Demographic Divergence: The Legacy of the Opioid Epidemic

Carolina Arteaga
University of Toronto
NBER

Victoria Barone
University of Notre Dame
NBER

Stephen Claassen
University of Toronto

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- Local population growth has emerged as a growing challenge: over half of counties lost population between 2010 and 2020. Mackun et al. (2021)
  - Population losses create a cascade of fiscal and economic challenges
  - Population dynamics are key to understanding a place's long-run economic viability of places

This paper: How did the epidemic & the hardship it induced affect population dynamics?

- The opioid epidemic ranks as one of the most tragic public health crises in US history
- Quasi-exogenous variation in exposure to the epidemic from Arteaga and Barone (2026)
  - Exploit geographic variation in the size of local cancer pain market in 1996
  - Proxies exposure to Purdue Pharma's initial marketing campaign for OxyContin
- Estimate causal effects of exposure to the epidemic on local population growth and
  - Its margins of adjustment: mortality, migration, and fertility
- Extend BDK (2022) spatial equilibrium model to college and non-college workers
  - Model the opioid epidemic as an amenity shock which deteriorated the quality of life
  - Generates testable predictions on selective migration by education and declining housing costs

Preview of Results

- Exposure to the opioid epidemic led to persistent local population decline:
  - 1 s.d. of exposure $\downarrow$ local population growth by 1.2pp by 2010 and 1.3pp by 2020
  - Strongest effects among working-age adults (ages 18–64): 2.8pp by 2020
- Direct mortality accounts for only a very small share of the population decline
- Local population declines are driven by selective out-migration:
  - Out-migration effects grow until 2011; stabilize at $\uparrow$ 5.5% per 1 s.d. of exposure
  - Effects concentrated among college-educated adults
- Declines are partially offset by increases in fertility:
  - 1 s.d. of exposure $\uparrow$ local fertility rates by 5.5%, on average
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  - 1 s.d. of exposure $\uparrow$ local fertility rates by 5.5%, on average
  - Concentrated among mothers: in their late 20s
- Mechanism: deterioration in local amenities
  - Population $\downarrow$ + house prices and rents $\downarrow$ + flat earnings
  - Local disamenities: open-air public drug use, homelessness, and perceived safety

Background & Empirical Strategy

Context: The Opioid Epidemic

- Before 1996, the use of opioids had focused on cancer and end-of-life pain treatment

- Since 1996, big pharma marketing campaigns downplayed the risk of opioids and aimed to increase the conditions for which opioids are prescribed

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- Since 1996, big pharma marketing campaigns downplayed the risk of opioids and aimed to increase the conditions for which opioids are prescribed

- OxyContin is introduced in 1996 to **take over the cancer pain market** served by Purdue Pharma's MS Contin

"OxyContin Tablets will be targeted at the cancer pain market."
OxyContin Team Meeting, 1994 /1995/1996

"Because a bioequivalent generic morphine sulfate is expected to be available sometime during the latter part of 1996, one of the primary objectives is to switch patients who would have been started on MS Contin onto OxyContin as quickly as possible"
OxyContin Launch Plan, September 1995

Identification Strategy: OxyContin and 1996 Cancer Mortality

- OxyContin: Opportunity to expand to the larger chronic and non-terminal pain market
- Purdue Pharma deployed a comprehensive marketing and lobbying strategy focusing (first) on its previously established network

  "The use of OxyContin in cancer patients, initiated by their oncologists and then referred back to FPs/GPs/IMs, will result in a comfort that will enable the expansion of use in chronic non-malignant pain patients also seen by the family practice specialists."

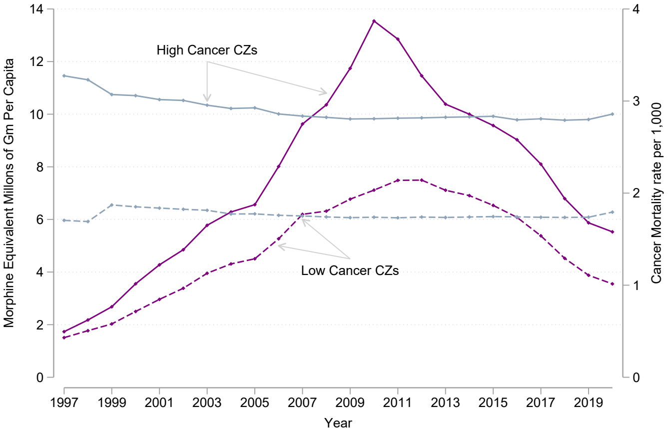
  OxyContin Launch Plan, September 1996.

- By 2003, half of physicians prescribing OxyContin were PCPs (Van Zee, 2009)

Higher cancer incidence in 1996 $\rightarrow$ higher exposure to marketing of opioids

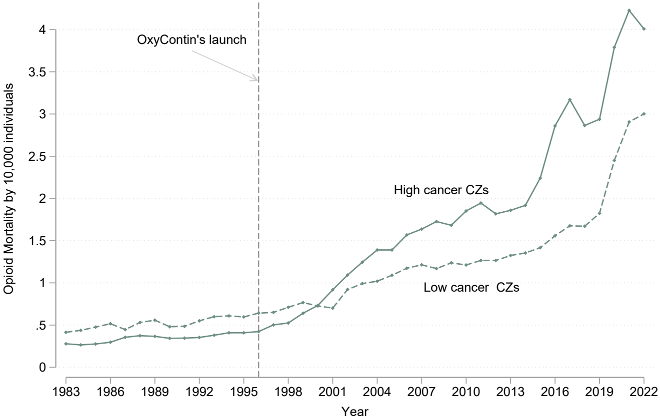
Evolution of Cancer Mortality and Prescription Opioid Distribution

▸ Reg



Notes: This figure shows the evolution of the distribution of prescription opioids in commuting zones (CZs) in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin along with the cancer mortality rate in these commuting zones. ARCOS data are available from 1997. Prescription opioid shipments combine: Oxycodone, hydrocodone, among other Schedule II drugs.
Source: Arteaga and Barone (2025)

High-cancer areas experienced higher levels of drug-induced deaths



- By 2020, drug-induced mortality rates in high-cancer (top quartile) CZs were 55% higher (raw data)
- By 2017, 1 s.d. in cancer mortality ↑ drug-induced deaths by 46% relative to the pre-epidemic average

Empirical Strategy

$$\Delta\ y_{ct} = \sum_{\tau=1989}^{2018} \boldsymbol{\phi_\tau}\ CancerMR_{c,1996}\mathbf{1}(Year = \tau) + \sum_{\tau=1989}^{2018} \alpha_\tau\ X_{c,t_0}\mathbf{1}(Year = \tau) + \gamma_{st} + \upsilon_{ct}$$

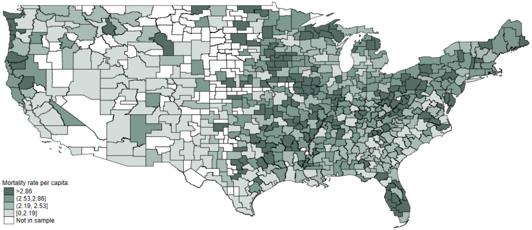
- y_{ct}: outcome of interest in commuting zone c in year t (e.g., total fertility rate)
- Δ: long-change operator relative to baseline year (t_0), i.e., W_{ct}, $\Delta W_{ct} = W_{ct} - W_{c,t_0}$
- $CancerMR_{c,1996}$: cancer mortality rate in commuting zone c in 1996
- X_{c,t_0}: demographic controls at baseline (share female, white, and age groups)
- γ_{st}: state-by-year fixed effects

$\Rightarrow$ $\phi_{1989}, \ldots, \phi_{1995}$ test for pre-trends

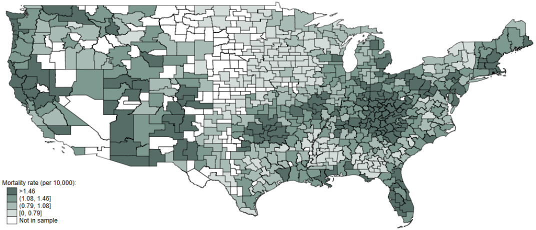
$\Rightarrow$ $\phi_{1997}, \ldots, \phi_{2018}$ dynamic effects of exposure to the opioid epidemic

Geographic Variation in Opioid Epidemic Exposure

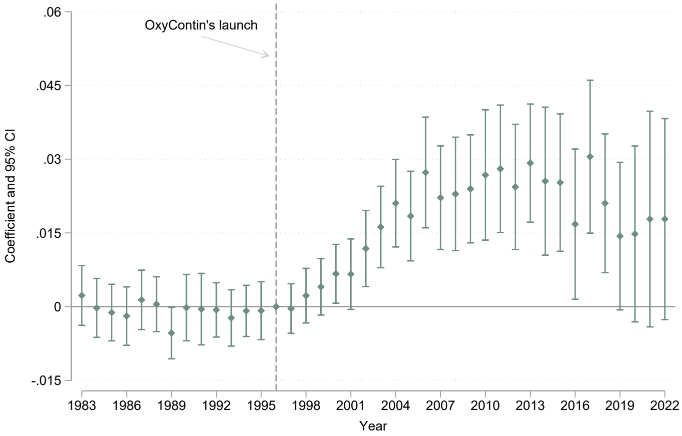
(a) Cancer mortality per capita (1996)



(b) Drug-induced mortality (1996–2018)



Exposure to the epidemic led to increased mortality



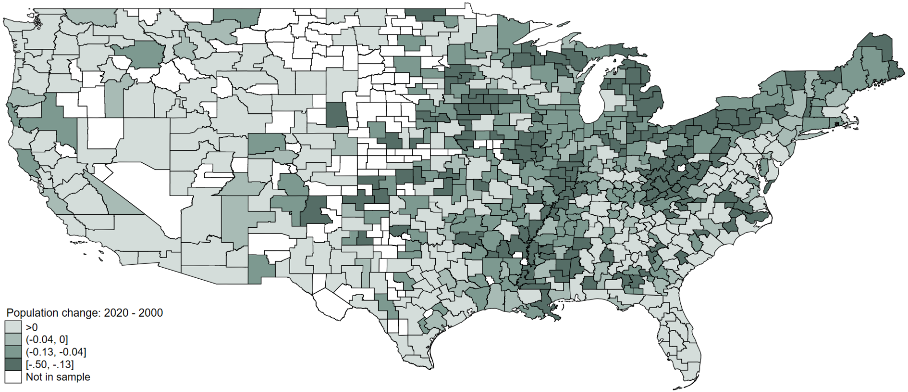
Notes: This figure shows estimates of the effects of cancer-market targeting on drug-induced mortality per 1,000. These estimates use continuous variation in 1996 cancer mortality and include time-varying controls and CZ and state–year fixed effects. *Source:* Arteaga and Barone (2025)

In 2017, 1sd ↑ in 1996 cancer mortality cause ↑ 46% drug induced deaths relative to the pre-epidemic average

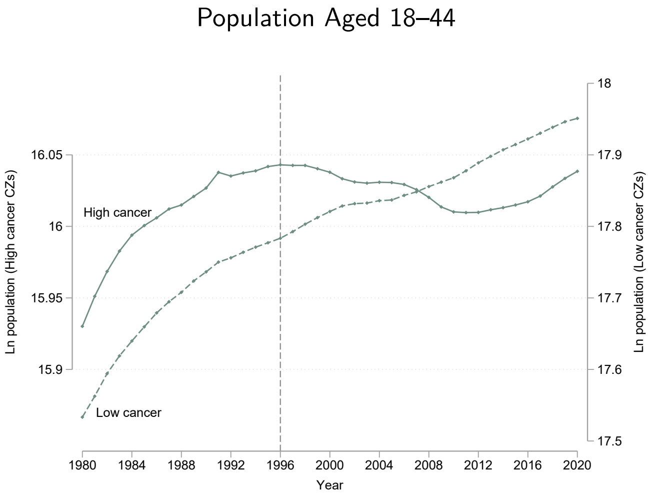
$$\Delta\ \textbf{Population} = \Delta\ \text{Mortality} + \Delta\ \text{Migration} + \Delta\ \text{Births}$$

A large share of communities experienced population decline, in a context of overall population growth

Population change: 2000 to 2020



Particularly true in places with higher exposure to the opioid epidemic



Effects of exposure to the epidemic on local population growth

Effects of exposure to the epidemic on local population growth

	Change in log population per 1 s.d. exposure				
1996 cancer mortality x	All (1)	Female (2)	Male (3)	No college (4)	College (5)
1990 – 2000	0.0042	0.0082	0.0009	0.0044	0.0091
	(0.0055)	(0.0052)	(0.0066)	(0.0056)	(0.0097)
2000 – 2010	-0.0129***	-0.0145***	-0.0124***	-0.0109***	-0.0201***
	(0.0035)	(0.0034)	(0.0039)	(0.0038)	(0.007)
2000 – 2020	-0.0242***	-0.0226***	-0.0267***	-0.02001***	-0.0378***
	(0.0055)	(0.0053)	(0.0078)	(0.0053)	(0.0097)

- Similar demographic trends in high- and low-exposure areas before the diffusion of OxyContin

Longer pre-trends table

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- Similar demographic trends in high- and low-exposure areas before the diffusion of OxyContin
  Longer pre-trends table
- By 2020, 1 s.d. ↑ in exposure ↓ pop. growth rates by 2.4 pp on average → 40% of the observed average local pop change from 2000–2020 (6%)
- Stronger effects among college educated workers → Statistically different 20 years (p-val = 0.0575)

$$\Delta \text{ Population} = \Delta \text{ Mortality} + \Delta \text{ Migration} + \Delta \text{ Fertility}$$

Δ Population $=$ Δ Mortality $+$ Δ **Migration** $+$ Δ Births

Estimating Migration Responses to the Opioid Epidemic

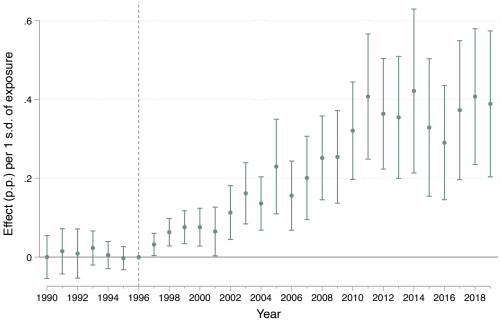
For all annual cross-sections t of geography pairs (o, ℓ) in our sample:

$$\Delta \underbrace{y_{o\ell}}_{} = \alpha_0 + \phi_o \underbrace{CancerMR_{o,1996}}_{\text{Origin shock}} + \phi_\ell \underbrace{CancerMR_{l,1996}}_{\text{Destination shock}} + \alpha_o X_{o,1996} + \alpha_\ell X_{\ell,1996} + \gamma_{so} + \gamma_{s\ell} + \upsilon_{o\ell}$$

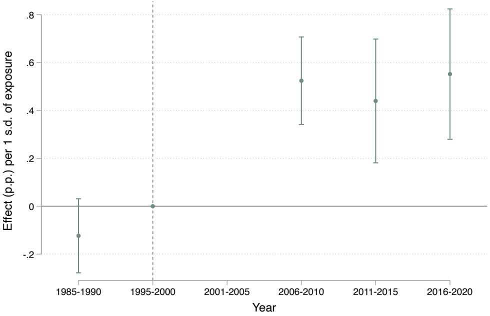
- $y_{o\ell}$: Log probability of migrating from origin o to destination ℓ
- $CancerMR_{o,1996}$: cancer mortality rate in origin o in 1996
  - $\Rightarrow$ ϕ_o: Semi-elasticity of *out-migration* with respect to epidemic exposure
- $CancerMR_{l,1996}$: cancer mortality rate in destination l in 1996
  - $\Rightarrow$ ϕ_ℓ: Semi-elasticity of *in-migration* with respect to epidemic exposure

By 2011, 1 s.d. ↑ in exposure ↑ out-migration by 5.5%

(a) Full population (IRS): Out-Migration



(b) 18+ population (Census and ACS)

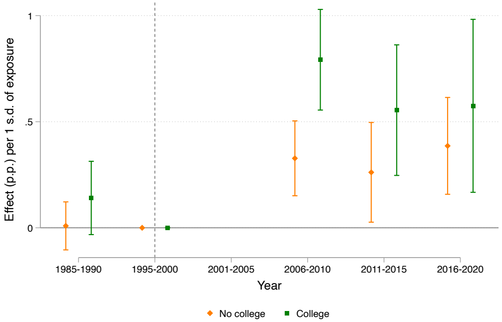


Note: Panel (b) uses Census and ACS data to construct inter-CZ migration of adults by sex and education. Decennial census data (1990, 2000) provides 5-year migration patterns and ACS data (2005, onward) provides 1-year migration patterns. For comparability, we pool ACS data into multi-year windows (e.g., 2005–2010) over which the underlying Public Use Microdata Area (PUMA) geographies, used for mapping to CZs, remain constant.

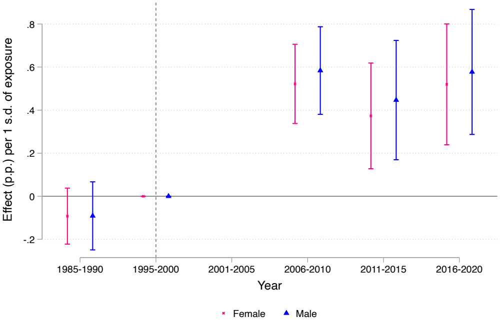
- No effects on the probability of in-migration ▸ Figure

Out-migration was concentrated among adults with college education

(a) By education (Census/ACS)

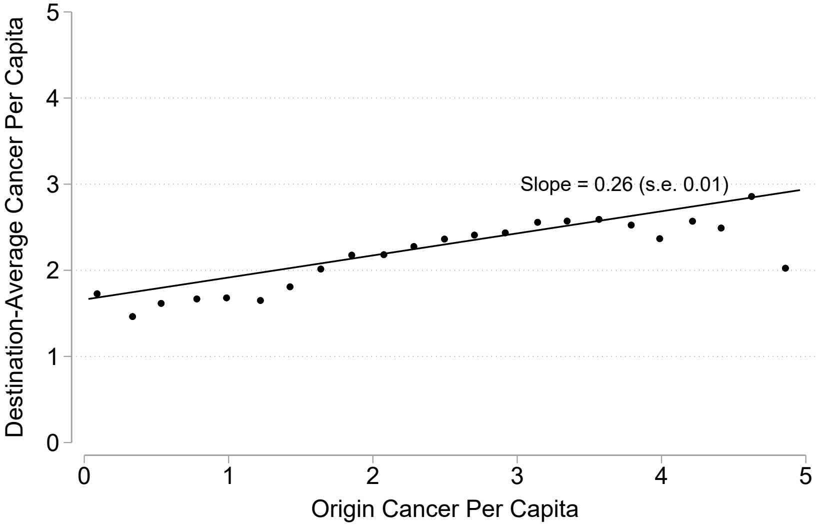


(b) By sex (Census/ACS)



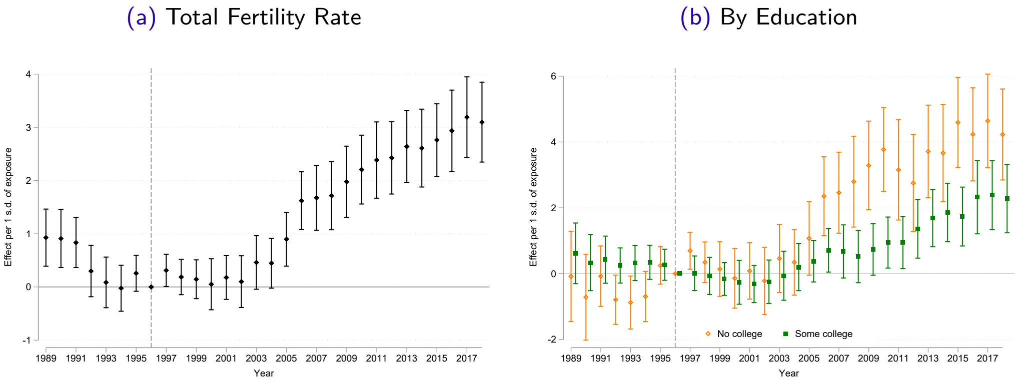
▸ Aggregate Census-ACS effects

Where do people migrate to?



$$\Delta \text{ Population} = \Delta \text{ Mortality} + \Delta \text{ Migration} + \Delta \textbf{ Births}$$

Effects of exposure to the epidemic on fertility rates



- By 2018, 1sd ↑ in 1996 cancer mortality causes ↑ overall fertility by 5.5% among women ages 15–44
- Increases at least twice as large among women w/o college as among women with some college
- Relative increase in fertility despite substantial out-migration, and not driven by compositional changes

Did births increase in levels? Oaxaca decomposition Heterogeneity summary

How much does each margin of adjustment contribute to explaining the change in population growth?

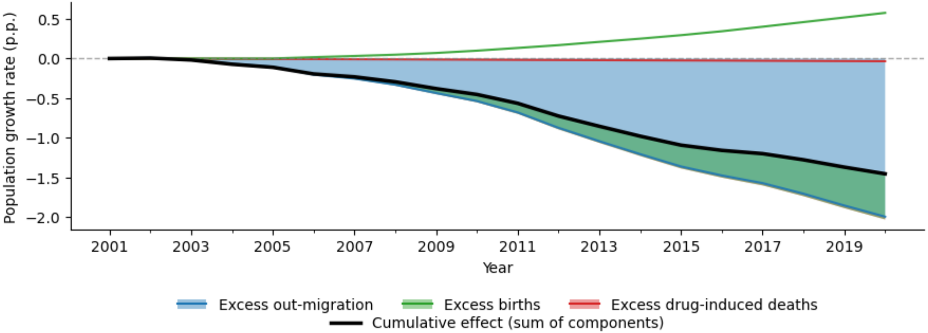
Decomposition Exercise

Exploit the estimated effects of the opioid epidemic to construct the implied population growth.

$$\Delta\text{Pop. Growth}_T = \ln \prod_{t=2000}^{T} \Big(1 \underbrace{- \quad \tilde{\phi}_t^{\text{out-mig}}}_{\text{Excess net-migration}} \underbrace{+ \quad \phi_t^{\text{birth}}}_{\text{Excess births}} \underbrace{- \quad \phi_t^{\text{DI mort}}}_{\text{Excess mortality}}\Big).$$

- $\tilde{\phi}_t^{\text{out-mig}} = \text{Out-mig. rate}_t \times \phi_t^{\text{out-mig}}$
- Excess net-migration: we estimate no in-migration responses, $\hat{\phi}^{\text{in-mig}} = 0$
- Excess mortality: we estimate null effects on non-drug-induced mortality, $\hat{\phi}^{\text{Non DI mort}} = 0$
  Non-drug induced mortality
- This decomposition exercise uses crude birth rate rather than fertility Crude birth rate results

Changes in out-migration rates emerge as the main driver of local demographic adjustment



Mechanisms

The decline in local amenities was characterized by:

- **Visible drug use and illegal markets**
  - Public drug use and overdose emergencies increase in more exposed communities
  - Illicit drug activity (Alpert et al 2018, Evans et al 2017)
- **Increased neighborhood disorder**
  - Higher incidence of local service (311) and emergency (911) calls
    - Boston: 4,654 needle pickup requests in 2018 (public injection exposure) Boston OPD
    - New York City: 7.2% of all EMS dispatches drug-related in 2018 (110,156 calls) FDNY
  - Nationwide, 215,906 doses of naloxone in 2019, 36% in public or outdoor spaces (NEMSIS)
- **Rising homelessness**
  - Exposure predicts increases in the homeless population (Olvera et al., 2024)
- **Perceived safety and crime**
  - Residents report lower safety perceptions (CCES, 2016)
  - Crime increases following exposure (Sim, 2023)

The opioid epidemic as a negative amenity shock

	Change per 1 s.d. exposure			
1996 cancer mortality x	**Population** (1)	Avg. Earnings (2)	House prices (3)	Rents (4)
Pre period	**0.0048**	0.4159	0.4588	6.729*
	(0.0054)	(0.2785)	(0.6837)	(3.5140)
Post (end of period)	**-0.0279*****	0.3168	-7.8253**	-15.45**
	(0.0057)	(1.4157)	(4.2926)	(6.8020)

Declines in population + Stable wages + Reduction in housing cost → Deterioration in amenities

Employment

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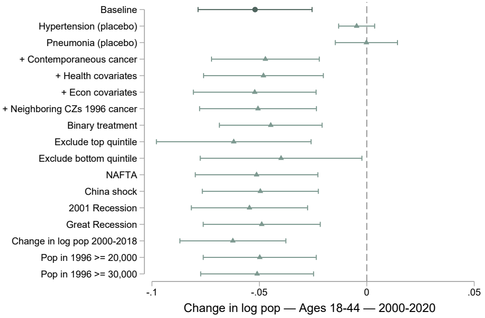
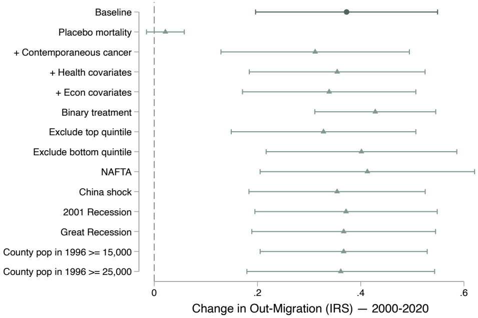
Employment

Robustness checks

(a) Population (2000-2020)



(b) Out-migration (2000-2020)



Out-of-sample exercises | Rob checks additional age groups | Migration | Leave one out exercises | Fertility not explained by abortion access

Conclusion

- New evidence on how the opioid epidemic reshaped fundamental demographic processes:
  - Mortality: higher among men and adults without college education
  - Moves: increase out-migration rates among adults with college education
  - Fertility: among unmarried mothers and women without college education
- The opioid epidemic contributed to the growing regional demographic divergence in U.S.
- Findings stand in contrast with the demographic responses to other local economic shocks
  - The opioid epidemic operated through economic hardship and also through a deterioration in local quality of life

Thank you!

Appendix

Model: Understanding Population and Migration Responses to a Local Amenity Shock

Model set-up

- Spatial equilibrium model: each location is characterized by a labor and a housing market.
- Workers choose locations (ℓ) based on wages, amenities (A_ℓ), and housing costs.
  - College vs non-college: differ in their valuation for local amenities (ψ^h) and responsiveness to location differences (θ^h)
- Production in each location combines both types of workers using a CES aggregator.
- Small change in local amenities across locations (A_ℓ) affects workers' location choice:
  - Directly: relative attractiveness of places change
  - Indirectly: population-induced effects on local wages and rents
- *Low-mobility* equilibrium: influence of indirect connections between locations is negligible

Population response to amenities shock

Equilibrium population response of type-h workers to a change in amenities A_ℓ:

$$\Delta \ln(pop)^h_\ell = \theta^h \zeta^h \; [\; \underbrace{(1-\pi^h_{\ell\ell})\Delta A_\ell}_{\text{Local amenity shock}} \; - \; \overbrace{\sum_{o \neq \ell} \gamma^h_{o\ell} \Delta A_o}^{\text{Shock to connected locations}} \;]$$

$(1-\pi^h_{\ell\ell})$ type-h baseline mobility, $\gamma^h_{o\ell}$ = share of type-h residents living in ℓ who came from o.

- Amenity shocks change populations for both worker types
- Larger changes among college-workers if:
  - Greater value on local amenities ζ^h (Diamond, 2016)
  - More responsive to differences in location attractiveness θ^h (Bound and Holzer, 2000)
  - Higher baseline mobility $(1-\pi^h_{\ell\ell})$ (Molloy et al., 2011)

Migration responses to amenities shock: migration probability

Change in the probability that type-h worker chooses to migrate from o to ℓ:

$$\Delta \ln(\text{Prob. of migrating})^h_{o\ell} = \theta^h \zeta^h \left[\underbrace{\Delta A_\ell}_{\text{Destination amenity shock}} - \overbrace{\Delta A_o}^{\text{Local amenity shock}} \right]$$

- Flows from o to ℓ increase when amenities in the origin o decline relative to the destination ℓ.
- Changes in the out-migration probability are larger among college workers.

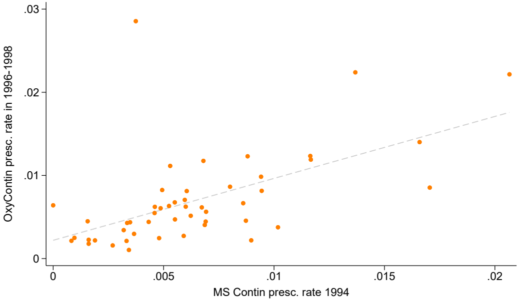
Data

Background & Empirical Strategy

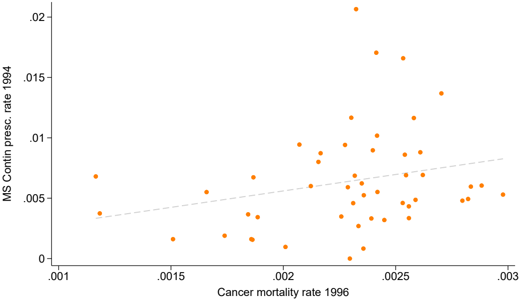
1994 MS Contin prescription rates are strongly correlated with 1996-1998 OxyContin prescription rates and with 1996 Cancer Mortality rates

Back

(a) MS Contin and OxyContin Prescription Rates



(b) MS Contin and 1996 Cancer Mortality



Notes: Panel (a) shows the correlation between OxyContin prescription rates in 1996-1998 and 1994 MS Contin prescription rates. We pool 1996–1998 OxyContin data to capture its initial rollout. The population-weighted correlation coefficient is 0.70. Panel (b) shows the correlation between 1994 MS Contin prescription rates and the 1996 cancer mortality rate. The population-weighted correlation coefficient is 0.45.
Source: Arteaga and Barone (2026)

Did Purdue Pharma follow through with this strategy? Evidence from Massachusetts

▸ Back

Extract Exhibit 1 - Sales Visits By Purdue Pharma Representatives In Massachusetts

Commonwealth of Massachusetts v. Purdue Pharma et al.

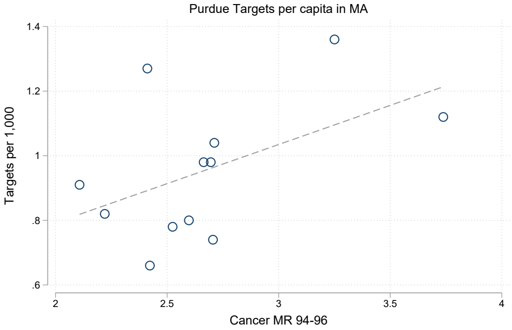
Exhibit 1 - Sales Visits By Purdue In Massachusetts

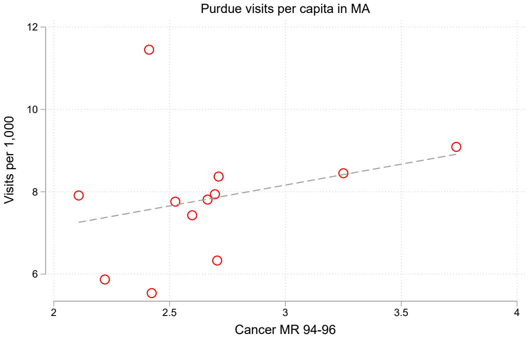
Date	Purdue Sales Rep	Target	Address	City
5/16/2007	Raczkowski, Paula J	Belezos, Elias	164 South Street Harrington Hospital Medical Arts Bld	Southbridge
5/16/2007	Raczkowski, Paula J	Jeznach, Gary	118 Main St Rte 131	Sturbridge
5/16/2007	Raczkowski, Paula J	Welch, Heidi	118 Main Street	Sturbridge
5/16/2007	Raczkowski, Paula J	Keaney, Stephanie	100 South Street Medical Arts Bldg Suite#201	Southbridge
5/16/2007	Raczkowski, Paula J	Kereshi, Stjepan	100 South St Harrington Hospital	Southbridge
5/16/2007	Raczkowski, Paula J	Litani, Vladas	100 South St Harrington Mem Hos	Southbridge
5/16/2007	Raczkowski, Paula J	CVS Pharmacy Southbridge	380 Main St	Southbridge
5/16/2007	Mulcahy, Maurice	Boyd, Kenneth	23 Whites Path	South Yarmouth
5/16/2007	Mulcahy, Maurice	Hartley, Marie	23 Whites Path	South Yarmouth
5/16/2007	Mulcahy, Maurice	Terrill, Donna	269 Chatham Rd	Harwich
5/16/2007	Mulcahy, Maurice	Fair, Dianne	269 Chatham Rd	Harwich
5/16/2007	Mulcahy, Maurice	CVS Patriot Square-So. Dennis	Paqtriot Square/Route 134	S Dennis
5/16/2007	Mulcahy, Maurice	CVS Rt 28 S.Yarm.	976 Route 28 Yarmouth Shopping Plaza	S Yarmouth
5/16/2007	Arias, Alexander	Huang, Wynne	1 Roosevelt	Peabody
5/16/2007	Arias, Alexander	CVS - Main St [Woburn]	415 Main St	Woburn
5/16/2007	Ritter, Andrew	Kehlman, Glenn	637 Washington St	Brookline

Notes: This figure represents an extract of "Exhibit 1 – Sales Visits By Purdue In Massachusetts. Commonwealth of Massachusetts v. Purdue Pharma c.a. No. 1884-cv-01808." These lists were released as part of the litigation between Purdue Pharma and the state of Massachusetts. They contain dates, sales representative names, target (either physicians or pharmacies), address, and city of visits conducted by Purdue Pharma representatives. We geolocate the targets to construct measures at the county level. *Source:* Arteaga and Barone (2026)

Did Purdue Pharma follow through with this strategy? Evidence from Massachusetts

Back

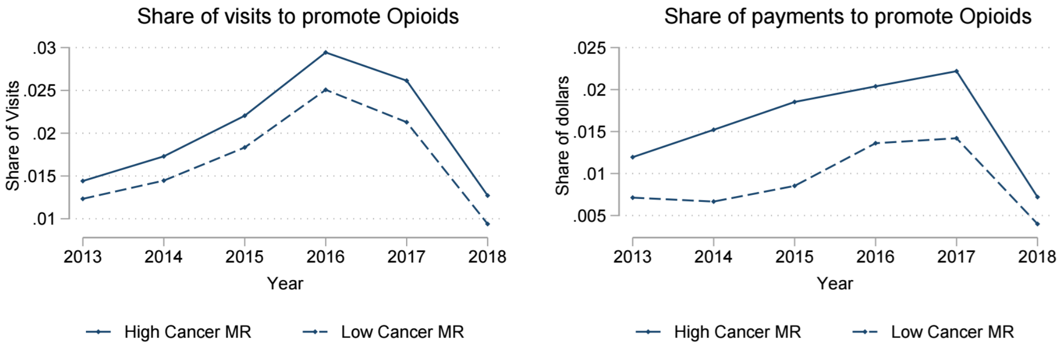




Notes: This figure shows the correlation between cancer mortality rates in mid-1990 and the number of physicians and visits per capita in Massachusetts. Data come from the digitized sales representatives visits records from the litigation documents.
Source: Arteaga and Barone (2026)

Evidence from CMS Open Payments data: More than a decade later, 1996 cancer still predicts marketing intensity

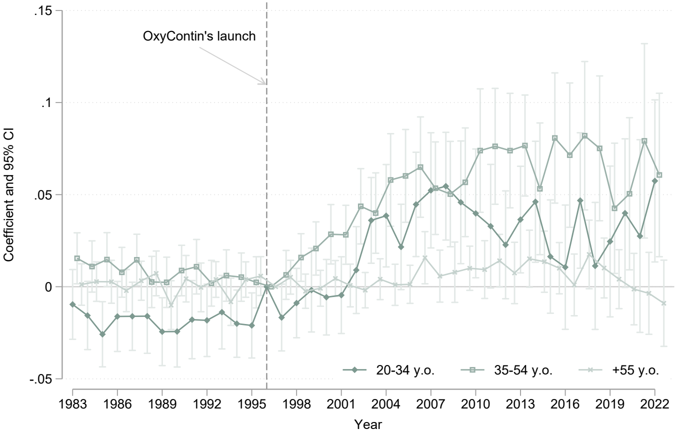
Back



Notes: This figure shows the correlation between cancer mortality rates in mid-1990 and share of visits and share of payments to promote opioids from the CMS Open Payments data.
Source: Arteaga and Barone (2026)

Exposure to the epidemic increased mortality among younger individuals ▸ Back

▸ Back - mortality results

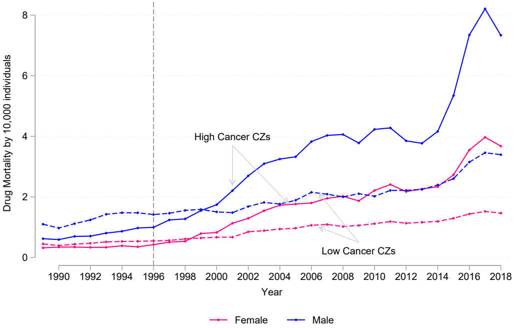


Notes: This figure shows estimates of the effects of cancer-market targeting on drug-induced mortality per 1,000 by age groups. These estimates use continuous variation in 1996 cancer mortality and include time-varying controls and CZ and state–year fixed effects. *Source:* Arteaga and Barone (2026)

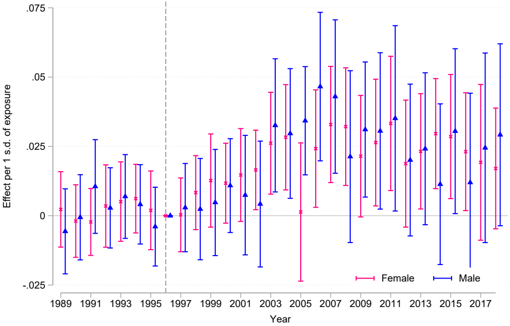
Exposure to the epidemic increased mortality among men and women

▸ Back

(a) Trends in Drug Induced Mortality by Sex



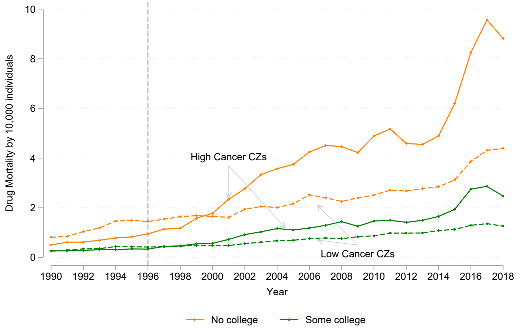
(b) Event-study by Sex



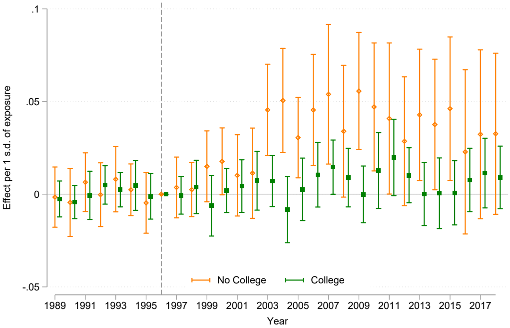
Exposure to the epidemic increased mortality especially among individuals w/o college

▸ Back

(a) Trends in Drug Induced Mortality by Education



(b) Event-study by Education



Exposure to the Opioid Epidemic on Drug Induced Mortality by Sex and Education

Back

1996 cancer mortality x	Female (1)	Male (2)	No college (3)	Some college (4)
1989 - 1995	0.0021	0.002	0.0009	0.0005
	(0.0061)	(0.0059)	(0.0071)	(0.0044)
1997 - 2003	0.0129**	0.0093	0.0151**	0.0025
	(0.0063)	(0.0078)	(0.0077)	(0.0051)
2004 - 2010	0.0238***	0.0338***	0.0453***	0.0059
	(0.0074)	(0.0098)	(0.0115)	(0.0056)
2011 - 2018	0.0241***	0.0234**	0.0355**	0.0074
	(0.0074)	(0.0112)	(0.0146)	(0.0056)
Mean of dep variable in 1996	0.0384	0.0753	0.0759	0.0263
Number of CZs	587	587	586	586
Observations	17,608	17,608	17,578	17,578

Notes: Years are grouped as listed in the left column of the table. We report effect sizes constructed by multiplying the estimated coefficient by the standard deviation of 1996 cancer mortality rates and dividing by the mean of the outcome variable in 1996. These estimates exploit continuous variation in cancer mortality in 1996 and control for baseline characteristics and state-by-year fixed effects. Standard errors are clustered at the CZ level. .

What determines mid-nineties cancer mortality?

‣ Validity

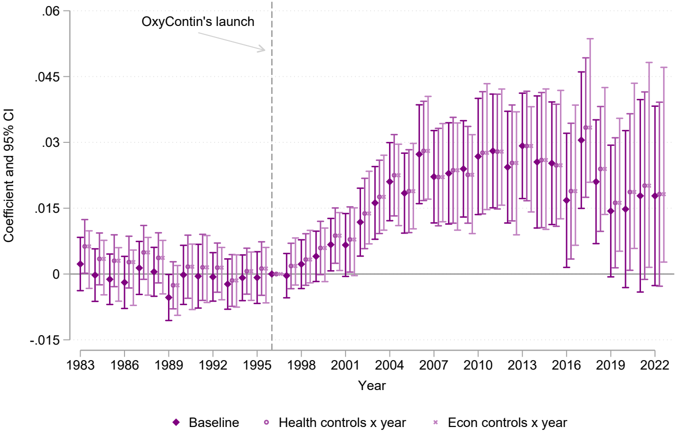
Dependent variable: Cancer mortality 1996

	(1)		(2)
Sh. of population 50 - 64	4.505***	Sh. HS diploma or less	0.60
	[1.697]		[0.394]
Sh. of population over 66	10.08***	Sh. empl in manufacture	-0.06
	[1.271]		[0.169]
Sh. White	-0.34	Ln. income	-0.05
	[0.218]		[0.226]
Sh. Hispanic	-1.179***	Employment rate	-1.89
	[0.197]		[1.385]
Sh. Female	-0.11	Labor force participation	-0.45
	[1.816]		[0.528]
Opioid mortality	3.642*	Adult non-cancer mortality	39.50**
	[1.956]		[17.29]
Rurality in 1993	-0.0207*	Republican vote share 1996	-0.107
	[0.0121]		[0.179]

Notes: This table presents estimated coefficients from a cross-sectional regression of cancer mortality rate in 1996 on demographic and economic characteristics and health outcomes at the c-zone level. Standard errors are robust to heteroskedasticity. *$p<0.10$, **$p<0.05$, *** $p<0.01$.

Additional health and economic controls: drug induced mortality

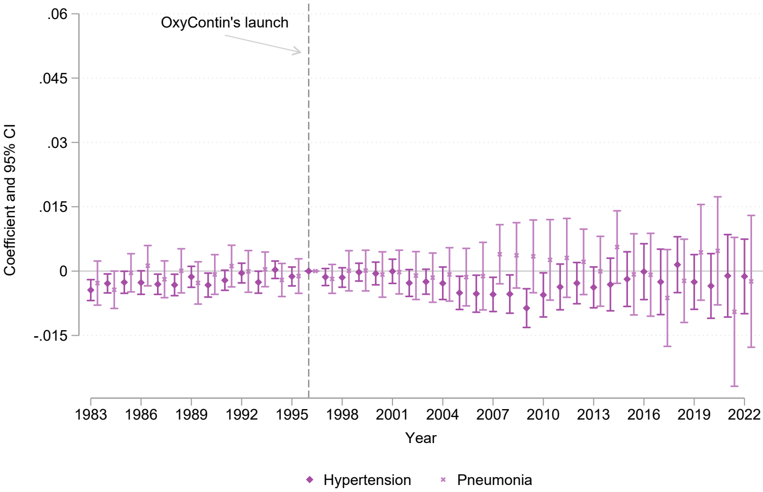
▸ Robustness checks ▸ Validity



Baseline: white and female pop shares, shares of pop aged 18–29, 30–49, 50–64, above 65 years, and under 1 year
Health controls: sh smokers, sh adults w/overweight, sh of primary care physicians, infant mortality rate + pollution
Eon controls: unemployment rate, sh of employment in manufacturing sector, income pc, sh of pop w/ some college

Placebo-test: Does mortality from other causes in 1996 predict drug deaths?

▸ Robustness checks ▸ Validity



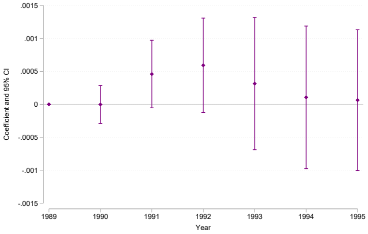
Out-of-sample: Does lagged cancer systematically predict drug deaths or other variables?

No relation between 1976 cancer mortality rates and future outcomes

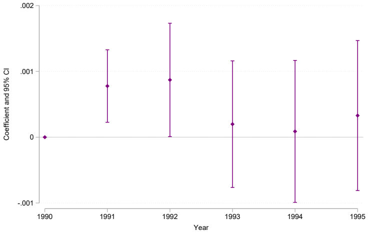
▸ Robustness checks ▸ Validity

(a) Drug-Induced Mortality

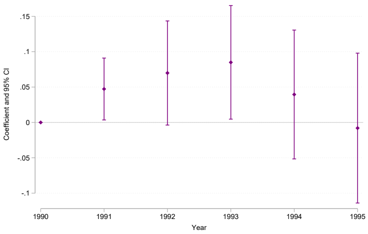
(b) SNAP Receipt Rate



(c) Employment in Manufacturing

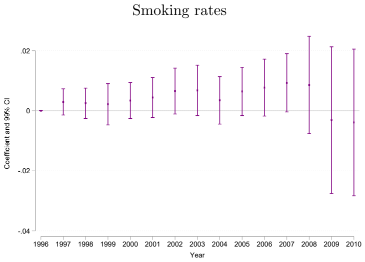


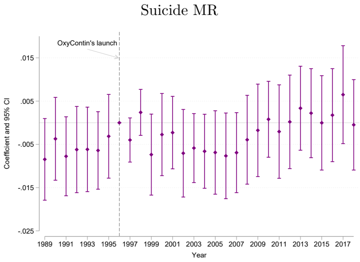
(d) Unemployment Rate

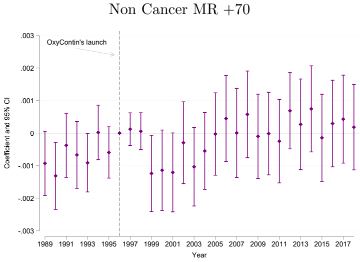


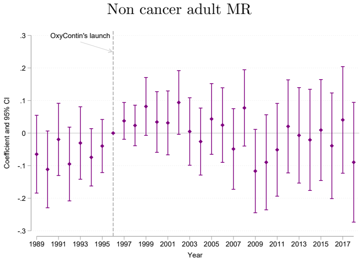
Pre-trends: Is 1996 cancer related to broader health behaviors and trends?

▸ Validity









Population

Population Growth – State Level Estimates

Back

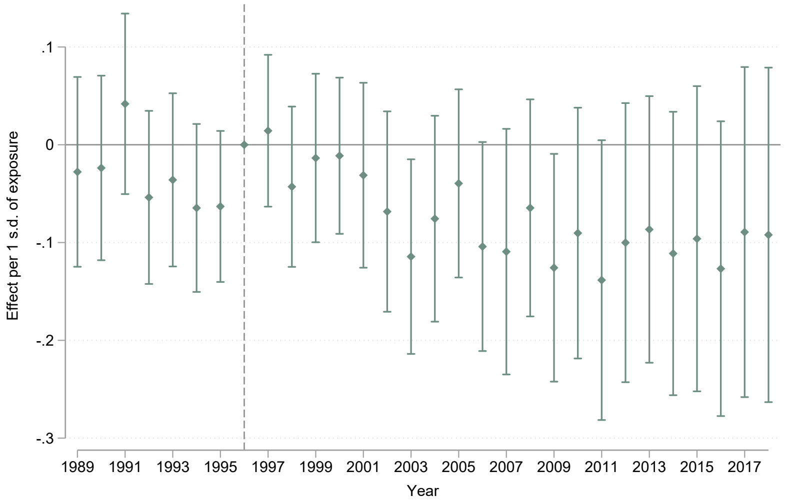
1996 cancer mortality x	Change in log population per 1 s.d. exposure					
		Ages 18-64				
	All ages	All	Female	Male	No college	College
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. State level regressions						
1970 – 1980	-0.0149	-0.0074	-0.0084	-0.0064	0.0076	-0.0099
	(0.0106)	(0.0094)	(0.0079)	(0.011)	(0.0094)	(0.0132)
1980 – 1990	0.0002	-0.0009	-0.0028	0.0009	0.0036	0.0117
	(0.0064)	(0.0063)	(0.0058)	(0.0068)	(0.0054)	(0.0078)
Panel B. CZ level regressions						
1990 – 2000	0.0023	0.0042	0.0082	0.0009	0.0044	0.0091
	(0.0048)	(0.0055)	(0.0052)	(0.0066)	(0.0056)	(0.0097)
2000 – 2010	-0.0094***	-0.0129***	-0.0145***	-0.0124***	-0.0109***	-0.0201***
	(0.0034)	(0.0035)	(0.0034)	(0.0039)	(0.0038)	(0.007)
2000 – 2020	-0.0103**	-0.0242***	-0.0226***	-0.0267***	-0.02***	-0.0378***
	(0.0048)	(0.0055)	(0.0053)	(0.0078)	(0.0053)	(0.0097)

Notes: This table presents estimates of the effects of exposure to the opioid epidemic on the change in log population. Panel A uses state-level data to construct population counts. Columns (1) to (4) leverage data from the 1960, 1970, 1980, and 1990 Censuses. Columns (5) and (6) leverage data from the 1950, 1970, 1980, and 1990 Census to construct population counts by years of schooling for adults aged 25 years and older. Educational level data are not available from the 1960 Census. These regressions include a vector of demographic controls measure in 1990 and 1980 to account for state baseline characteristics. Standard errors are clustered at the state level. Panel B reproduces the results presented in Tables **??** and **??**. *$p<0.10$, **$p<0.05$, *** $p<0.01$.

Mortality

No effects on non-drug induced mortality

▸ Summary of mortality effects ▸ Decomposition Exercise

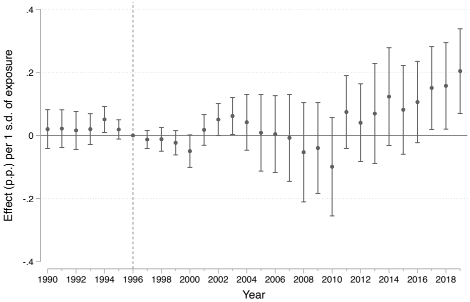


Migration

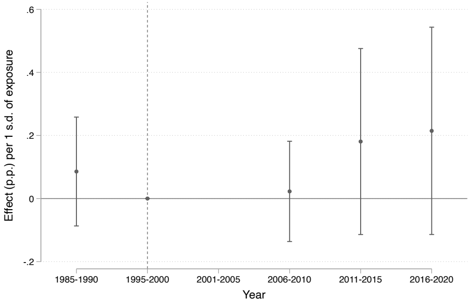
No effects on in-migration probability (ϕ_I)

▸ Back

(a) In-migration, overall (IRS)



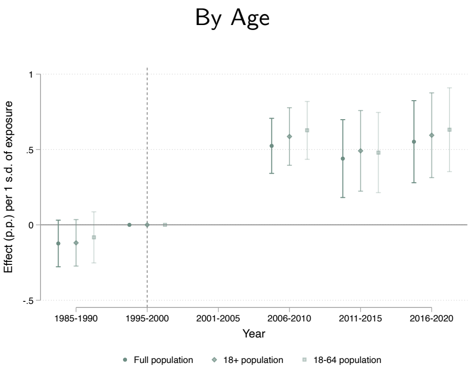
(b) In-migration, overall (Census and ACS)

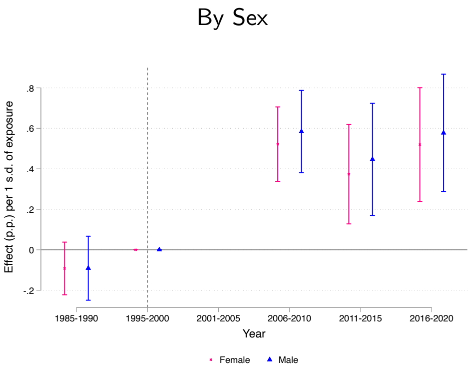


Note: Panel (b) uses Census and ACS data to construct inter-CZ migration of adults by sex and education. Decennial census data (1990, 2000) provides 5-year migration patterns and ACS data (2005, onward) provides 1-year migration patterns. For comparability, we pool ACS data into multi-year windows (e.g., 2005–2010) over which the underlying Public Use Microdata Area (PUMA) geographies, used for mapping to CZs, remain constant.

Effects are concentrated among working-age adults and similar by sex

▸ Back

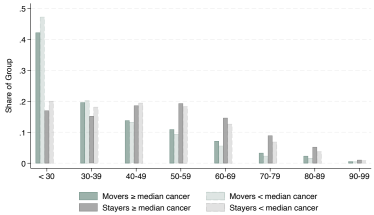




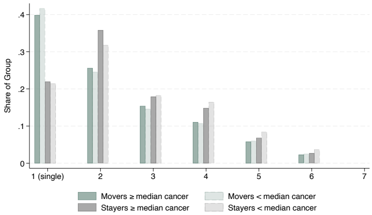
Socioeconomic and Demographic Compositions of Movers and Stayers by Epidemic Exposure

▸ Back

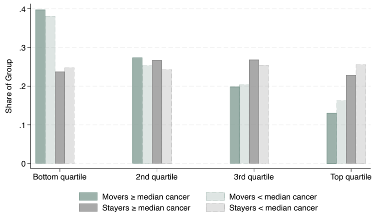
(a) Age (10-year bins)



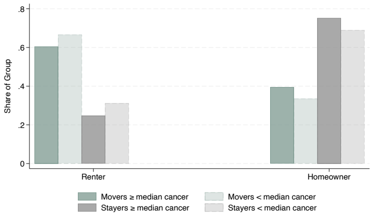
(b) Household size



(c) Income Quartiles



(d) Homeownership



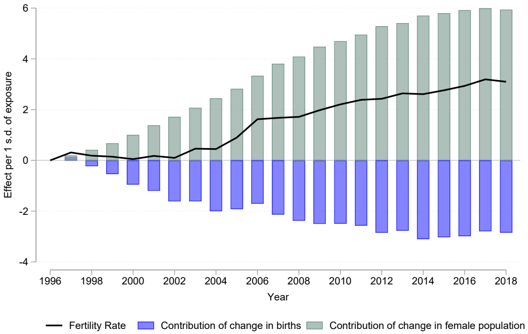
Fertility

Births declined in more exposed areas, but by less than the female population

Back

$$\Delta \text{Fertility Rate}_{ct} = \underbrace{\frac{\text{births}_{ct}}{\text{fem pop}_{c,1996}} - \frac{\text{births}_{c,1996}}{\text{fem pop}_{c,1996}}}_{\text{Birth effect}} + \underbrace{\frac{\text{births}_{ct}}{\text{fem pop}_{ct}} - \frac{\text{births}_{ct}}{\text{fem pop}_{c,1996}}}_{\text{Population effect}}.$$

- Birth effect: how the fertility rate would have changed if female population remained fixed at its 1996 level
- Population effect: captures the mechanical contribution of a shrinking denominator, holding births fixed.



Can differential out-migration explain the fertility increase? Back

- To formally quantify the relative contribution of composition versus within-group changes, we perform an Oaxaca decomposition of the aggregate change in fertility:

$$\Delta F_{ct} = \underbrace{\sum_g \Delta S^g_{ct} F^g_{ct_0}}_{\substack{\text{Changes in group shares} \\ \text{baseline fertility}}} + \underbrace{\sum_g S^g_{ct_0} \Delta F^g_{ct}}_{\substack{\text{Within-group fertility changes} \\ \text{baseline group shares}}} + \sum_g \Delta S^g_{ct} \Delta F^g_{ct},$$

  where g indexes education groups: college and non-college
- More than 95% of the observed increase is driven by within-group fertility changes
- Shifts in the educational composition of women account for a negligible share

Effects of Exposure to the Opioid Epidemic on Fertility Rates - Heterogeneity

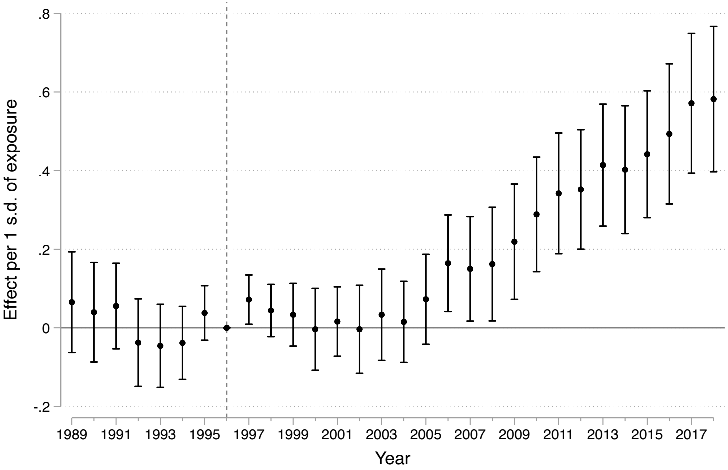
Back

	Unmarried	Married	No college	Some college
	(1)	(2)	(3)	(4)
1996 cancer mortality x				
1989 - 1995	0.5934*	-0.1161	-0.4279	0.3651
	(0.3285)	(0.3079)	(0.3124)	(0.2552)
1997 - 2003	0.5382	-0.1848	0.1939	-0.1593
	(0.3502)	(0.3608)	(0.3622)	(0.2552)
2004 - 2010	1.612***	0.5828	2.2971***	0.5927*
	(0.4372)	(0.555)	(0.5345)	(0.3289)
2011 - 2018	1.746***	2.0366***	3.8721***	1.8205***
	(0.4663)	(0.6977)	(0.6156)	(0.4052)
Mean of dep variable in 1996	0.0479	0.0751	0.0829	0.0531
Number of CZs	583	583	586	586
Observations	17,456	17,456	17,580	17,580

Decomposition Exercise

Effects of Exposure to the Opioid Epidemic on the Crude Birth Rate

Back



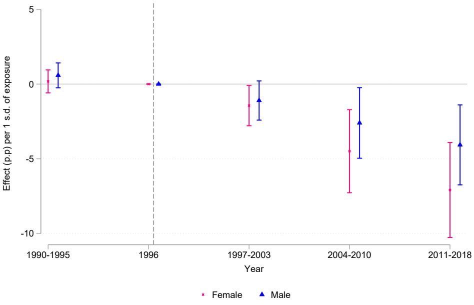
Notes: This figure presents effects on the crude birth rate, i.e., the ratio of births to women aged 15-44 to the total population times 1,000.These are estimates of the ϕ_τ coefficients multiplied by the standard deviation of the 1996 cancer mortality rate. These estimates exploit continuous variation in cancer mortality in 1996 and control for baseline characteristics and state-by-year fixed effects. Standard errors are clustered at the CZ level.

Economic Effects

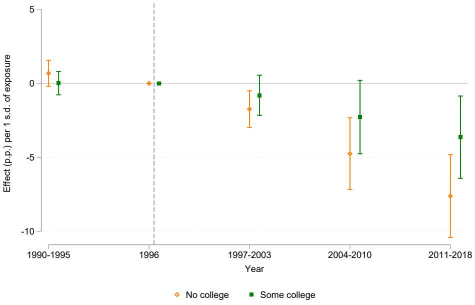
Employment

Back – Mechanisms

(a) Employment by sex



(b) Employment by Education



- By 2018, 1 s.d. ↑ in exposure ↓ employment growth by 6 p.p. (female) and 4 p.p. (male)
- Larger employment declines for no-college workers

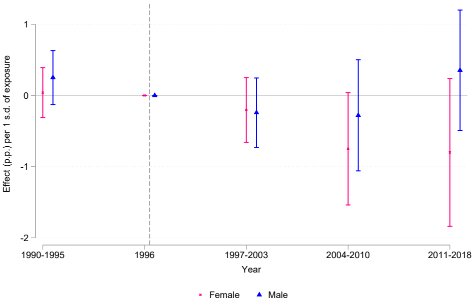
Employment-to-population ratio

Back – Mechanisms

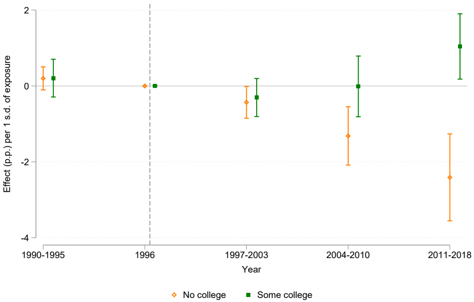
Employment-to-population ratio

Back – Mechanisms

(a) By sex



(b) By Education

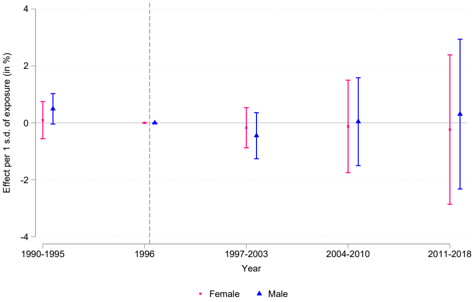


- Negative effects on employment-to-population ratio → relative losses in employment were stronger than those in population

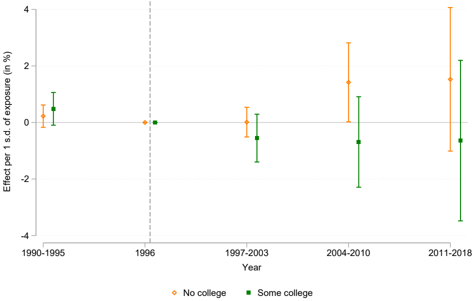
Average Earnings

Back – Mechanisms

(a) By sex



(b) By Education

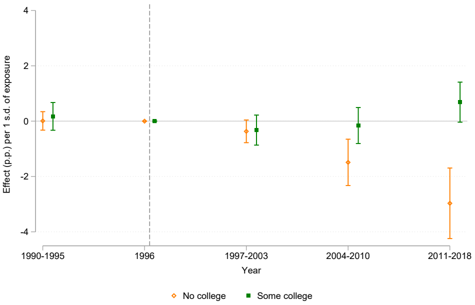


Reductions in the opportunity cost of childbearing

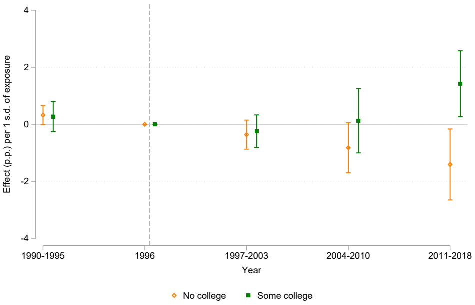
Back – Mechanisms

Effects of exposure to the opioid epidemic on the employment-to-population ratio

(a) Female

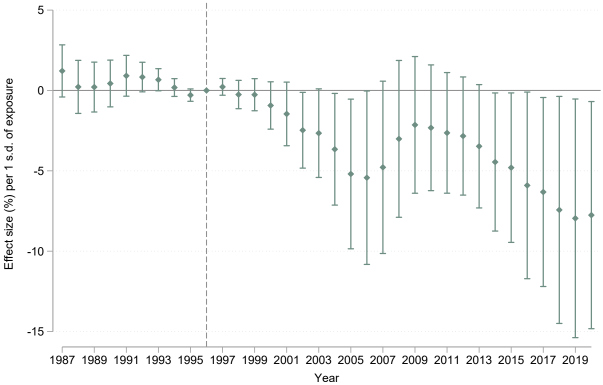


(b) Male



Amenities

The opioid epidemic worsen local amenities
By 2020, 1sd ↑ in exposure lead to an 7.8% decline in house prices



- House prices → proxy of households' willingness to pay for local living conditions
- Data: House Price Index (HPI) from the Federal Housing Finance Agency (FHFA), it tracks changes in single-family home values using mortgage transactions.

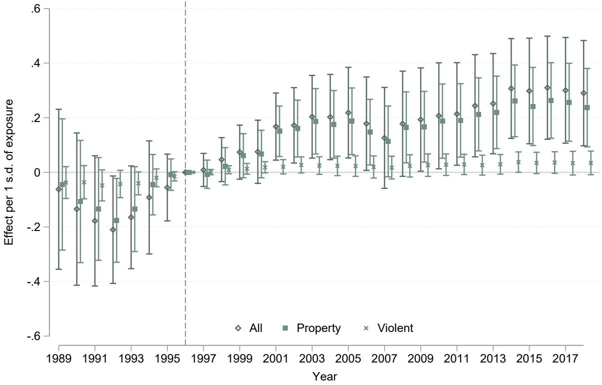
The opioid epidemic worsen local amenities
By 2020, 1sd $\uparrow$ in exposure reduced rents by 2.5%

Back – House prices

	Change per 1 unit of exposure
1996 cancer mortality x	Median rent
1990 – 2000	6.729*
	(3.514)
2000 – 2010	-12.55**
	(5.129)
2000 – 2020	-15.45**
	(6.802)
Observations	8,190
Number of CZs	585

- Data: Median contracted rents from the Decennial Census and the American Community Survey.

By 2020, 1sd ↑ in exposure lead to an 9.8% increase in the crime rate



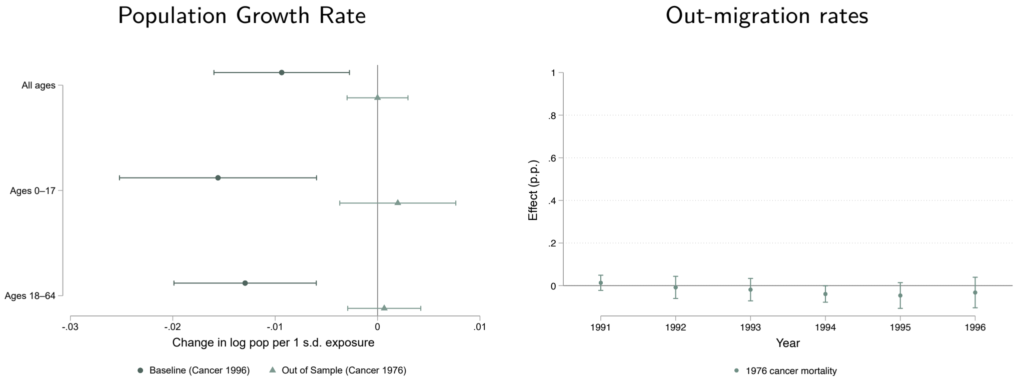
- Data: Uniform Crime Reports (UCR - FBI). "Index crimes" are the major offenses originally selected by the FBI to measure the volume and trends of crime across the U.S.
- Property index crimes: burglary, theft, and motor vehicle theft
- Violent index crimes: murder, rape, robbery, and aggravated assault

Back – Amenities

Robustness Checks

Out-of-sample: No mechanical relationship between cancer and population growth or out-migration rates

Back

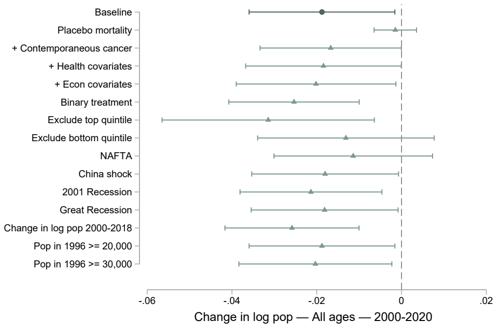


Note: This figure shows an out-of-sample exercise where we use 1976 cancer mortality rates as our measure of exposure to the epidemic. The left-hand-side panel presents estimates on log population change between 1990 and 2000 (i.e., a 10-year population change) and the right-hand-side panel presents estimates on migration rates relative to 1993.

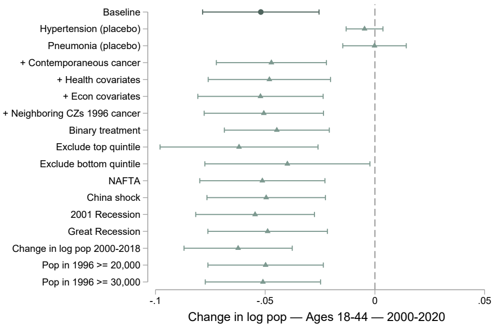
Additional robustness checks: Population Effects

Back

(a) Total population (2000-2020)



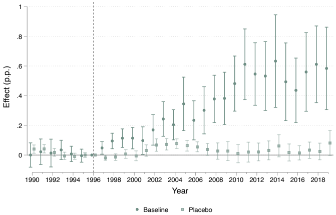
(b) 18-64 year old population (2000-2020)



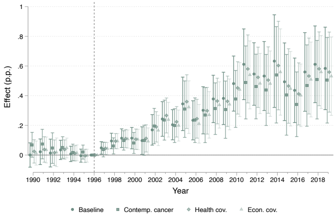
Additional robustness checks: Migration Effects

Back

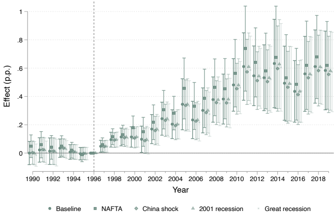
(a) Placebo mortality



(b) Additional controls



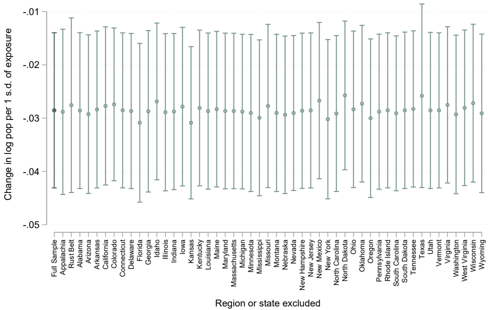
(c) Exposure to economic shocks



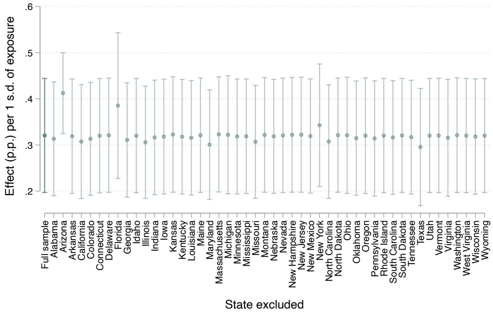
Leave one out exercise

Back

(a) Population 18-64 (2000-2020)

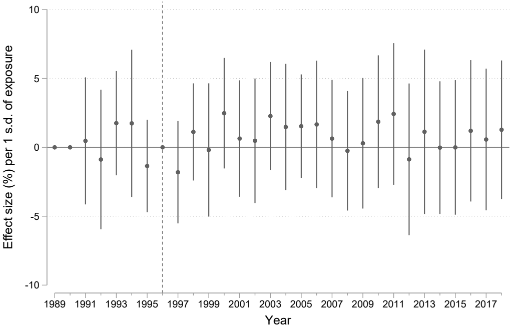


(b) Out-Migration (IRS)

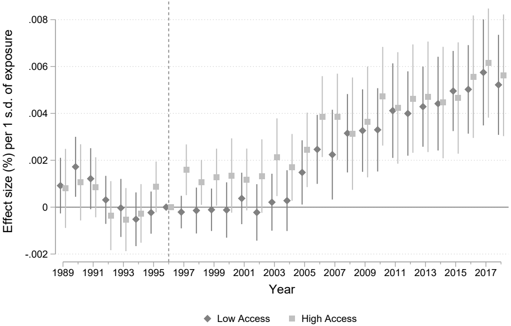


The role of abortion access

(a) Abortion rate



(b) Heterogeneity



Back