The Effects of Layoffs on Opioid Use and Abuse

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The labor market and opioid use and abuse

- Over the past 20 years, global consumption of opioids more than doubled (INCB (2018))
- Economic instability and opioid use and abuse often rise together
- Little causal evidence of relationship between economic conditions and opioid use

This paper

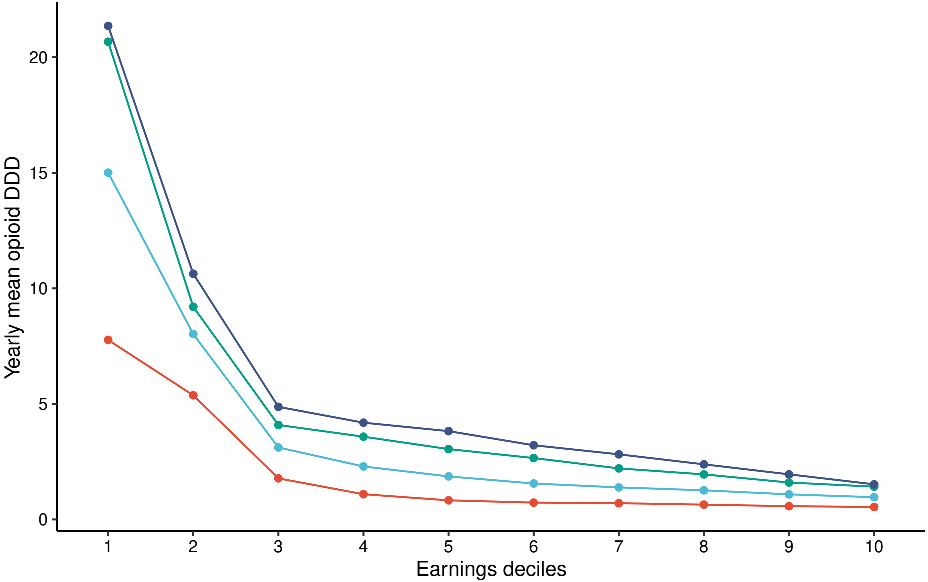
- **Aim**: Investigate the effect of job displacement on use and abuse of opioids
- **Identification**: Compare individuals who experienced mass layoffs to otherwise-similar individuals who did not
- **Data**: Leverage high-quality Danish administrative data
- **Main results**: Job displacement increases both the propensity to get an opioid prescription ($\sim$ 15%) and usage/intensity ($\sim$ 64%)
- **Spillovers**: Layoffs cause spouses to increase use
- **Geographical variation**: Supply of opioids is important for the magnitude of the effect

Literature on the opioid epidemic

- Mortality due to opioid overdoses is rising in several rich countries, especially the United States (e.g. Case and Deaton (2015, 2017))
- Opioid use and abuse is more common among individuals facing worse economic conditions (e.g. Case and Deaton (2017), Krueger (2017), Ruhm (2018))
- Economic conditions (and layoffs in particular) harm other health outcomes (e.g. Browning and Heinesen (2012), Kuhn et al. (2009), Sullivan and von Wachter (2009))
- Opioid use and abuse may lead to deteriorating economic outcomes (e.g. Harris et al. (2019), Laird and Nielsen (2016), Thingholm (2019), Park and Powell (2019))

Most literature claiming causality explores the effect of local economic conditions rather than individual-level shocks.

Earnings and opioid use



Danish health care

Health care services in Denmark

- Publicly provided through the National Health Insurance
- Primary and secondary health care services free of charge

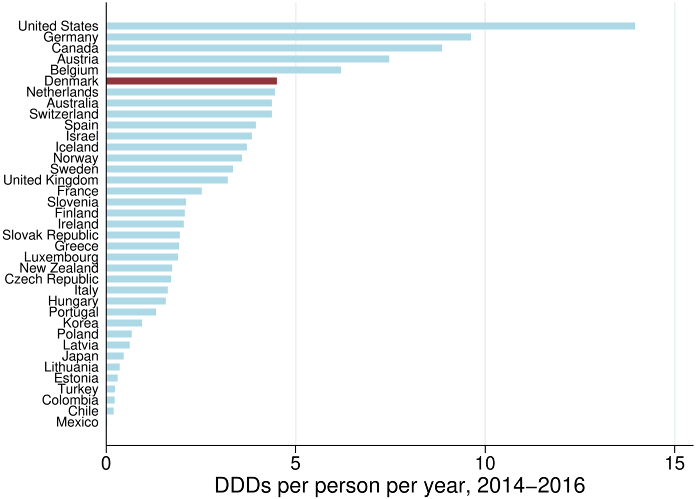
Primary care physicians

- Operate in small private practices
- Act as gatekeepers to practicing specialists and the hospital sector

Medicines

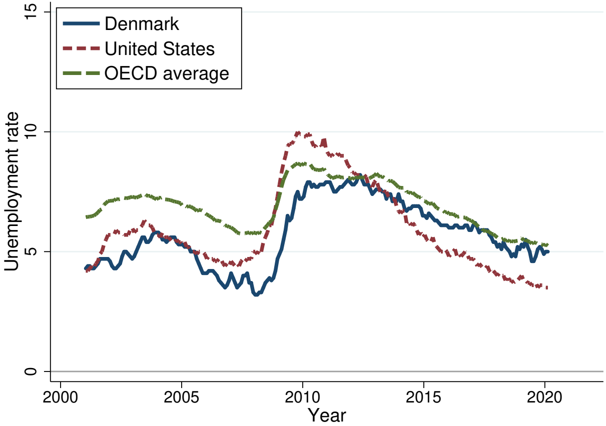
- Prescriptions redeemed at community pharmacies
- Most medicines (including opioids) are subsidized

Opioids prescribed per capita in Denmark and other countries



Danish labour market

- Lower inequality: Gini of 0.264, vs 0.390 (US)
  - But rising in Denmark similarly to elsewhere
- (Mostly) similar unemployment rates



Identification

Investigate the effect of job displacement on use and abuse of opioids

- For causality: analyze changes in employment status that are possibly exogenous to the worker

Mass-layoffs are likely unrelated to any individual worker's propensity to use opioids.

- Compare individuals who experienced this negative economic shock to otherwise-similar individuals who did not (Davis and von Wachter, 2011)

Example of a mass layoff

Recent headlines in Danish media after Danish Crown annonced the closing of a large slaughterhouse in Ringsted (April 18th 2024)

Penge

Danish Crown lukker slagteri i Ringsted: Nedlægger 1.200 stillinger

Penge

Borgmester er i chok over Danish Crown-lukning: 'Vi var slet ikke forberedt på det'

Data

Danish administrative registry data:

- **Employer-employee data**:
  - Identifying mass-layoffs
  - Measuring labor market outcomes
- **National Prescription Register**: Registry containing all pharmacy claims.
- Detailed demographics obtained through relevant registries
- Data is linked using the unique Danish civil registration number

Sample selection in three steps

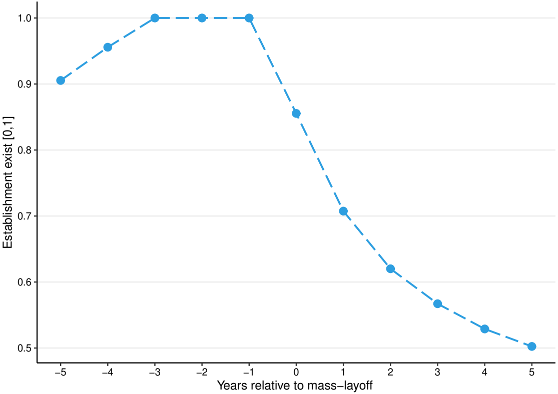
- 1) Define a mass layoff
- 2) Sample displaced workers and potential comparison works
- 3) Find match between displaced and comparison worker

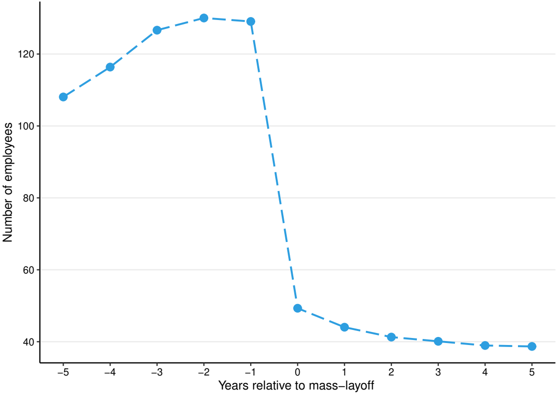
Sample selection: 1. Mass-layoffs

Defining a mass-layoff following Bertheau et al. (2023):

- Private single-plant firms with $\geq$50 employees
- Firm exists in years $t-3$, $t-2$, $t-1$
- Employment contracts by $\geq$30% from year $t-1$ to t
- No more than 20% of the separators are employed by same new employer in $t+1$

Sample selection: 1. Mass-layoff dynamics





Sample selection: 2. Displaced workers and comparison group

- We select workers who experience a mass-layoff in year *t*:
  - Employed at the establishment in years $t-1$, $t-2$, $t-3$
  - Aged 20-50 in year *t*
  - First time experiencing an mass-layoff
  - Not employed at the establishment
  - 2000-2011: 129,826 laid-off individuals

- Potential comparison group:
  - Employed at same (private) establishment in years $t-1$, $t-2$, $t-3$
  - Aged 20-50 in year *t*
  - Over 2 million individual-year observations in the period

Sample selection: 3. Matching treatment and comparison groups

Matching in three steps

- First step: Exact matching on
  - Calendar year (of mass-layoff)
  - Sex
  - Industry (*manufacturing*, *service* or *other*)

- Second step: Compute propensity score
  - Prior earnings
  - Age
  - Tenure
  - Employer size

- Third step: select suitable comparison worker based on nearest neighbor matching (on the propensity score) without replacement.

Two-way fixed effects specification

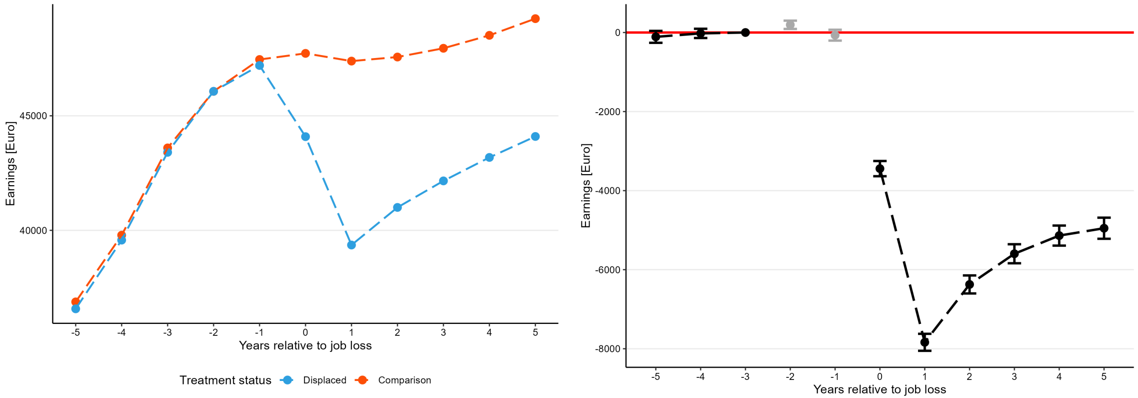
Estimate by OLS:

$$y_{it} = \alpha_i + \gamma_t + \sum_{\tau} \delta_{\tau} Displaced_i \times \mathbb{1}(t - d = \tau) + \epsilon_{it} \quad (1)$$

where

- i indexes people
- t indexes years
- $Displaced_i$ is an indicator for being displaced
- d is the year of displacement (for one's own displacement, or the displacement of the matched laid off worker in the case of comparisons)
- $\mathbb{1}(\cdot)$ is an indicator function.
- Standard errors are clustered at the level of the establishment of the displaced worker

Labour market trajectories of displaced workers

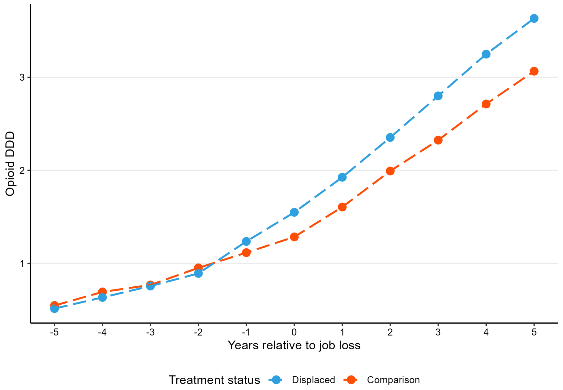


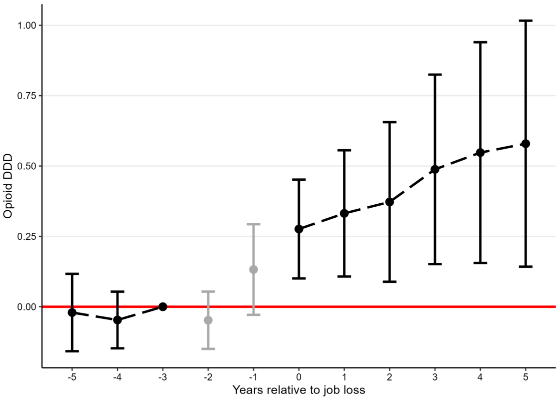
Effects on labour market outcomes

	Earnings [Euro] (1)	Income [Euro] (2)	Earnings>0 [0,1] (3)
Displaced × Post	-5,935.279***	-4,389.258***	-0.035***
	(110.216)	(107.531)	(0.001)
Mean in Time = -3	[43405.72]	[46184.008]	[1]
Observations	1,240,720	1,240,720	1,240,720

Effect on opioid defined daily doses

Defined daily doses (DDDs): average maintenance dose per day for main indication





Effect on opioid prescriptions

Oral morphine equivalents (OMEQ): pain-relieving strength vs 100mg morphine

	Any opioids [0,1]	Opioid DDD	Opioid OMEQ
	(1)	(2)	(3)
Displaced $\times$ Post	0.004***	0.486***	0.282**
	(0.001)	(0.151)	(0.127)
Mean in Time = -3	[0.026]	[0.756]	[0.403]
Observations	1,240,720	1,240,720	1,240,720

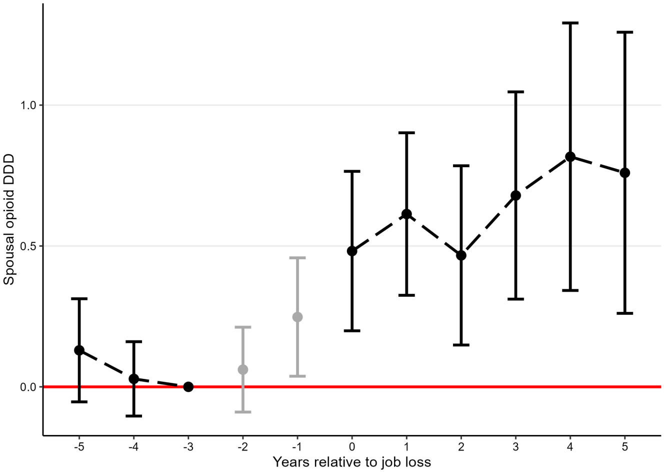
Related drugs

	Any benzodiazepine (1)	Benzodiazepine DDD (2)	Any opioid dependence drug (3)	Any antidepressant (4)	Antidepressant DDD (5)
Displaced $\times$ Post	0.00022**	0.03318***	0.00030***	0.00511***	2.14942***
	(0.00010)	(0.01122)	(0.00009)	(0.00088)	(0.39781)
Mean in Time = -3		[0.009]		[0.026]	[6.444]
Observations	1,240,720	1,240,720	1,240,720	1,240,720	1,240,720

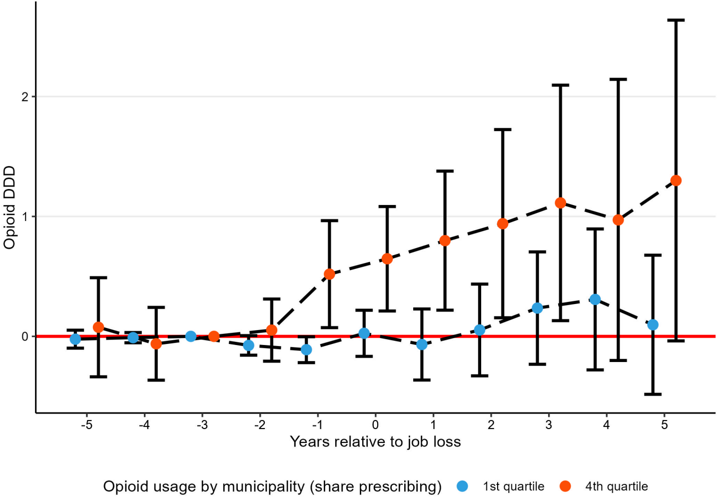
Other measures of pain

	Any NSAID drugs, [0,1] (1)	Any cancer-related hospital admission, [0,1] (2)
Displaced $\times$ Post	-0.00112	0.00009
	(0.00136)	(0.00021)
Mean in Time = -3	[0.146]	[0.002]
Observations	1,240,720	1,240,720

Spillover to spousal opioid consumption



Results by geography



- Higher use driven by both supply **and** demand

Contributions

- We document that economic hardship increases both:
  - Propensity to get an opioid prescription
  - Intensity of opioid prescriptions

Extrapolation

- Suggestive evidence of opioid abuse
- Spillovers to spousal opioid use
- Effects are related to geographical variation in opioid supply

Appendix

Literature: other causal avenues and policy

- If local economic conditions affect opioid use and abuse, the mechanism matters:
  - Directly through economic instability
    - Policy example: mental health counseling for laid-off workers
    - Evidence: this paper
  - Family or social networks
    - Policy example: mental health counseling for families and communities
    - Evidence: this paper (in later versions); some evidence from Barnett et al. (2019), Kennedy-Hendricks et al. (2016), Khan et al. (2019), Nguyen et al. (2020)
  - Pharmaceutical company actions
    - Policy example: rules on opioid marketing
    - Evidence: Alpert et al. (2019), Hadland et al. (2019)
  - Physician behavior
    - Policy example: change opioid prescription policies
    - Evidence: Popovici et al. (2018), Schnell and Currie (2018)
  - Or another mechanism, such as endogenous location choice

Descriptive statistics

	Displaced workers	Comparison workers	Differences	SDM
Worker characteristics				
Earnings [Euro]	41,237.555	41,182.406	-55.150	-0.002
	(24,857.953)	(24,453.713)	(96.865)	
Income [Euro]	43,855.246	43,715.316	-139.927	-0.004
	(26,525.902)	(25,686.156)	(102.592)	
Age	34.824	34.425	-0.399***	-0.032
	(8.842)	(8.769)	(0.035)	
Tenure	6.227	6.217	-0.010	-0.002
	(4.199)	(4.250)	(0.017)	
Female [0,1]	0.354	0.354	0.000	0.000
	(0.478)	(0.478)	(0.002)	
Full time [0,1]	0.829	0.829	-0.001	-0.002
	(0.376)	(0.377)	(0.001)	
Any opioid [0,1]	0.019	0.021	0.001**	0.006
	(0.138)	(0.142)	(0.001)	
Opioid DDDs	0.622	0.646	0.024	0.001
	(14.405)	(17.369)	(0.063)	
Firm characteristics				
Industry: manufacturing [0,1]	0.446	0.446	0.000	0.000
	(0.497)	(0.497)	(0.002)	
Industry: services [0,1]	0.322	0.322	-0.000	0.000
	(0.467)	(0.467)	(0.002)	
Industry: other [0,1]	0.231	0.231	-0.000	0.000
	(0.422)	(0.422)	(0.002)	
Establishment size	341.080	347.116	6.037***	0.007
	(595.888)	(551.431)	(2.253)	
Sample characteristics				
Percentage of workforce displaced	3.099			
Number of establishments	6,886	4,845		
Number of workers	129,836	129,836		
Number of worker-observations	1,428,000	1,428,000		

Heterogeneous effects

	Gender		Place of residence		Prior opioid use		Education			Sector			Family		Age		
	Male	Female	Other	Copenhagen area	Never used	User	Basic	Vocational- or short further	Medium og long further	Manufacturing	Services	Other	No children	Children	<30	30-40	>40
Earnings [Euro]	-6,738.631*** (150.589) [47641.509]	-4,502.450*** (147.778) [35847.979]	-5,896.810*** (114.775) [42409.154]	-5,960.405*** (288.520) [47025.842]	-5,753.252*** (115.829) [43387.774]	-7,085.122*** (343.728) [43568.13]	-6,036.113*** (164.866) [33197.35]	-5,236.122*** (132.928) [44223.42]	-6,472.009*** (417.968) [63590.988]	-6,836.759*** (140.461) [42413.103]	-4,335.599*** (218.525) [46134.284]	-6,332.435*** (243.035) [41522.28]	-5,675.768*** (174.913) [36856.298]	-5,756.284*** (143.016) [48986.198]	-3,304.460*** (210.941) [23786.428]	-4,831.081*** (193.750) [46065.025]	-7,266.577*** (178.919) [51040.676]
Opioid DDD	0.448** (0.196) [0.745]	0.556** (0.233) [0.775]	0.543*** (0.182) [0.85]	0.262 (0.232) [0.413]	0.319*** (0.083) [0]	1.301 (1.381) [7.596]	0.287 (0.359) [0.966]	0.577*** (0.188) [0.734]	0.138 (0.209) [0.359]	0.843*** (0.271) [0.925]	0.096 (0.178) [0.429]	0.282 (0.274) [0.871]	0.289 (0.251) [0.476]	0.647*** (0.191) [0.994]	0.391* (0.217) [0.156]	0.284 (0.224) [0.491]	0.502* (0.264) [1.31]
Any opioid prescription [0,1]	0.003*** (0.001) [0.025]	0.006*** (0.001) [0.027]	0.004*** (0.001) [0.027]	0.002 (0.001) [0.02]	0.004*** (0.001)	0.015*** (0.005) [0.26]	0.005*** (0.002) [0.029]	0.003*** (0.001) [0.027]	0.000 (0.001) [0.014]	0.006*** (0.001) [0.03]	0.002** (0.001) [0.02]	0.002 (0.002) [0.025]	0.003*** (0.001) [0.018]	0.005*** (0.001) [0.033]	0.003** (0.001) [0.013]	0.004*** (0.001) [0.022]	0.002 (0.001) [0.036]
Observations	795,200	445,496	970,144	270,576	1,122,656	118,064	377,304	674,440	188,976	583,136	394,048	263,536	517,152	707,871	235,595	414,763	444,726

Effects on weak and strong opioids

	Any strong opioids [0,1] (1)	Any weak opioids [0,1] (2)	Strong opioid DDD (3)	Weak opioid DDD (4)
Displaced $\times$ Post	0.001***	0.004***	0.156	0.331***
	(0.000)	(0.001)	(0.105)	(0.105)
Mean in Time = -3	[0.004]	[0.023]	[0.162]	[0.594]
Observations	1,240,720	1,240,720	1,240,720	1,240,720

Spousal effects

	Displaced worker		Spouse	
	Any opioid prescription [0,1]	Opioid DDDs	Any opioid prescription [0,1]	Opioid DDDs
	(1)	(2)	(3)	(4)
Displaced × Post	0.004***	0.393***	0.002**	0.614***
	(0.001)	(0.152)	(0.001)	(0.170)
Mean in Time = -3	[0.026]	[0.734]	[0.023]	[1.386]
Observations	502,792	502,792	502,792	502,792

Geographies

	Opioid DDD		
	Baseline	Municipal volume	
		1st quintile	4th quintile
	(1)	(2)	(3)
Displaced $\times$ Post	0.486***	0.137	1.019**
	(0.151)	(0.201)	(0.454)
Observations	1,240,720	310,179	310,181

Extrapolation: Denmark

- Layoffs increased nonemployment by $\sim$3.5 pp and increased opioid use by $\sim$.6 pp
- Assuming effect is through nonemployment, nonemployment causes an increase in $\sim$.6/3.5 = .17 people using opioids
- With Denmark's unemployment rate during sample of $\sim$6%, unemployment would cause $\sim$1% of people to use opioids, out of about 4% who actually do (so around 25% of the total)
- On the other hand, many more people are underemployed, discouraged, or marginally attached, so the actual effect could be higher
- Note: US unemployment rate is comparable, but opioid use much higher

Back to conclusion

Could there be a feedback loop?

- Negative labor market outcomes $\Longrightarrow$ opioid use, and opioid use $\Longrightarrow$ negative labor market outcomes
- We find layoffs cause earnings to decline by $\sim$ 0.24 SD, and opioid DDDs to increase by about 64%
- Extrapolating from Thingholm (2019), opioid DDDs increasing by 64% causes earnings to decline by 0.09 SD
- Thus there may be a modest feedback loop: a direct earnings decline of $1,000 $\Longrightarrow$ indirect $375 lost earnings through increased opioid use

Back to conclusion

Relation to other literature

- Most studies linking economic conditions to opioid use measure the effect of employment outcomes on mortality
- In the US, there are $\sim 1.5 \times 10^{-5}$ deaths/DDD
- Layoffs increase nonemployment by $\sim$ 0.035, and about 0.8 additional DDD
- So (with similar assumptions to before) nonemployment $\implies$ 23 additional DDDs $\implies$ 34 $\times 10^{-5}$ deaths
- Extrapolating from Pierce and Schott (2020), who look at local employment shocks, nonemployment $\implies$ $\sim$ 1.5 $\times 10^{-5}$ deaths

Back to conclusion