The Effects of the Opioid Crisis on Employment: Evidence from Labor Market Flows

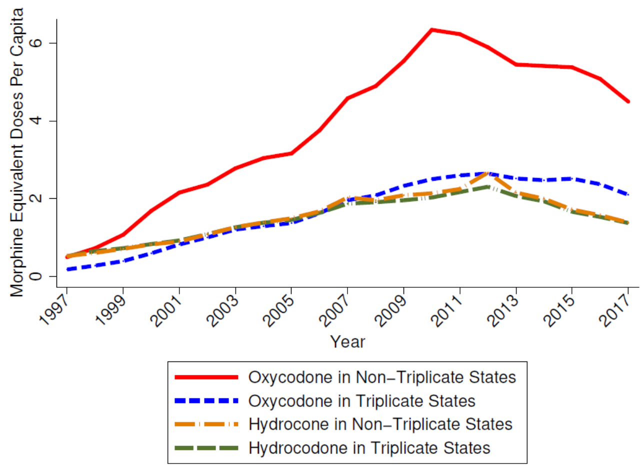
Anita Mukherjee, Daniel W. Sacks, and Hoyoung Yoo

Online Appendix

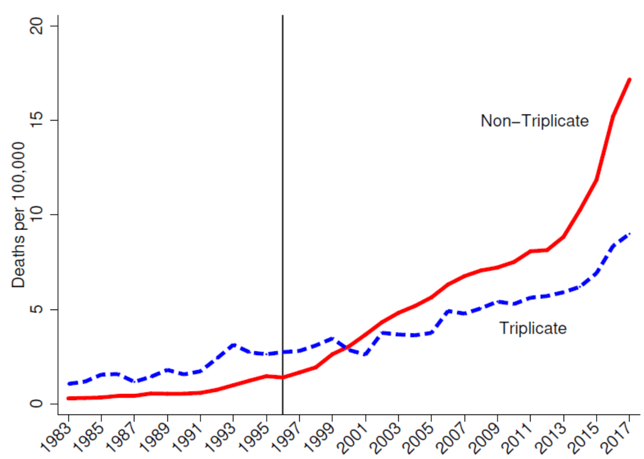
A. Opioid Crisis in Triplicate and Non-triplicate States

Appendix Figure A1. *Impact of Triplicate Regulation on Opioid Prescriptions and Deaths*

(a) Oxycodone and Hydrocodone Doses

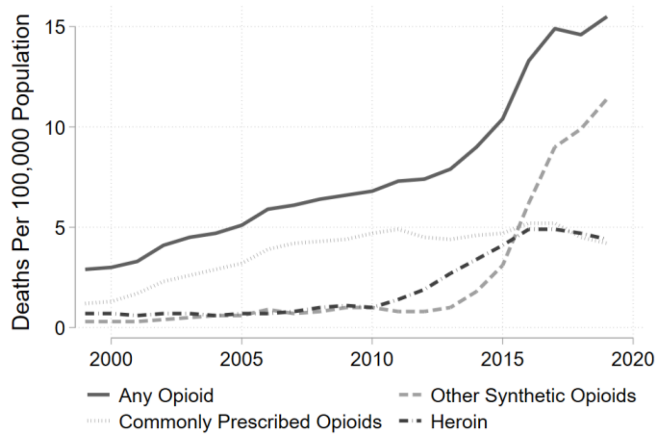


(b) Opioid Overdose Deaths



Notes: These plots are taken directly from Alpert et al. (2022) to provide context for the effect of triplicate regulation on opioid prescriptions and opioid overdose deaths. In the top panel, hydrocodone is contrasted to oxycodone because the former substance was not affected by triplicate regulation. We observe that oxycodone, which was subject to the regulation, experienced a sharp increase in non-triplicate states. In the second panel, we observe that non-triplicate states experienced a differential rise in opioid overdose deaths following the introduction of OxyContin in 1996 (indicated by the vertical line).

Appendix Figure A2. *Temporal Patterns in Opioid-Related Deaths (1999-2019)*



Notes: This figure is generated based on data provided by the Centers for Disease Control and Prevention (CDC) (https://www.cdc.gov/drugoverdose/data/OD-deaths-2019.html). The plot shows the pattern in opioid-related deaths between 1999 and 2019 by type of opioid. Other synthetic opioids include fentanyl and tramadol, and commonly prescribed opioids include natural and semi-synthetic opioids and methadone.

B. Drug Misuse by Employment Status

We use data from the 2015-2019 waves of the National Survey on Drug Use and Health (NSDUH; Substance Abuse and Mental Health Services Administration (2015-2019)) to show that drug use is much greater among the unemployed than among the employed conditional on sex, age, and survey year. NSDUH asks respondents a large battery of questions about prescription drug misuse (defined as using a prescription drug in a way other than directed by a doctor), as well as questions about illicit drug use. The survey instruments are designed to encourage truthful reporting, but given the sensitive nature of the topic, it is likely that drug use and misuse is underreported. NSDUH also collects demographic information, including age and sex, as well as employment status in the prior week. NSDUH samples Americans aged 12 and older but, to parallel our main analytic sample, we limit the NSDUH sample to respondents aged 15-64.

We focus on five categories of misuse. Our first is any misuse, defined as any prescription drug misuse or heroin use. The next three are misuse of OxyContin, any painkiller, or any tranquilizer. Fifth is use of heroin. These categories reflect our interest in opioids, which are used and misused as both prescription painkillers and heroin. We examine tranquilizer misuse because tranquilizer use and overdose has grown alongside the opioid crisis in the United States (Bachhuber et al. 2016). In addition to measuring misuse, we measure initiation, defined as misuse beginning in the previous 12 months (according to self-reported, retrospective information about when misuse began).

We report the level of misuse and initiation among the employed, and we measure the association between misuse and unemployment/non-participation. Because age and sex differ between the employed, unemployed, and non-participation, we adjust this association for age and sex differences (as well as survey year differences) with the following regression for outcome *y* of person *i* in survey year *t*:

(3) $$y_{it} = \beta_0 + \beta_1 Unemployed_{it} + \beta_2 NonParticipation_{it} + \beta_3 Female_{it} + \theta_{age(i)} + \mu_t + \epsilon_{it}$$

Our interest is in β1 and β2, the association between *y* and employment status, adjusting for sex, age, and survey year. We report the results in Table B1. Panel A reports the rate of misuse among the employed, and the difference in misuse among the unemployed and non-participating. Panel B reports the analogous statistics for new misuse. The table shows uniformly higher rates of misuse among the unemployed than among the employed. The probability of misusing any drug is 3.6 percentage points higher among the unemployed than among the employed, a difference of 60 percent of the baseline rate of 6.1 percent. In absolute (percentage point terms) this higher drug use is concentrated in pain relievers and tranquilizers. However in relative terms, the rates of misuse of OxyContin and Heroin are particularly high among the unemployed: unemployed people are three times as likely to report misuse OxyContin, and five times as likely to report using heroin, as are employed people. We also see greater rates of drug use among the non-participating, relative to the employed, although the differences are not so large as for the unemployed. Unemployed show greater rates of initiation as well as greater overall use; the overall rate of initiation is about a third higher among the unemployed.

Appendix Table B1. *Drug Misuse by Type and Employment Status*

Drug misuse	Any (1)	OxyContin (2)	Pain reliever (3)	Tranquilizer (4)	Heroin (5)
<u>A. Rate of drug misuse</u>					
Employed level	0.0609	0.0058	0.0455	0.0255	0.0025
Unemployed differential	0.0363	0.0101	0.0302	0.0139	0.0117
	(0.0037)	(0.0015)	(0.0033)	(0.0024)	(0.0014)
NILF differential	0.0062	0.0016	0.0073	0.0005	0.0035
	(0.0016)	(0.0005)	(0.0015)	(0.0011)	(0.0004)
Observations	230,599	230,297	230,599	230,599	230,553
<u>B. Rate of new drug misuse</u>					
Employed level	0.0128	0.0004	0.0074	0.0055	0.0002
Unemployed differential	0.0045	-0.0000	0.0026	0.0014	0.0006
	(0.0017)	(0.0002)	(0.0012)	(0.0011)	(0.0003)
NILF differential	-0.0011	-0.0002	0.0004	-0.0015	0.0002
	(0.0007)	(0.0001)	(0.0005)	(0.0004)	(0.0001)
Observations	230,590	230,238	229,973	230,131	226,220

Notes: "Employed level" row reports the rate of misuse of the indicated drug among employed NSDUH respondents (2015-2019) in age 15-64. The remaining rows are the coefficients on unemployed and NILF from a regression of drug misuse on those variables plus indicators for sex, age group, and survey year. "Any" misuse is misuse of any of the four types. New misuse is misuse beginning in the prior 12 months. Robust standard errors, clustered on household, in parentheses.

Appendix Table B2. *Drug Use and Misuse by Race/Ethnicity and Employment Status*

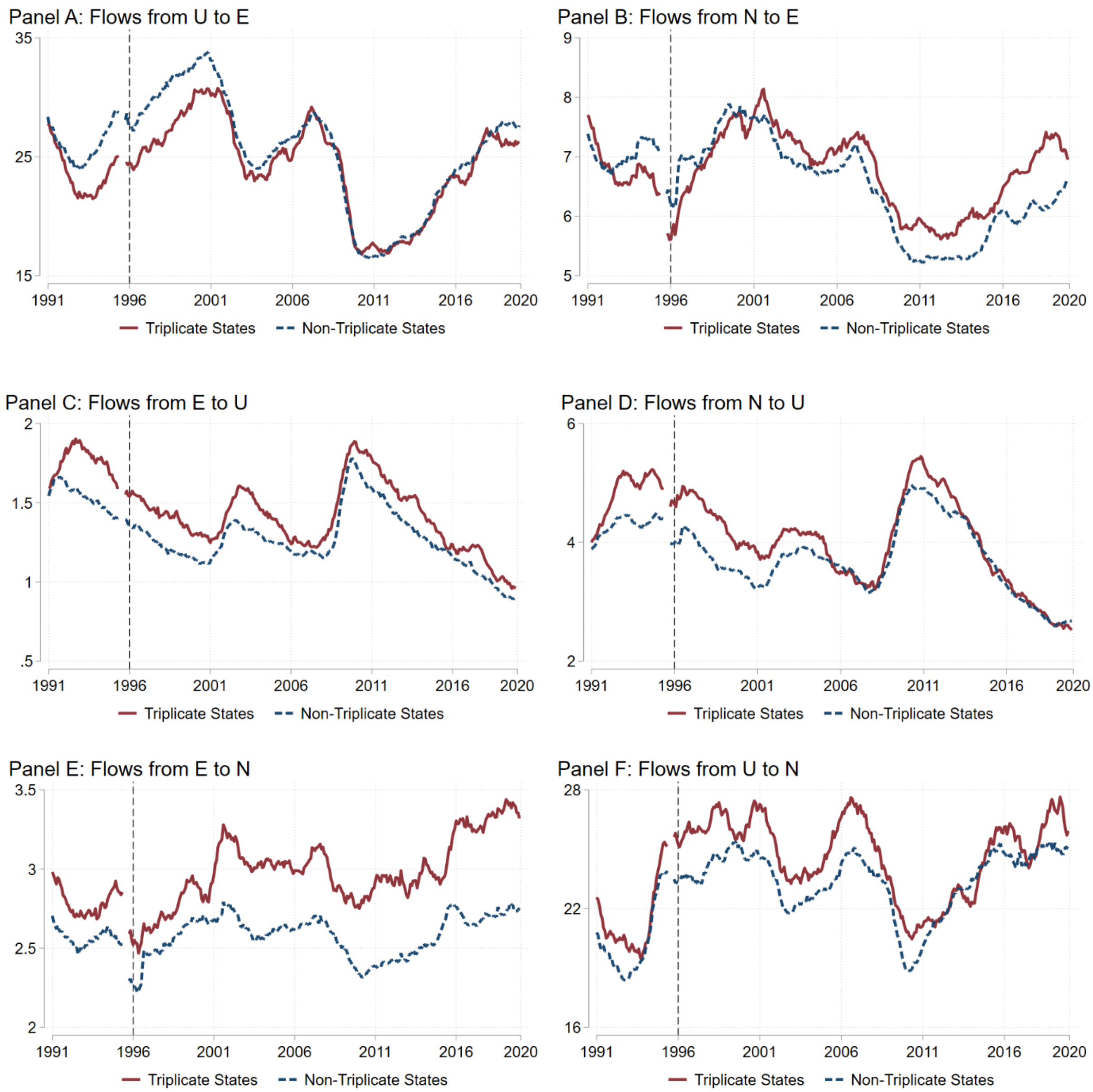
Race/Ethnicity	White, non-Hispanic (1)	Black, non-Hispanic (2)	Hispanic (3)	Others (4)
A. Total Population				
% Opioid Use	11.70	10.90	6.69	6.41
% Misuse	4.46	3.93	4.21	3.16
B. Employed				
% Opioid Use	10.46	9.98	6.31	5.95
% Misuse	4.75	3.75	4.17	3.11
C. Unemployed				
% Opioid Use	15.65	11.28	9.11	7.17
% Misuse	10.28	5.85	7.64	5.53
D. NILF				
% Opioid Use	13.51	12.34	6.88	7.13
% Misuse	3.40	3.70	3.60	2.89

Notes: This table reports the rate of opioid use and misuse by race/ethnicity conditional on employment status for NSDUH respondents (2015-2019) in age 15-64.

C. Drug Misuse by Employment Status

C.1 Labor Market Dynamics

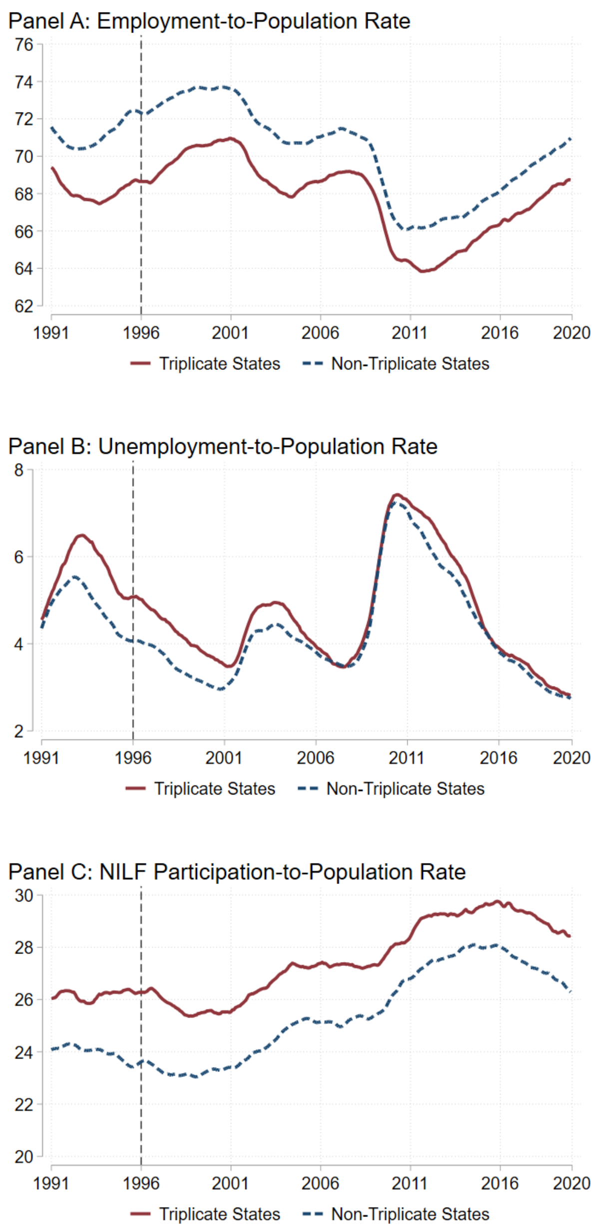
Appendix Figure C1. *Labor Market Flow by Triplicate Regulation Status (Seasonally Adjusted)*



Notes: This figure shows the seasonally adjusted rates (in %) of labor market flows between employment (*E*), unemployment (*U*), and non-participation (*N*) by triplicate regulation. The dashed vertical line (January 1996) indicates the beginning of regulatory effect due to the entry of OxyContin. The underlying data are individual observations from the entire US aggregated (using sample weights) to the month-year-triplicate level. The data span January 1991 to December 2019.

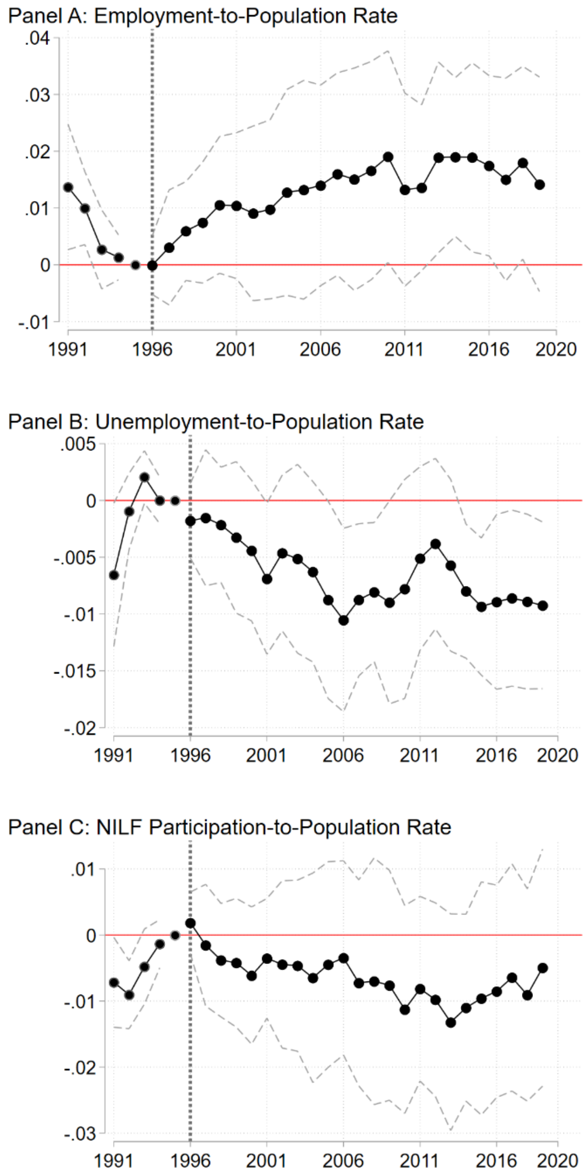
C.2 Labor Market Activity Levels

Appendix Figure C2. *Labor Market Activity Levels, 1991-2019*



Notes: This figure shows the seasonally adjusted rates (in % of population) of employment, unemployment, and non-participation by triplicate regulation. The dashed vertical line (January 1996) indicates the beginning of regulatory effect due to the entry of OxyContin. The underlying data are individual observations from the entire US aggregated (using sample weights) to the month-year-triplicate level. The data span January 1991 to December 2019.

Appendix Figure C3. *Event Study Analysis: Effect of Triplicate Regulation on Labor Market Levels*



Notes: This figure shows the estimated coefficients of the triplicate regulation on employment (*E*), unemployment (*U*), and non-participation (*N*) to population rate. The specification includes triplicate indicators for whether the state has the regulation in force by 1996, the beginning of regulatory effect due to the entry of OxyContin. The excluded (reference) year is 1995. The data span January 1991 to December 2019. The dashed horizontal lines represent 95% confidence intervals based on state-clustered standard errors.

Appendix Table C1. *Difference-in-Difference Analysis: Labor Market Activity Levels*

A. Pooled Difference-in-Difference Analysis			
	e	*u*	*n*
1996-2019	0.78	-0.56	-0.22
	(-0.43, 1.98)	(-0.94, -0.17)	(-1.44, 1.00)
	[-0.58, 2.13]	[-1.05, -0.07]	[-1.53, 1.09]

B. Difference-in-Difference Analysis with Three Time Periods			
	e	*u*	*n*
1996 - 2000	-0.00	-0.16	0.16
	(-0.76, 0.76)	(-0.60, 0.28)	(-0.56, 0.88)
	[-1.00, 0.99]	[-0.79, 0.47]	[-0.60, 0.92]
2001 - 2010	0.82	-0.65	-0.16
	(-0.61, 2.24)	(-1.08, -0.23)	(-1.47, 1.14)
	[-0.95, 2.59]	[-1.14, -0.17]	[-1.55, 1.22]
2011 - 2019	1.10	-0.65	-0.45
	(-0.27, 2.47)	(-1.08, -0.21)	(-1.92, 1.01)
	[-0.37, 2.57]	[-1.20, -0.09]	[-2.21, 1.31]
Joint *p*-value	0.58	0.28	0.60
N	17,748	17,748	17,748

Notes: This table uses labor market activity levels (not flows) as the outcome variable and follows the pooled post-period specification in Table 3 for Panel A, and the temporal heterogeneity specification in Table 4 for Panel B. The underlying data are individual observations from the entire US aggregated (using sample weights) to the month-year-state level. The data span January 1991 to December 2019. Below each coefficient, we report the 95% coefficient confidence intervals estimated by state-clustered standard errors (parentheses) and by wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013) (brackets). The reported joint *p*-value in Panel B tests the joint statistical significance of the three coefficients using the wild bootstrap method.

C.3 Categorization of Physically Demanding Occupations

Appendix Table C2. *List of Physically Demanding Occupations*

Code	Description
226	Airplane pilots and navigators
357	Messengers
364	Shipping and receiving clerks
417	Firefighting, prevention, and inspection
455	Pest control occupations
473	Farmers (owners and tenants)
474	Horticultural specialty farmers
483	Marine life cultivation workers
496	Timber, logging, and forestry workers
498	Fishers, hunters, and kindred
505	Automobile mechanics
507	Bus, truck, and stationary engine mechanics
508	Aircraft mechanics
509	Small engine repairers
514	Auto body repairers
516	Heavy equipment and farm equipment mechanics
518	Industrial machinery repairers
523	Repairers of industrial electrical equipment
526	Repairers of household appliances and power tools
527	Telecom and line installers and repairers
533	Repairers of electrical equipment, n.e.c.
534	Heating, air conditioning, and refrigeration mechanics
536	Locksmiths and safe repairers
538	Office machine repairers and mechanics
539	Repairers of mechanical controls and valves
543	Elevator installers and repairers
544	Millwrights
549	Mechanics and repairers, n.e.c.
563	Masons, tilers, and carpet installers
567	Carpenters
575	Electricians
577	Electric power installers and repairers
579	Painters, construction and maintenance
583	Paperhangers
585	Plumbers, pipe fitters, and steamfitters
588	Concrete and cement workers
589	Glaziers
593	Insulation workers
596	Sheet metal duct installers
597	Structural metal workers

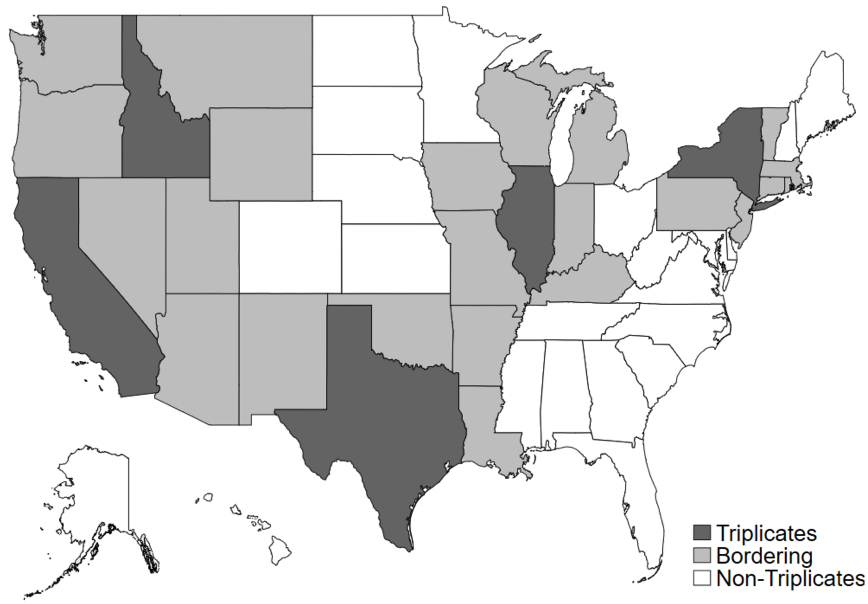
Appendix Table C2 *(Continued)*

Code	Description
599	Construction trades, n.e.c.
614	Drillers of oil wells
615	Explosives workers
617	Other mining occupations
643	Boilermakers
646	Lay-out workers
653	Tinsmiths, coppersmiths, and sheet metal workers
668	Upholsterers
726	Wood lathe, routing, and planing machine operators
733	Other woodworking machine operators
804	Truck, delivery, and tractor drivers
808	Bus drivers
809	Taxi cab drivers and chauffeurs 813 Parking lot attendants
823	Railroad conductors and yardmasters
824	Locomotive operators (engineers and firemen)
825	Railroad brake, coupler, and switch operators
829	Ship crews and marine engineers
853	Excavating and loading machine operators
865	Helpers, constructions
866	Helpers, surveyors
869	Construction laborers
877	Stock handlers
883	Freight, stock, and materials handlers
885	Garage and service station related occupations
887	Vehicle washers and equipment cleaners
889	Laborers outside construction
905	Military

Notes: This table lists the occupation codes and descriptions that fall into the physically demanding categorization used in certain analyses. The codes are obtained from the OCC1990 in the CPS; OCC1990 is a modified version of the 1990 Census Bureau occupational classification scheme. Physically demanding occupations are those with the largest non-routine manual physical skills among other five different skills based on task measures from the Occupational Information Network data (O*NET) following Acemoglu and Autor (2011): non-routine cognitive analytical skills, non-routine cognitive interpersonal skills, routine cognitive skills, routine manual skills, non-routine manual interpersonal skills, and offshorability. We use the occupation crosswalk file for OCC1990 from (David and Dorn 2013).

C.4 Stacked DID Analysis Using Bordering States as Controls

Appendix Figure C5. *Geography of Triplicate States and their Bordering States*



Notes: This figure shows the geography of triplicate states and their bordering states used in the stacked difference-in-differences analysis in Table D2. The bordering states are Arizona, Nevada, and Oregon (to California); Montana, Nevada, Oregon, Utah, Washington, and Wyoming (to Idaho); Indiana, Iowa, Kentucky, Michigan, Missouri, and Wisconsin (to Illinois); Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont (to New York); and Arkansas, Louisiana, New Mexico, and Oklahoma (to Texas). Note that Oregon and Nevada are counted as bordering states to both California and Idaho.

We estimate the stacked DID analysis in Table D2 using:

$$(4) \qquad y_{s,t} = \alpha_s + \gamma_t^{CA} + \gamma_t^{ID} + \gamma_t^{IL} + \gamma_t^{NY} + \gamma_t^{TX}$$

$$+\delta_0 \times \mathbf{1}(Triplicate_s)\mathbf{1}(1996 \leq year_t \leq 2019) + \epsilon_{s,t}$$

where γ is a group-time fixed effect in which each group is a triplicate state and its bordering states.

D. Robustness Check Results

Appendix Table D1. *Robustness Check: Including State-Specific, Time-Varying Covariates*

	Flows to *E*		Flows to *U*		Flows to *N*	
Triplicate ×	From *U*	From *N*	From *E*	From *N*	From *E*	From *U*
	(1)	(2)	(3)	(4)	(5)	(6)
A. Pooled Difference-in-Difference Analysis						
1996-2019	1.46	0.52	-0.10	-0.43	0.17	0.16
	(0.55, 2.38)	(0.17, 0.86)	(-0.19, 0.00)	(-0.73, -0.13)	(0.07, 0.27)	(-0.64, 0.96)
	[0.53, 2.40]	[0.06, 0.97]	[-0.82, -0.03]	[-0.22, 0.03]	[-0.65, 0.98]	[0.06, 0.28]
B. Difference-in-Difference Analysis with Three Time Periods						
1996-2000	-0.60	0.13	-0.06	-0.06	0.00	0.68
	(-2.01, 0.80)	(-0.15, 0.42)	(-0.16, 0.04)	(-0.42, 0.31)	(-0.09, 0.09)	(-0.18, 1.54)
	[-2.38, 1.18]	[-0.19, 0.46]	[-0.20, 0.07]	[-0.53, 0.42]	[-0.10, 0.10]	[-0.25, 1.61]
2001-2010	2.31	0.54	-0.10	-0.51	0.20	0.46
	(0.97, 3.65)	(0.10, 0.99)	(-0.20, 0.00)	(-0.85, -0.17)	(0.04, 0.35)	(-0.52, 1.44)
	[0.80, 3.82]	[-0.06, 1.14]	[-0.23, 0.03]	[-0.99, -0.03]	[0.02, 0.37]	[-0.64, 1.55]
2011-2019	2.25	0.84	-0.12	-0.62	0.29	-0.67
	(0.87, 3.63)	(0.43, 1.25)	(-0.25, 0.01)	(-0.97, -0.27)	(0.17, 0.41)	(-1.58, 0.25)
	[0.63, 3.86]	[0.34, 1.34]	[-0.27, 0.04]	[-1.12, -0.12]	[0.15, 0.42]	[-1.68, 0.35]
Joint *p*-value	0.03	0.04	0.60	0.01	0.01	0.07

Notes: This table follows the pooled post-period specification in Table 3 for Panel A, and the temporal heterogeneity specification in Table 4 for Panel B. All columns include the following state-specific, time-varying covariates: median age and proportion of white and non-Hispanic, black and non-Hispanic, education more than college, manufacturing industry sector, services industry sector, and working in physically demanding occupations. The underlying data are individual observations aggregated (using sample weights) to the month-year-state level. Below each coefficient, we report the 95% coefficient confidence intervals estimated by state-clustered standard errors (parentheses) and by wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013) (brackets). The reported joint *p*-value in Panel B tests the joint statistical significance of the three coefficients using our wild bootstrap method.

Appendix Table D2. *Robustness Check: Stacked Difference-in-Differences Analysis with Bordering States*

Triplicate ×	Flows to E		Flows to U		Flows to N	
	From U	From N	From E	From N	From E	From U
	(1)	(2)	(3)	(4)	(5)	(6)
A. Pooled Difference-in-Difference Analysis						
1996-2019	1.03	0.82	-0.07	-0.22	0.25	0.07
	(-0.04, 2.09)	(0.50, 1.14)	(-0.13, 0.00)	(-0.50, 0.06)	(0.15, 0.35)	(-0.99, 1.12)
	[-0.30, 2.35]	[0.52, 1.13]	[-0.13, -0.00]	[-0.55, 0.11]	[0.14, 0.35]	[-1.02, 1.16]
B. Difference-in-Difference Analysis with Three Time Periods						
1996-2000	-0.90	0.25	-0.04	0.14	0.01	0.53
	(-2.28, 0.49)	(-0.03, 0.53)	(-0.15, 0.07)	(-0.33, 0.61)	(-0.12, 0.13)	(-0.65, 1.72)
	[-2.44, 0.65]	[-0.03, 0.52]	[-0.15, 0.07]	[-0.43, 0.71]	[-0.16, 0.17]	[-0.71, 1.78]
2001-2010	1.51	0.87	-0.07	-0.17	0.29	0.52
	(0.29, 2.73)	(0.49, 1.25)	(-0.13, -0.01)	(-0.48, 0.14)	(0.15, 0.43)	(-0.58, 1.63)
	[0.18, 2.85]	[0.49, 1.25]	[-0.12, -0.01]	[-0.59, 0.25]	[0.11, 0.46]	[-0.63, 1.67]
2011-2019	1.48	1.06	-0.07	-0.42	0.31	-0.58
	(0.18, 2.79)	(0.61, 1.52)	(-0.16, 0.01)	(-0.71, -0.13)	(0.18, 0.44)	(-1.94, 0.79)
	[-0.05, 3.02]	[0.57, 1.56]	[-0.15, 0.00]	[-0.73, -0.11]	[0.18, 0.44]	[-2.03, 0.88]
Joint p-value	0.00	0.01	0.18	0.01	0.01	0.28

Notes: This table follows the pooled post-period specification in Table 3 for Panel A, and the temporal heterogeneity specification in Table 4 for Panel B. We use control states as Oregon, Arizona, and Nevada (for California), Washington, Montana, Wyoming, Oregon, Nevada, and Utah (for Idaho), Iowa, Wisconsin, Missouri, Michigan, Indiana, and Kentucky (for Illinois), New Jersey, Vermont, Massachusetts, Connecticut, Pennsylvania, and Rhode Island (for New York), and Arkansas, Louisiana, New Mexico, and Oklahoma (for Texas). The detail of geography is in Appendix C.4. The underlying data are individual observations aggregated (using sample weights) to the month-year-state level. Below each coefficient, we report the 95% coefficient confidence intervals estimated by state-clustered standard errors (parentheses) and by wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013) (brackets). The reported joint p-value in Panel B tests the joint statistical significance of the three coefficients using our wild bootstrap method.

Appendix Table D3. *Robustness Check: Omitting Each Triplicate State*

	Flows to *E*		Flows to *U*		Flows to *N*	
	From *U*	From *N*	From *E*	From *N*	From *E*	From *U*
	(1)	(2)	(3)	(4)	(5)	(6)
Nothing	1.84	0.73	-0.09	-0.38	0.22	0.21
	(0.89, 2.78)	(0.37, 1.09)	(-0.19, -0.00)	(-0.72, -0.05)	(0.14, 0.29)	(-0.55, 0.96)
	[0.86, 2.82]	[0.34, 1.13]	[-0.21, 0.02]	[-0.85, 0.08]	[0.14, 0.29]	[-0.61, 1.02]
CA	1.62	0.82	-0.05	-0.26	0.22	0.38
	(0.52, 2.72)	(0.35, 1.30)	(-0.16, 0.05)	(-0.73, 0.21)	(0.13, 0.31)	(-0.50, 1.26)
	[0.39, 2.85]	[0.17, 1.48]	[-0.18, 0.07]	[-1.03, 0.51]	[0.12, 0.33]	[-0.59, 1.35]
ID	1.88	0.77	-0.09	-0.39	0.22	0.20
	(0.94, 2.82)	(0.41, 1.13)	(-0.18, 0.00)	(-0.72. -0.05)	(0.15, 0.29)	(-0.56, 0.96)
	[0.90, 2.86]	[0.33, 1.20]	[-0.21, 0.03]	[-0.84, 0.07]	[0.14, 0.30]	[-0.63, 1.04]
IL	2.07	0.75	-0.12	-0.40	0.23	0.35
	(1.24, 2.89)	(0.35, 1.16)	(-0.19, -0.04)	(-0.77, -0.04)	(0.16, 0.30)	(-0.41, 1.11)
	[1.22, 2.92]	[0.27, 1.24]	[-0.21, -0.03]	[-0.91, 0.10]	[0.15, 0.31]	[-0.55, 1.25]
NY	1.69	0.57	-0.08	-0.52	0.20	0.10
	(0.66, 2.72)	(0.36, 0.77)	(-0.19, 0.02)	(-0.72, -0.33)	(0.12, 0.27)	(-0.73, 0.94)
	[0.50, 2.87]	[0.36, 0.77]	[-0.25, 0.08]	[-0.72, -0.33]	[0.12, 0.27]	[-0.79, 1.00]
TX	1.86	0.77	-0.11	-0.31	0.20	0.00
	(0.81, 2.90)	(0.33, 1.21)	(-0.21, -0.01)	(-0.70, 0.09)	(0.12, 0.28)	(-0.71, 0.72)
	[0.67, 3.04]	[0.21, 1.33]	[-0.22, 0.00]	[-1.00, 0.39]	[0.12, 0.28]	[-0.72, 0.73]

This table follows the pooled post-period specification in Table 3 and drops the listed triplicate state at a time in rows CA through TX. Row Nothing provides the result including all the states for reference, thus replicating the estimates in Table 3. The underlying data are individual observations aggregated (using sample weights) to the month-year-state level. Below each coefficient, we report the 95% coefficient confidence intervals estimated by state-clustered standard errors (parentheses) and by wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013) (brackets).

E. Earlier Pre-periods Necessitate Covariate Adjustment

This section discusses the role of time-varying covariates in establishing parallel (pre)trends in our context, a key assumption in the difference-in-difference framework. We begin with Figure E1 to show the descriptive evidence of differential time trends in four covariates across triplicate regulation: shares of White and non-Hispanic, Hispanic, College+, and age 45-64. We estimate the following regression and present the δ_ts in Figure E1.

(5) $$y_{s,t} = \alpha_s + \gamma_t + \sum_{\mathrm{t=1981,t\neq 1995}}^{2019} \delta_t \times 1(\mathrm{Triplicate_s})1(\mathrm{year_t} = t) + \epsilon_{s,t}.$$

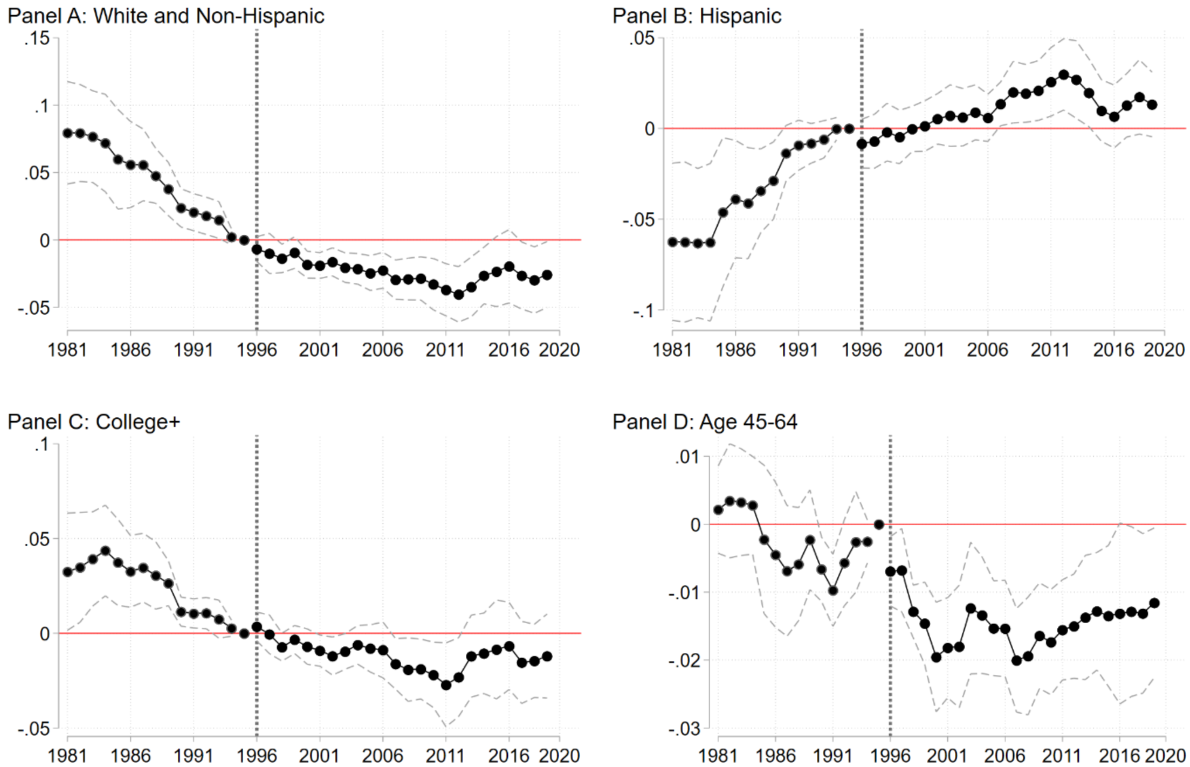
We observe that triplicate states and non-triplicate states show the diverging differential pretrends in four covariates and they are more distinctive in 1981-1990 than in 1991-1995.[1]

Given this evidence, we investigate how addressing covariates changes our coefficients. Table E1 displays three specification results: no covariates adjustment in Panel A as a baseline, the Callaway and Sant'Anna (2021) method in Panel B, and the Powell (2021) method in Panel C. Callaway and Sant'Anna (2021) uses a matching to balance covariates between a treated group and a control group. On the other hand, Powell (2021) allows a rich set of fixed effects (sex-triplicate and sex-year-month fixed effects) as well as triplicate varying covariates coefficients and uses a residualization method.

Table E1 and Figure E2 show the results from these exercises. Table E1 shows the triplicate effect in aggregated time bands as in Tables 3 and 4. The triplicate effect size is larger in Callaway and Sant'Anna (2021) and Powell (2021) methods than in no covariate adjustment specification, and even larger in Powell (2021) than in Callaway and Sant'Anna (2021). This implies that incorporating the differential time trends in covariates enlarges the triplicate treatment effect. Second, Figure E2 shows the year-by-year triplicate effect corresponding to Figure 1, consistent with Table E1 specification but with the granular level of triplicate-time interaction dummies. Noticeably, the specification without covariate adjustment shows pretrends in all six labor dynamic outcomes. We leave in-depth investigation for time-varying covariates in difference-in-difference framework to the future research.

[1]. In all analyses in the main paper, our sample begins in 1991.

Appendix Figure E1. *Event Study Analysis: Covariates*



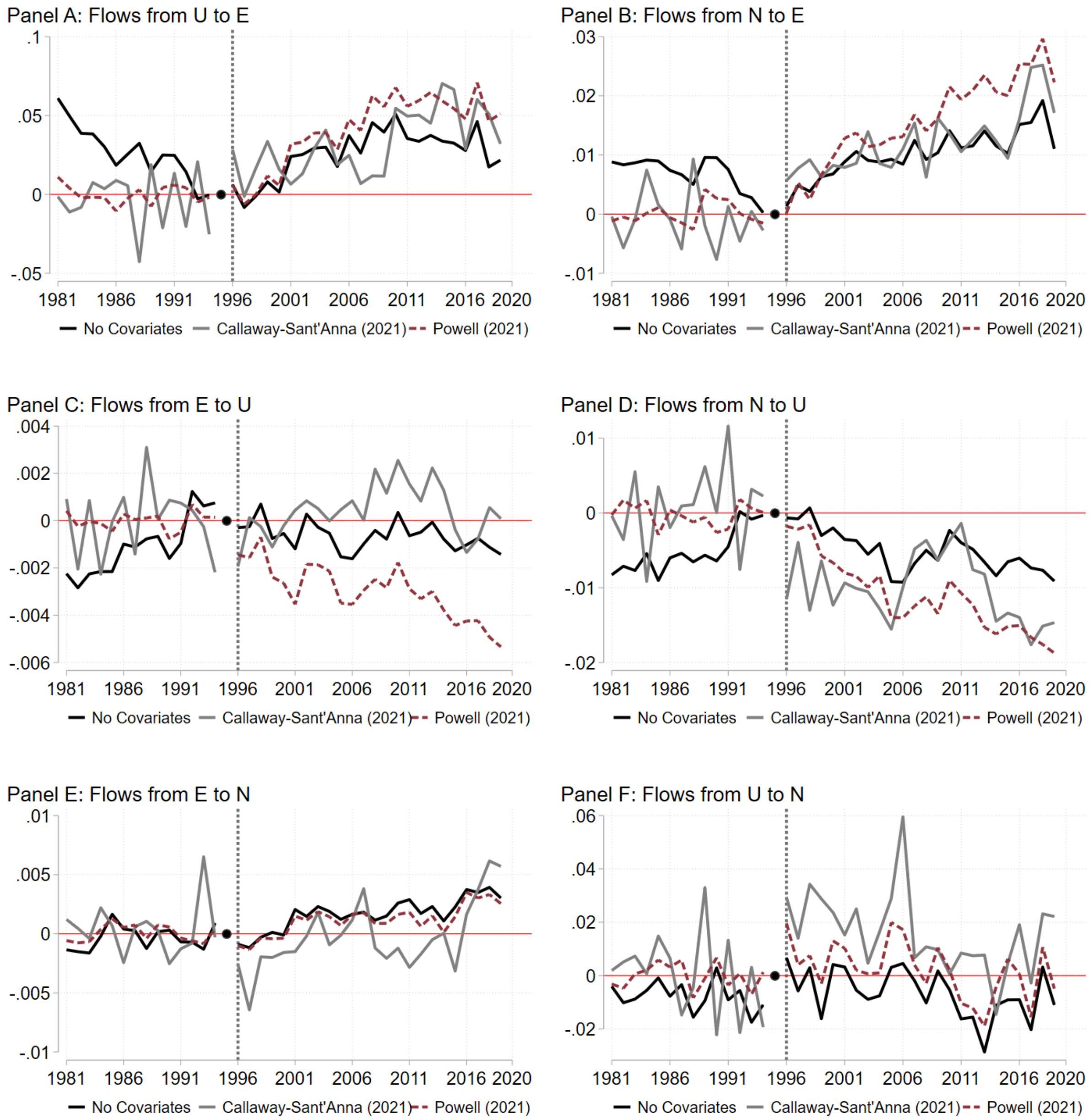
Notes: This figure shows the estimated coefficients of the triplicate regulation on the four main covariates: share of White and non-Hispanic, Hispanic, college+, and age 45-64 to see the differential trends in covariates for triplicate and non-triplicate states. The specification includes triplicate indicators for whether the state has the regulation in force by 1996, the beginning of regulatory effect due to the entry of OxyContin. The data span January 1981 to December 2019. The dashed horizontal lines represent 95% confidence intervals based on state-clustered standard errors.

Appendix Table E1. *Difference-in-Differences Analysis with Covariates Adjustment and Different Time Samples*

	Flows to *E*		Flows to *U*		Flows to *N*	
Triplicate ×	From *U*	From *N*	From *E*	From *N*	From *E*	From *U*
	(1)	(2)	(3)	(4)	(5)	(6)
A. No Covariates						
1996 - 2019	0.20	0.39	0.04	-0.02	0.21	0.04
	(0.67)	(0.21)	(0.05)	(0.20)	(0.04)	(0.33)
1996 - 2000	-2.28	-0.17	0.08	0.37	-0.01	0.57
	(0.82)	(0.23)	(0.04)	(0.22)	(0.05)	(0.35)
2001 – 2010	0.85	0.37	0.04	-0.05	0.21	0.46
	(0.56)	(0.26)	(0.05)	(0.18)	(0.05)	(0.44)
2011 – 2019	0.76	0.69	0.03	-0.15	0.31	-0.58
	(1.04)	(0.23)	(0.06)	(0.23)	(0.05)	(0.43)
B. Callaway and Sant'Anna (2021), Doubly Robust Method						
1996 - 2019	3.19	1.21	0.04	-1.00	-0.02	1.60
	(1.24)	(0.47)	(0.09)	(0.42)	(0.11)	(1.40)
1996 - 2000	1.87	0.74	-0.07	-0.95	-0.29	2.60
	(1.36)	(0.37)	(0.08)	(0.52)	(0.06)	(1.32)
2001 – 2010	2.18	1.09	0.09	-0.87	-0.00	1.78
	(1.72)	(0.51)	(0.08)	(0.40)	(0.14)	(1.34)
2011 – 2019	5.04	1.59	0.04	-1.18	0.10	0.84
	(0.98)	(0.51)	(0.10)	(0.40)	(0.13)	(1.57)
C. Powell (2021) Method, Triplicate Varying Covariates						
1996 - 2019	4.13	1.60	-0.29	-1.11	0.13	0.18
	(0.46)	(0.10)	(0.04)	(0.19)	(0.02)	(0.29)
1996 - 2000	0.35	0.49	-0.17	-0.34	-0.07	0.82
	(0.68)	(0.21)	(0.02)	(0.18)	(0.06)	(0.16)
2001 – 2010	4.46	1.44	-0.25	-1.08	0.13	0.65
	(0.20)	(0.15)	(0.05)	(0.16)	(0.03)	(0.34)
2011 – 2019	5.66	-0.53	-0.38	-1.47	0.20	-0.53
	(0.72)	(0.36)	(0.05)	(0.23)	(0.04)	(0.36)

Notes: This table provides three panels with different specifications, all using 1981-2019 data. Panel A follows the same specification in Table 3 and Table 4. Panel B follows Callaway and Sant'Anna (2021), doubly robust method using covariates of White and non-Hispanic share, Hispanic share, college+ share, and age 45-64 share. Sex dummy is included being fully interacted with each covariate. Panel C follows Powell (2021) specification with triplicate varying covariates. The statefip clustered robust standard errors are in parentheses.

Appendix Figure E2. *Event Study Analysis with Different Covariates Adjustment*



Notes: This figure shows the point estimates of the triplicate regulation effect on the six labor market flows between employment (*E*), unemployment (*U*), and non-participation (*N*) with three different specifications regarding covariates adjustment. The specification includes triplicate indicators for whether the state has the regulation in force by 1996, the beginning of regulatory effect due to the entry of OxyContin. The data span January 1981 to December 2019.

F. Method for Steady State Effects

We begin by introducing notation for the Markov process between one of three labor market states: *e* (employed), *u* (unemployed), and *n* (not in labor force). Let $P_{s,t}$ be the transition matrix between these states, with each matrix element denoted by *p*. For example, $p_{s,t}^{e|u}$ denotes the transition probability from unemployment (*u*) to employment (*e*) for state (*s*) in a given year-month-of-sample (*t*). The matrix $P_{s,t}$ contains nine elements, as shown below, from which we estimate the six unique transition probabilities (transitions that keep an individual in the same state are defined by 1 minus the probabilities of exiting the state):

(6)
$$P_{s,t} = \begin{bmatrix} 1 - p_{s,t}^{u|e} & p_{s,t}^{u|e} & p_{s,t}^{n|e} \\ p_{s,t}^{e|u} & 1 - p_{s,t}^{n|u - p_{s,t}^{e|u}} & p_{s,t}^{n|u} \\ p_{s,t}^{e|n} & p_{s,t}^{u|n} & 1 - p_{s,t}^{u|n - p_{s,t}^{e|n}} \end{bmatrix}$$

We proceed with the first step of our methodology. The Markov chain enables calculation of the steady state distribution of employment for each individual, $\pi_{s,t}$, by solving $\pi_{s,t} = \pi_{s,t}P_{s,t}$— steady state is unchanging in time. The vector $\pi_{s,t}$ contains the steady state distributions of each employment status, i.e., $\pi_{s,t} = \left[\pi_{s,t}^{e}, \pi_{s,t}^{u}, \pi_{s,t}^{n}\right]$ where $\pi_{s,t}^{e}$ is the steady state density of the individuals being employed. For a three-state Markov chain with $\pi_{s,t}^{e} + \pi_{s,t}^{u} + \pi_{s,t}^{n} = 1$, the steady state levels of each element are given by the following:

(7)
$$\pi_{s,t}^{e} = \frac{\lambda_e}{\lambda_e + \lambda_u + \lambda_n}, \quad \pi_{s,t}^{u} = \frac{\lambda_u}{\lambda_e + \lambda_u + \lambda_n}, \quad \pi_{s,t}^{n} = \frac{\lambda_n}{\lambda_e + \lambda_u + \lambda_n}$$

where

$$\lambda_e = p_{s,t}^{e|n} \cdot p_{s,t}^{n|u} + p_{s,t}^{e|u} \cdot p_{s,t}^{u|n} + p_{s,t}^{e|n} \cdot p_{s,t}^{e|u}$$

$$\lambda_u = p_{s,t}^{u|n} \cdot p_{s,t}^{n|e} + p_{s,t}^{u|e} \cdot p_{s,t}^{e|n} + p_{s,t}^{u|n} \cdot p_{s,t}^{u|e}$$

$$\lambda_n = p_{s,t}^{n|u} \cdot p_{s,t}^{u|e} + p_{s,t}^{n|e} \cdot p_{s,t}^{e|u} + p_{s,t}^{n|u} \cdot p_{s,t}^{n|e}$$

We use the observed labor market flows for triplicate states to plug in for $\boldsymbol{P_{s,t}}$ and solve for $\pi_{s,t}$. We use the notation "obs" to denote these values as they are calculated based on observed data, e.g., $\pi_{s,t}^{e,obs}$ represents the steady state employment level based on observed data.

In the second step of our methodology, we subtract *(ii)* counterfactual steady state levels without triplicate effect from *(i)* the realized steady state levels in triplicate states:

$$\underbrace{\Delta SS_{s,t}}_{\text{steady state effect}} = \underbrace{SS_{s,t}^{obs}}_{\text{(i) observed steady state in triplicate states}} - \underbrace{SS_{s,t}^{cf}}_{\text{(ii) counterfactual steady state without triplicate regulation effect}}$$

To obtain *(ii)*, we adjust the observed transition rates of triplicate states by the regression coefficients in Panel B of Table 4 (estimated from Equation 2). These are estimated at the year-month-of-sample level to be consistent with our regressions. We use the superscript "cf" to denote these counterfactual values, e.g., the counterfactual transition rates from employed to unemployed are calculated as $p_{s,t}^{u|e,cf} = p_{s,t}^{u|e,obs} - \delta_1$ where 1996m1 $\leq$ t $\leq$ 2000m12 for $\forall$s. Once we have counterfactual transition rates for each state *s* in each time period *t*, we follow the same procedure as in our first step and obtain the counterfactual steady state rates $\pi_{s,t}^{e,cf}$, $\pi_{s,t}^{u,cf}$, and $\pi_{s,t}^{n,cf}$ of triplicate states, e.g. the steady state rates of triplicate states if they were not triplicate states.

The third step of our methodology results in the subtraction of the results from our interim steps, notated as $\Delta SS_{s,t}$ ($\Delta\pi_{s,t}^{e}$, $\Delta\pi_{s,t}^{u}$, and $\Delta\pi_{s,t}^{n}$). Our final results are the average of $\Delta\pi_{s,t}^{e}$, $\Delta\pi_{s,t}^{u}$, and $\Delta\pi_{s,t}^{n}$ for the five triplicate states and the relevant time bands in our analysis (1996−2019, 1996−2000, 2001−2010, and 2011−2019).

G. Inference Method for the Steady State Effects

G.1 Delta Method

We use a delta method as an inference method for the steady state effects for two main reasons: (i) the availability of a closed form solution and (ii) the property of asymptotic normality. With the central limit theorem and the assumption that a consistent estimator B converges in probability to its true value β, the following asymptotic normality is obtained:

$$\sqrt{n}(B-\beta) \xrightarrow{d} N(0,\Sigma),$$

where *n* is the number of observations and Σ is a symmetric positive semi-definite covariance matrix. By taking the first two terms of the Taylor series, the delta method implies:

$$\sqrt{n}\big(h(B)-h(\beta)\big) \xrightarrow{D} N\Big(0, \nabla \mathrm{h}(\beta)^{\mathrm{T}}\Sigma\nabla \mathrm{h}(\beta)\Big).$$

G.2 Steady State Estimators

Let us denote the coefficients obtained from transition rate ($e|u$, n$|u$, e$|n$, u$|n$, u$|e$, n$|e$) regressions $\hat{\beta}^{e|u}, \hat{\beta}^{n|u}, \hat{\beta}^{e|n}, \hat{\beta}^{u|n}, \hat{\beta}^{u|e}, \hat{\beta}^{n|e}$. As we explained in Section V.C, the steady state effect estimate of L ∈ {u, n, e} can be expressed as:

$$\begin{aligned}\Delta\widehat{\pi}_{L,t} &= \underbrace{\pi^{*}_{L,t}}_{\text{observed}} - \underbrace{\pi^{cf}_{L,t}}_{\text{counterfactual}} \\ &= \underbrace{\frac{\lambda^{*}_{L,t}}{\lambda^{*}_{e,t}+\lambda^{*}_{u,t}+\lambda^{*}_{n,t}}}_{\text{observed}} - \underbrace{\frac{\lambda^{cf}_{L,t}}{\lambda^{cf}_{e,t}+\lambda^{cf}_{u,t}+\lambda^{cf}_{n,t}}}_{\text{counterfactual}} \\ &= f\big(\hat{\beta}^{e|u}_{t}, \hat{\beta}^{n|u}_{t}, \hat{\beta}^{e|n}_{t}, \hat{\beta}^{u|n}_{t}, \hat{\beta}^{u|e}_{t}, \hat{\beta}^{n|e}_{t}\big)\end{aligned}$$

G.3 Standard Error Calculation

By asymptotic normality assumption on coefficients and delta method,

$$\sqrt{n}\big(\Delta\pi_{L,t}-\Delta\widehat{\pi}_{L,t}\big) \xrightarrow{d} N(0, \widehat{Var}(\Delta\hat{\pi}_{L,t}))$$

where

$$\widehat{Var}\big(\Delta\hat{\pi}_{L,t}\big) = \nabla \mathrm{f}^{\mathrm{T}}_{\mathrm{L,t}}\big(\hat{\beta}^{e|u}_{t}, \hat{\beta}^{n|u}_{t}, \hat{\beta}^{e|n}_{t}, \hat{\beta}^{u|n}_{t}, \hat{\beta}^{u|e}_{t}, \hat{\beta}^{n|e}_{t}\big)\widehat{\Sigma}_{L,t}\nabla \mathrm{f}_{\mathrm{L,t}}\big(\hat{\beta}^{e|u}_{t}, \hat{\beta}^{n|u}_{t}, \hat{\beta}^{e|n}_{t}, \hat{\beta}^{u|n}_{t}, \hat{\beta}^{u|e}_{t}, \hat{\beta}^{n|e}_{t}\big).$$

By using chain rule, each element of the gradient of $\Delta\widehat{\pi}_{L,t}$ with respect to $\hat{\beta}^{e|u}_{t}, \hat{\beta}^{n|u}_{t}, \hat{\beta}^{e|n}_{t}, \hat{\beta}^{u|n}_{t}, \hat{\beta}^{u|e}_{t}$, and $\hat{\beta}^{n|e}_{t}$,

$$\nabla f^{T}_{L,t}\,(\hat{\beta}^{e|u}_{t}, \hat{\beta}^{n|u}_{t}, \hat{\beta}^{e|n}_{t}, \hat{\beta}^{u|n}_{t}, \hat{\beta}^{u|e}_{t}, \hat{\beta}^{n|e}_{t}) = \Big[\frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{e|u}_{t}}\ \frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{n|u}_{t}}\ \frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{e|n}_{t}}\ \frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{u|n}_{t}}\ \frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{u|e}_{t}}\ \frac{\partial\Delta\widehat{\pi}_{L,t}}{\partial\hat{\beta}^{n|e}_{t}}\Big],$$

can be acquired. For example, $\frac{\partial \Delta \hat{\pi}_u}{\partial \hat{\beta}_t^{e|u}}$ is as follows:[2]

$$\frac{\partial \Delta \hat{\pi}_u}{\partial \hat{\beta}_t^{e|u}} = \frac{\partial \Delta \hat{\pi}_u}{\partial \lambda_e^{cf}} \cdot \frac{\partial \lambda_e^{cf}}{\partial \hat{\beta}_t^{e|u}} + \frac{\partial \Delta \hat{\pi}_u}{\partial \lambda_u^{cf}} \cdot \frac{\partial \lambda_u^{cf}}{\partial \hat{\beta}_t^{e|u}} + \frac{\partial \Delta \hat{\pi}_u}{\partial \lambda_n^{cf}} \cdot \frac{\partial \lambda_n^{cf}}{\partial \hat{\beta}_t^{e|u}}$$

$$= \frac{\lambda_u^{cf}}{\left(\lambda_e^{cf} + \lambda_u^{cf} + \lambda_n^{cf}\right)^2} \cdot \left\{-\left(\overline{p_s^{u|n}}^{*} - \hat{\beta}^{u|n}\right) - \left(\overline{p_s^{e|n}}^{*} - \hat{\beta}^{e|n}\right)\right\}$$

$$+ \frac{\lambda_u^{cf}}{\left(\lambda_e^{cf} + \lambda_u^{cf} + \lambda_n^{cf}\right)^2} \cdot \left\{-\left(\overline{p_s^{n|e}}^{*} - \hat{\beta}^{n|e}\right)\right\}.$$

Next, each element of the covariance matrix consists of as follows, where the square roots of the diagonal elements yield the standard errors:

$$\hat{\sum}_{L,t} = \begin{bmatrix} \widehat{Var}(\hat{\epsilon}_t^{e|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{e|u}, \hat{\epsilon}_t^{n|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{e|u}, \hat{\epsilon}_t^{e|n}|X) & \widehat{Cov}(\hat{\epsilon}_t^{e|u}, \hat{\epsilon}_t^{u|n}|X) & \cdots & \widehat{Cov}(\hat{\epsilon}_t^{e|u}, \hat{\epsilon}_t^{n|e}|X) \\ \widehat{Cov}(\hat{\epsilon}_t^{n|u}, \hat{\epsilon}_t^{e|u}|X) & \widehat{Var}(\hat{\epsilon}_t^{n|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{n|u}, \hat{\epsilon}_t^{e|n}|X) & \widehat{Cov}(\hat{\epsilon}_t^{n|u}, \hat{\epsilon}_t^{u|n}|X) & \cdots & \widehat{Cov}(\hat{\epsilon}_t^{n|u}, \hat{\epsilon}_t^{n|e}|X) \\ \widehat{Cov}(\hat{\epsilon}_t^{e|n}, \hat{\epsilon}_t^{e|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{e|n}, \hat{\epsilon}_t^{n|u}|X) & \widehat{Var}(\hat{\epsilon}_t^{e|n}|X) & \widehat{Cov}(\hat{\epsilon}_t^{e|n}, \hat{\epsilon}_t^{u|n}|X) & \cdots & \widehat{Cov}(\hat{\epsilon}_t^{e|n}, \hat{\epsilon}_t^{n|e}|X) \\ \widehat{Cov}(\hat{\epsilon}_t^{u|n}, \hat{\epsilon}_t^{e|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{u|n}, \hat{\epsilon}_t^{n|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{u|n}, \hat{\epsilon}_t^{e|n}|X) & \widehat{Var}(\hat{\epsilon}_t^{u|n}|X) & \cdots & \widehat{Cov}(\hat{\epsilon}_t^{u|n}, \hat{\epsilon}_t^{n|e}|X) \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \widehat{Cov}(\hat{\epsilon}_t^{n|e}, \hat{\epsilon}_t^{e|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{n|e}, \hat{\epsilon}_t^{n|u}|X) & \widehat{Cov}(\hat{\epsilon}_t^{n|e}, \hat{\epsilon}_t^{e|n}|X) & \widehat{Cov}(\hat{\epsilon}_t^{n|e}, \hat{\epsilon}_t^{u|n}|X) & \cdots & \widehat{Var}(\hat{\epsilon}_t^{n|e}|X) \end{bmatrix}.$$

[2]. The time period subscript *t* is omitted for convenience.

Appendix References not cited in the main text

Bachhuber, Marcus A, Sean Hennessy, Chinazo O Cunningham, and Joanna L Starrels. 2016. "Increasing Benzodiazepine Prescriptions and Overdose Mortality in the United States, 1996–2013." *American journal of public health*, 106(4): 686–88.

David, H, and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103(5): 1553–97.

Substance Abuse and Mental Health Services Administration. 2015-2019. "National Survey on Drug Use and Health." Available at https://www.datafiles.samhsa.gov/.