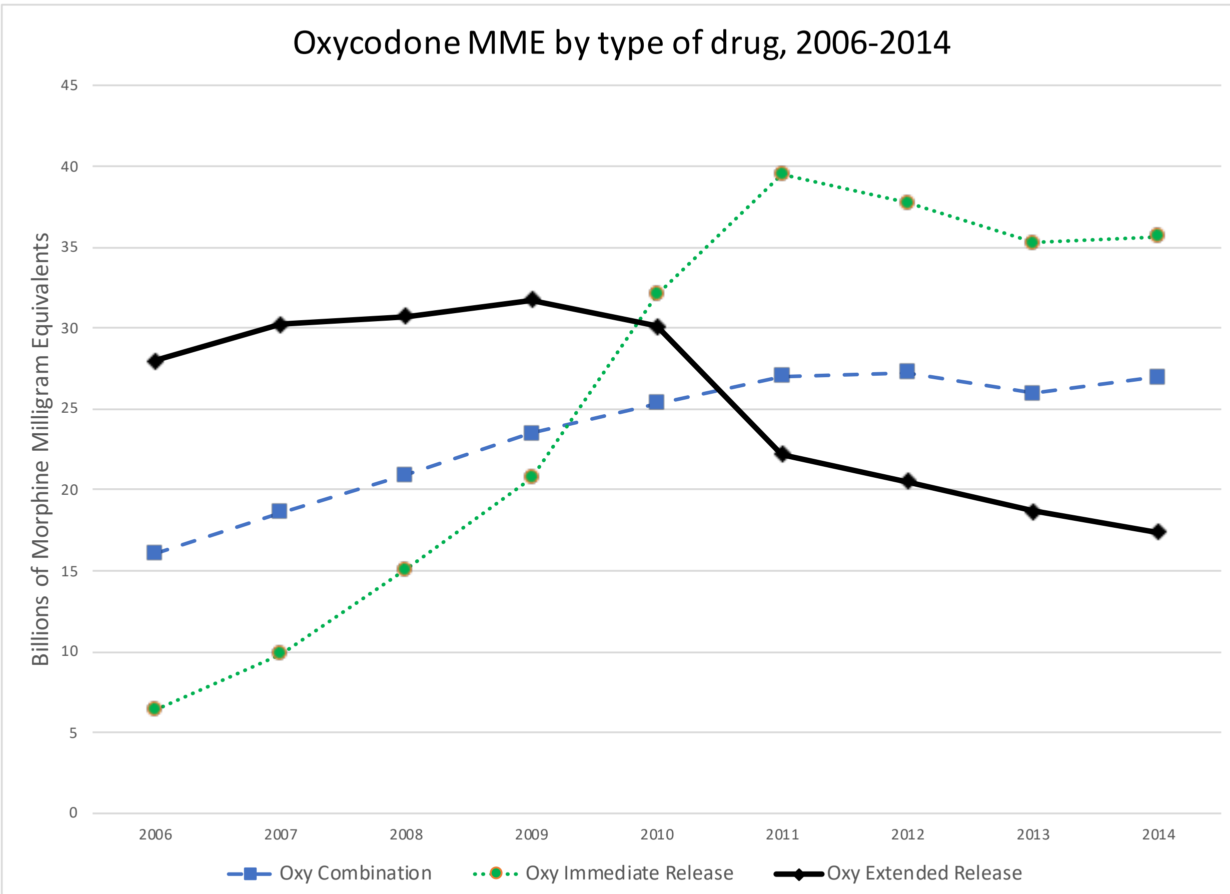


Figure A4: Out-Migration among Sectors with High and Low Opioid Abuse

This figure plots coefficients from two separate state-year level difference-in-differences regressions estimated using Equation 1, each examining the relation between our state-level measure of exposure to opioid abuse and worker out-migration. The solid line plots a regression for low-abuse sectors (i.e., *Information*, *Professional and Scientific*, *Education*, *Public Administration*), and dashed line plots a regression for high-abuse sectors (i.e., *Construction*, *Waste Services*, *Food Services*, and *Other Services*). The regressions include interactions between calendar year indicator variables and our primary measure of exposure to local opioid abuse (along with our full set of year-2000 control variables interacted with a post-2010 indicator variable). Each point on the line represents one of these interaction coefficients. The coefficient on the year 2010 interaction is normalized to zero. The state-level measure of exposure to opioid abuse is the state's average rate of non-medical use of OxyContin during the period 2004–2009 collected from biennial NSDUH surveys (made available by Alpert et al. (2018)). This rate measures the number of people per 100 surveyed that report misusing OxyContin during the past year. The dependent variable in both regressions is the number of is number of job-to-job worker outflows minus the number of job-to-job worker outflows (from LEHD data), scaled by the state's population. Standard errors are clustered at the state-year level. The vertical line at the year 2010 marks the transition from the pre-OxyContin reformulation period to the post-reformulation period. The vertical bars denote 95% confidence intervals.

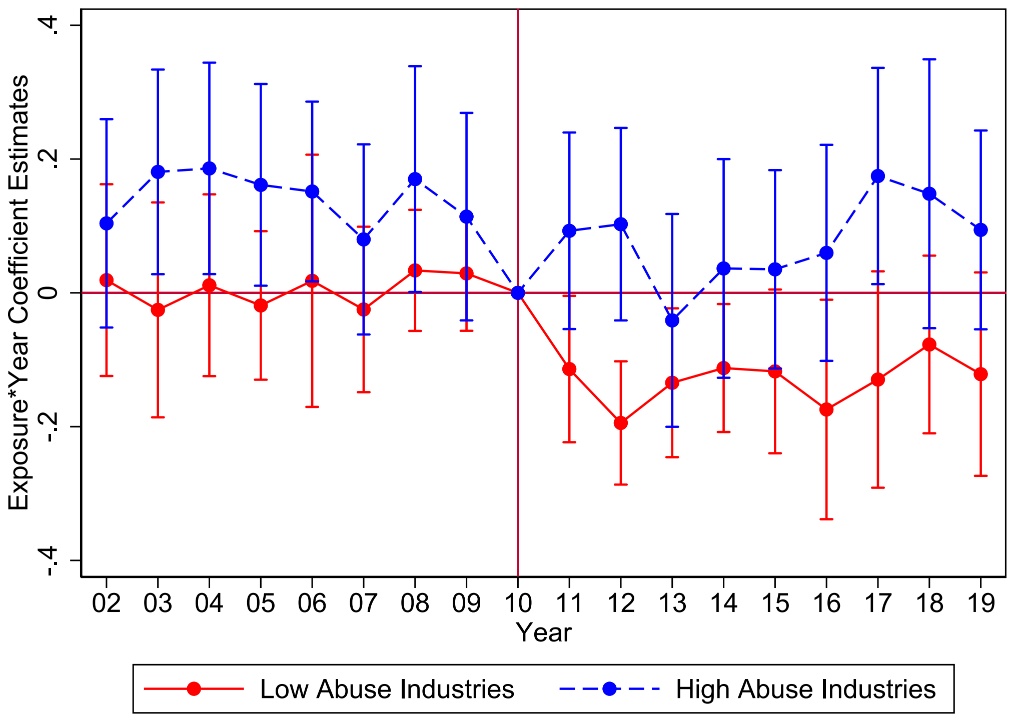
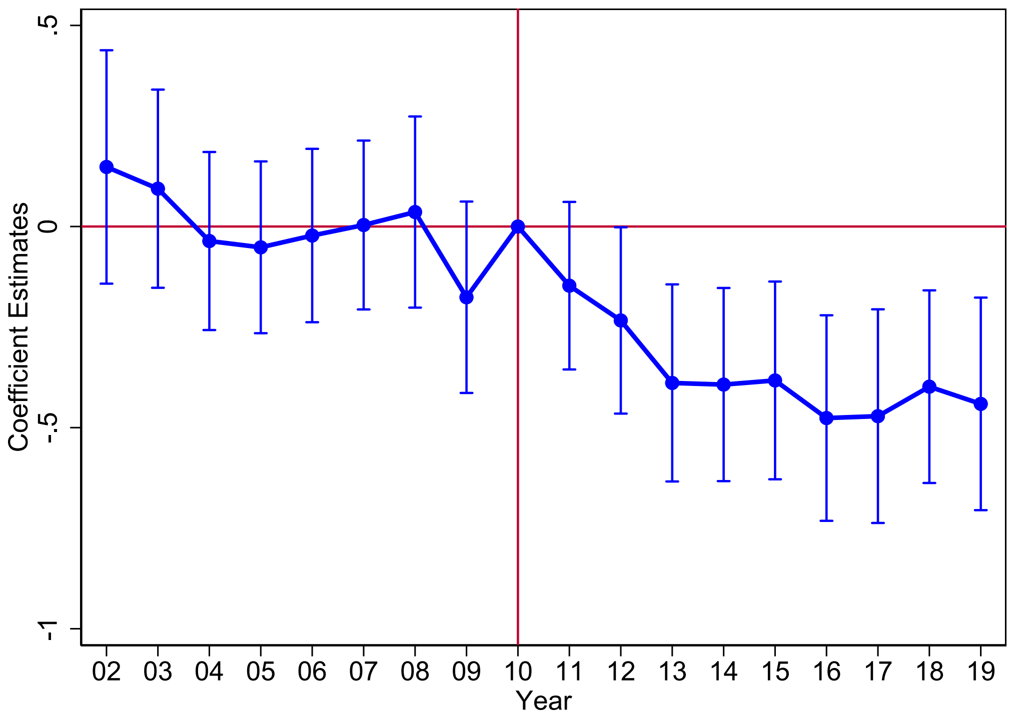


Figure A5: Pre-Sample Oxycodone and the Evolution of County Real GDP

These figures plot coefficients from county-year level difference-in-differences regressions estimated using Equation 1 in the paper, examining the relation between our primary county-level measure of pre-reformulation exposure and inventor migration and patent innovation. The regressions include interactions between calendar year indicator variables and our primary exposure variable, along with our full set of year-2000 control variables interacted with a post-2010 indicator variable. Each point on the line represents one of these interaction coefficients. The coefficient on the year 2010 interaction is normalized to zero. The primary exposure measure is the total MME of morphine, oxycodone, oxymorphone, hydromorphone, and fentanyl prescribed to Medicare beneficiaries in county *i* during the year 2007, scaled by the number of 65 and older residents in the county that year. The dependent variable is the number of inventors that leave the county during year *t*. Standard errors are clustered at the state-year level. The vertical line at the year 2010 marks the transition from the pre-OxyContin reformulation period to the post-reformulation period. The vertical bars denote 95% confidence intervals.



B. Matching Inventors to CoreLogic Transactions

We match inventors to home purchase and sale transactions in the CoreLogic Sales and Transfer Database based on first and last name of the inventor and the county in which the inventor filed his or her most recent patent. For most inventors we are able to match, this information produces a single match to a home purchase and a later sale of the same property, which we use to identify the number of inventors who leave a county each year.

However, there are also several cases where matching on name and county results in either multiple inventors matching to the same property, or the same inventor matching to multiple different properties in the same county. Because both of these issues can distort our measure of inventor migration, we take several steps to limit instances of bad matches and improve the precision of our inventor migration measure.

To address cases where multiple inventors match to the same property, we retain only a single match in these instances. Although we may retain the "wrong" inventor, the identity of the inventor is not critical. We are only interested in counting the number of home sales by inventors in a county each year.

To address cases where the same inventor matches to multiple properties in the same county and year (e.g., due to either a common name or the inventor sharing a name with a repeat buyer/seller), we first limit the sample to matched buyers/sellers with fewer than ten total transactions. We then exclude moves where the seller buys or sells a separate property in the same county during the subsequent ten years. This step results in under counting moves, but rids the sample of false positives attributable to common names and real estate investor matches.

To further improve precision, we remove transactions where the buyer and seller share the same name, and we restrict our sample of moves to those where the seller buys the house at least 180 days prior to the sale date. While these steps likely remove some true matches, they help limit type 1 errors, which is the more problematic source of noise in our setting.

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