Opioids and Post-COVID Labor Force Participation*

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Abstract

At the onset of the COVID-19 pandemic, the labor force participation of the working-age US population dropped by about three percentage points. The recovery was slow, and three years after the start of the pandemic, the labor force participation was still below its pre-pandemic level. The pace of recovery of the labor supply varied widely across US states. To understand this variation, the role of the opioid crisis, which was unfolding in the US before the COVID-19 pandemic, is studied. Labor supply recovery in the aftermath of COVID-19 was slower in states with greater pre-COVID exposure to the opioid crisis, measured by pre-COVID age-adjusted opioid overdose death rates. An event-study analysis shows that a one-standard-deviation increase in pre-COVID age-adjusted death rate is associated with a one percentage point drop in labor force participation after COVID-19. The effect of prior opioid exposure had a more significant impact on individuals without a college degree. The slow recovery in states with more opioid exposure was characterized by an increase in individuals who are not in the labor force due to disability.

Keywords: Labor Force Participation, Health, Opioids, COVID-19

JEL Codes: I12, I14, J11, J12, J21

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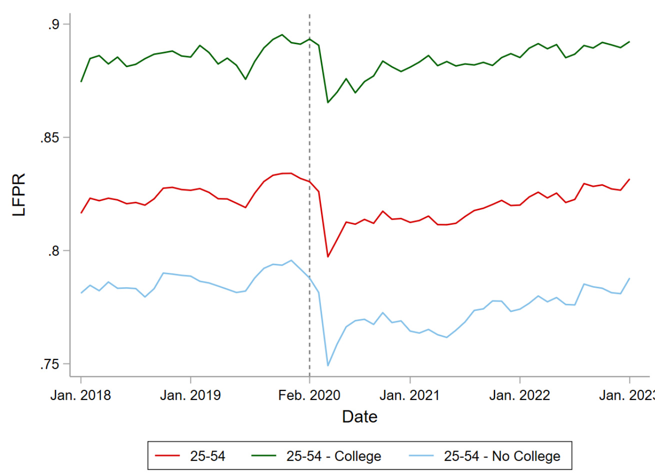
1 Introduction

At the onset of the COVID-19 pandemic between February and May 2020, labor force participation (LFP) in the US dropped about 3 percentage points. The recovery was slow, and by December 2022, nearly 3 years later, the LFP was still below its pre-pandemic level. A part of this slow recovery was due to older workers who chose to retire after the pandemic (Bauer and Edelberg, 2021). However, as Figure 1 shows, recovery of labor supply was also prolonged among prime-age workers between ages 25 and 54, and in particular, for those without a college degree. The pace of recovery of the labor supply was significantly different across US states. In December 2022, for example, the LFP among prime-age workers was still 5 percentage points below the trend in Michigan, while the LFP gap with the trend disappeared in Georgia. On average, in December 2022, the LFP was around 1 percentage point below the trend, with a standard deviation of 2 percentage points across US states.

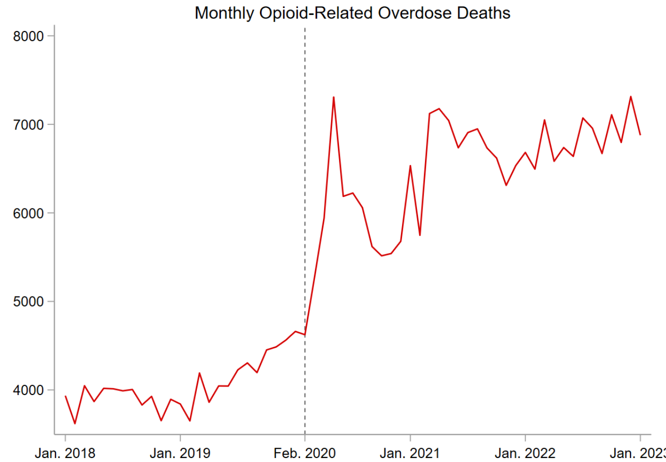
Figure 1: Labor Force Participation Rate, Ages 25-54



Notes: *The figure shows the monthly labor force participation rates among 25-54-year-olds across education groups. Source: Current Population Survey (CPS).*

The COVID-19 epidemic occurred in the US as another epidemic, the opioid crisis, was unfolding (Cutler and Glaeser, 2021, Alpert et al., 2022, Greenwood, Guner and Kopecky, 2024). Between 2000 and 2019, nearly half a million people died from an opioid overdose. The deaths from opioid overdoses increased significantly during COVID-19, as shown in Figure 2. The number of deaths increased from around 50,000 thousand in 2019 to more than 80 thousand in 2021 and 2022. The deaths from other substances, such as alcohol and methamphetamine, also increased substantially during this period (Mulligan, 2022).

Figure 2: Monthly Deaths from Opioid Overdose



Notes: *The figure shows monthly deaths due to opioid-related overdoses. An overdose opioid death has an underlying cause with ICD–10 codes X40–X44, X60–X64, X85, or Y10–Y14, and a multiple cause with ICD-10 codes T40.0 - T40.4, or T40.6. Source: CDC- Multiple Causes of Death data.*

Individuals who misuse opioids are significantly less likely to participate in the labor force compared to those who either do not use opioids at all or use them strictly as prescribed (Greenwood, Guner and Kopecky, 2022). It is shown here that labor supply recovery after the COVID-19 pandemic was slower in U.S. states with higher pre-pandemic exposure to the opioid crisis, using an event-study approach following Alpert, Powell and Pacula (2018) and Beheshti (2023). The identification strategy leverages a treatment effect that varies based on an initial moderating condition—in this case, the onset of COVID-19 as the treatment and pre-COVID opioid exposure as the moderator. The central hypothesis is that while COVID-19 led to increased opioid use nationwide, states with higher initial opioid exposure experienced more substantial increases, which further delayed their labor force recovery.

Pre-COVID opioid exposure is measured by the age-adjusted death rates from opioid overdose in 2017. The opioid deaths are used as a comprehensive summary measure of the intensity of the opioid crisis in a state. The results show that an increase of one standard deviation of initial opioid exposure lowers labor force participation after the COVID-19 shock by around 1 percentage point below the trend. Hence, moving from a state that is at the 25th percentile of opioid exposure, like Minnesota, to a state at the 7th percentile, like Michigan or Pennsylvania, is associated with a 1.6 percentage point drop in labor force participation.

The results are robust to alternative measures of pre-COVID exposure, such as the fraction of individuals with an opioid use disorder and shipments of medications that are used to treat opioid addiction. An alternative strategy using a synthetic control group, following Abadie and Gardeazabal (2003), also produces results with similar magnitude. We find similar results for men and women. The results, however, differ by educational attainment and are significant for those without a college degree but not for those without one. The impact of opioids on labor force participation is also larger for individuals between 44 and 54.

Furthermore, we provide evidence that these findings are not driven by general health differences across states. To do this, we run a series of placebo regressions in which we replace the initial opioid exposure with the age-adjusted death rate from leading causes of death unrelated to opioid overdoses. These placebo regressions show no significant difference in post-COVID-19 labor force participation between states with higher versus lower death rates from non-opioid-related causes.

Finally, we document that individuals with opioid use disorder tend to have lower labor force participation, are more likely to report being out of the labor force due to disability, and have overall worse health. Furthermore, the differences in labor force participation and disability between nonusers and those with opioid use disorder widened during COVID-19. Using our empirical strategy, we find that states with higher pre-COVID exposure to opioids experienced a greater increase in the share of individuals who are not in the labor force due to disability after COVID-19, highlighting the role of health-related factors on slow labor supply recovery.

Related Literature This study adds to recent literature on the opioid epidemic's impact on labor market outcomes. The link between worsening labor market conditions and increased opioid use has been highlighted by Hollingsworth, Ruhm and Simon (2017), Carpenter, McClellan and Rees (2017), Pierce and Schott (2020), and Venkataramani et al. (2020). Others, such as Krueger (2017), Harris et al. (2020), Powell (2022), and Aliprantis, Fee and Schweitzer (2023), have examined how opioid use reduces labor force participation and employment by leveraging geographic variations in opioid exposure.

Within this literature, exogenous changes in prescription drug formulas or their availability have been explored to tease out the causal effects of opioid use on labor market outcomes. The introduction of an abuse-deterrent version of OxyContin in 2010 is used by Alpert, Powell and Pacula (2018) to show that it led to a higher number of heroin deaths in states with higher initial OxyContin exposure. The same strategy is also used by Cho et al. (2021) to estimate the negative effects of heroin use on employment and labor force participation. Beheshti (2023) performs a similar analysis, using as an exogenous shock the change in regulations that made the prescription of hydrocodone more difficult in 2014. Like Alpert, Powell and Pacula (2018), he compares units affected differently by a treatment (changes in drug availability) and shows that areas that experienced larger reductions in hydrocodone prescriptions experienced relative improvements in labor force participation and employment.

The findings are also related to the literature on the effects of the COVID-19 pandemic on the labor market. Several studies focused on differences across demographic or socioeconomic characteristics, occupations, and industries in their suitability to remote work and, as a result, on how they are impacted by the epidemic. Alon et al. (2020) and Albanesi and Kim (2021) focus on gender, while Bartik et al. (2020), Dingel and Neiman (2020), Adams-Prassl et al. (2022*b*), and Mongey, Pilossoph and Weinberg (2021) highlight the role of occupations and their task contents. Another strand of the literature, which is more closely related to the current analysis, documents labor market dynamics during and after the epidemic. The labor market after the epidemic has been surprisingly tight with low unemployment and labor force participation rates (Coibion, Gorodnichenko and Weber, 2020, Forsythe et al., 2022). Quits and number of workers looking for new jobs also increased (Gittleman, 2022, Barlevy et al., 2024). There has also been a decline in the desired work hours that persisted throughout the end of 2021, as shown in Faberman, Mueller and Şahin (2022). Bagga et al. (2023) suggest that the post-COVID period was characterized by a shift in workers' valuation of specific job amenities, mainly remote work, which led to persistent labor reallocation. This analysis contributes to the literature by focusing on opioid use, a factor influencing labor supply behavior that was significantly impacted during the COVID-19 pandemic.

The rest of the paper is structured as follows: Section 2 discusses the data. Section 3 presents the empirical methodology. Section 4 shows the results from the main specification. Robustness checks are presented in Section 5, while Section 6 highlights potential mechanisms. Section 7 concludes.

2 Data and Motivating Evidence

The empirical analysis is conducted at the U.S. state level, covering each month from January 2018 to January 2023. The primary outcome variable is the labor force participation rate of prime-age civilians (ages 25 to 54), calculated for each state and month using data from the Current Population Survey (CPS). CPS data on gender and educational attainment are also used to analyze outcomes of different socioeconomic groups. Respondents are classified as college-educated if they have attained at least a bachelor's degree.[1] Additionally, CPS data is used to construct state-level employment levels by industry, which can affect variations in COVID-19's impact on labor force participation.

The primary measure of pre-COVID opioid exposure is the age-adjusted mortality rate from opioid overdoses in 2017, sourced from the Centers for Disease Control's Multiple Cause of Death database (CDC-MCOD).[2] An opioid overdose death is identified when the underlying cause of death is a drug overdose, and opioids are listed among the multiple causes. For underlying causes, we include ICD-10 codes X40-X44 (accidental drug poisonings), X60-X64 (intentional self-poisoning by drugs), X85 (assault by drug poisoning), and Y10-Y14 (drug poisoning of undetermined intent). Opioids as a multiple cause of death are identified using codes T40.0 (Opium), T40.1 (Heroin), T40.2 (Other opioids), T40.3 (Methadone), T40.4 (Other synthetic narcotics), and T40.6 (Other and unspecified narcotics).

Opioid-related deaths are used as a comprehensive measure of opioid exposure, encompassing both legal and illegal opioid consumption and accounting for variations in the types of opioids used, such as OxyContin, Fentanyl, and heroin, each differing significantly in potency. Summary statistics for age-adjusted opioid overdose mortality rates across U.S. states are presented in Table 1. Notably, the age-adjusted opioid death rate rose by over 50% between 2019 and 2021 (Mulligan, 2022). There is also considerable variation in death rates across states, a disparity that has widened since the COVID-19 pandemic. In 2021, opioid death rates ranged from approximately 6 deaths per 100,000 people in the lowest-affected states to as high as 77 per 100,000 in the hardest-hit states. The geographic distribution of opioid death rates in 2017 is shown in Figure 3. The regions with the highest death rates, ranging from 16 to 50 per 100,000, are the Appalachian, Rust Belt, and New England.[3]

[1] In 2020, 38% of males and 45% of females aged 25 to 54 were college-educated.

[2] Available at https://wonder.cdc.gov/mcd.html. Causes of death are coded using ICD-10, the 10th revision of the International Classification of Diseases by the World Health Organization.

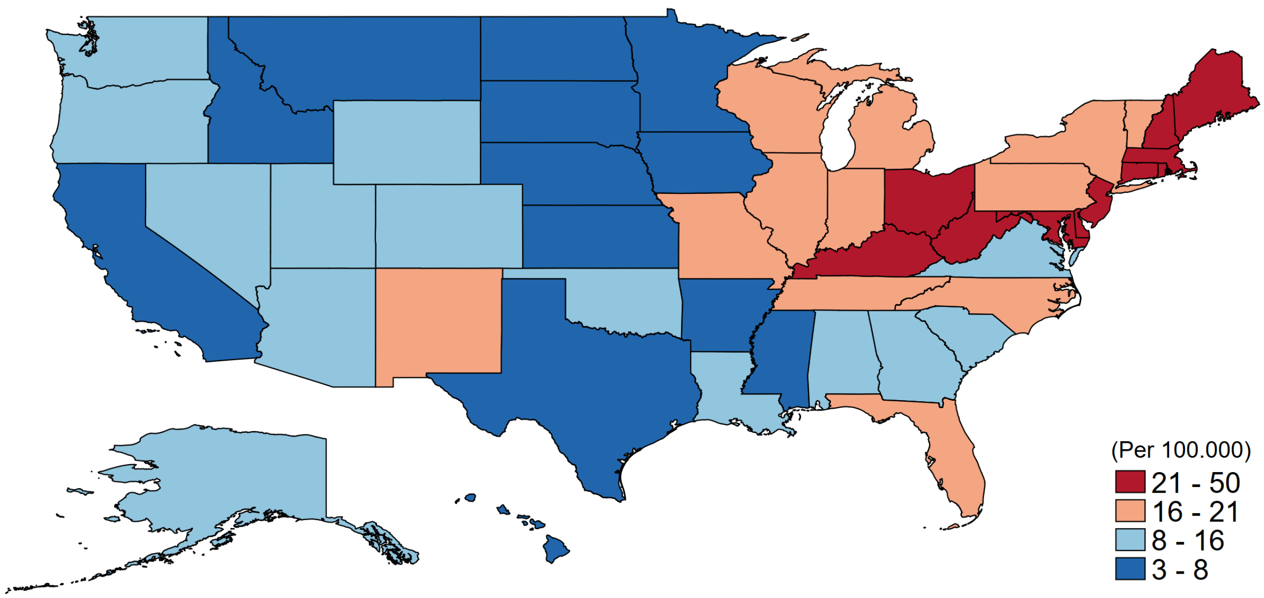
[3] Further details on the demographic and geographic variation in fatal drug overdoses over time can be

Table 1: Age-Adjusted Opioid Overdoses Death Rate

	Mean	*sd*	Min	Max
2017	16.26	10.52	3.1	49.6
2019	16.66	10.16	3.5	43.0
2021	26.26	13.77	5.7	77.2
2022	26.82	13.03	5.6	72.5

Notes: *The table shows the summary statistics of the age-adjusted opioid-related overdose death rate for 2017, 2019, 2021, and 2022. Death rates are computed per 100,000 people. Source: CDC-MCOD.*

Figure 3: Age-Adjusted Death Rates from Opioid Overdose, 2017



Notes: *The figure shows the age-adjusted opioid-related overdose death rate for 2017 across the US States. Death rates are computed per 100,000 people. Source: CDC-MCOD.*

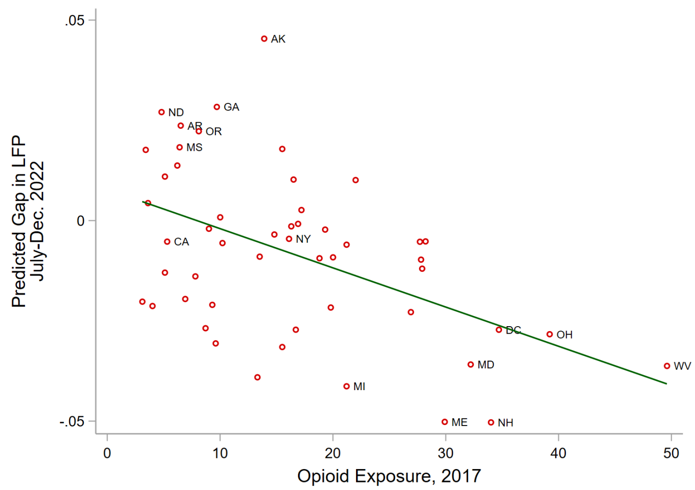
The relation between pre-COVID opioid exposure and post-COVID labor supply recovery across U.S. states is presented in Figure 4. As a measure of recovery, the gap between the observed and predicted labor force participation for prime-age individuals during the last six months of 2022 is used. The predicted post-COVID values are based on state-level regressions of labor force participation on a polynomial in time.[4] More than two years after the onset of COVID-19, states with higher initial opioid death rates in 2017, such as West Virginia and Ohio, had labor force participation rates that were well below the predicted

found in Monnat (2022).

[4]Further details on the estimation of trends are provided in Appendix A.

values.

Figure 4: Relationship Between Opioid Exposure and Prime Age LFP Gap



Notes: *The figure shows the correlation between the predicted gap in prime-age LFP and age-adjusted opioid-related overdose death rate for 2017. The predicted gap in prime-age LFP is constructed by subtracting the predicted LFP from the observed one. The average of the predicted gap between July and December 2022 is reported. Appendix A describes the construction of the predicted LFP values. Source: CDC-MCOD and CPS.*

Two alternative measures of pre-COVID opioid exposure are also considered in the analysis. The first measure is the percentage of individuals with opioid use disorder in 2017-2018, based on data from the National Survey on Drug Use and Health (NSDUH). This annual survey provides national and state-level data on tobacco, alcohol, illicit drug use (including non-medical use of prescription drugs), and mental health in the United States. Opioid use includes both prescription pain relievers and heroin, assessed based on usage in the past 12 months. Prescription misuse is defined as any use not directed by a doctor, such as using without a prescription, in higher amounts, or more frequently than prescribed. All heroin users are considered misusers. Misusers are further screened for substance use disorder, indicated by health problems, disabilities, or significant responsibilities impacted by recurrent use.[5]

The second measure of opioid exposure is the total shipment of medications used to treat opioid addiction in each state. Data on these medications, primarily methadone and

[5]State-level data on opioid use disorder is obtained from the Restricted-Use Data Analysis System (RDAS) by the Substance Abuse and Mental Health Services Administration, as NSDUH's public filed lacks geographical indicators.

buprenorphine, is taken from the Drug Enforcement Agency's (DEA) Automation of Reports and Consolidated Orders System (ARCOS).[6] The DEA provides data on the quantity (in grams) of these drugs distributed to each zip-3 area, which is then aggregated at the state level. Morphine milligram equivalents (MME) are then used to calculate a per capita MME amount for each state in 2017.[7] The summary statistics for these alternative exposure measures and their correlations with age-adjusted death rates are presented in Table 2. Notably, differences in these exposure measures are observed across states, with a fairly high correlation between these measures and age-adjusted death rates.

Table 2: Alternative Opioid Exposure Measures

	Mean	*sd*	Min	Max	Corr. with Death Rate
Death Rate, 2017	16.26	10.52	3.10	49.60	1.00
Disorder, 2017-18 (%)	0.84	0.30	0.32	1.60	0.41
Treatment MME pc, 2017	925.43	601.09	157.06	2809.07	0.78

Notes: *The table shows the summary statistics for measures of state opioid exposure. The second row shows the percentage of people with an opioid use disorder in 2017-2018, obtained from the NSDUH. The third row shows the quantity of drugs to treat opioid use disorder distributed to the state in 2017, measured as MME per capita, obtained from ARCOS. The last column shows Spearman's rank correlation between these two measures and the age-adjusted death rate.*

The empirical analysis also includes control variables reflecting differences in COVID-19 intensity and policy responses across states. State-level COVID-19 cases and deaths are taken from the CDC's COVID-19 Tracker.[8] Policy data is obtained from the Oxford Tracker Dataset (Hale et al., 2021); specifically, the Stringency Index (covering school and workplace closures and stay-at-home orders) and the Economic Support Index (summarizing income support policies during COVID-19) are used.[9] The average value of these two indices and their standard deviations across U.S. states are shown in Figure B1 in the Appendix.[10]

[6]Available at https://www.deadiversion.usdoj.gov/arcos/arcos.html. For details on opioid-treatment medications, see (Mutter and Duchovny, 2022). Naltrexone is excluded from ARCOS as it is not a scheduled drug.

[7]MME standardizes opioid potency relative to morphine, allowing cross-opioid comparisons. The conversion to MME is based on data from Cutler and Glaeser (2021).

[8]Available at https://covid.cdc.gov/covid-data-tracker/#datatracker-home.

[9]The Oxford Tracker Dataset categorizes various COVID-19 policies into indexes representing different policy strengths, normalized between 0 and 100.

[10]Ruhm (2024) finds that if all states had imposed COVID-19 restrictions similar to those used in the 10 most restrictive states, excess deaths would have been 10% to 21% lower.

3 Empirical Strategy

The simultaneous impact of COVID-19 across all states makes a standard difference-in-differences estimator unsuitable for analyzing why some states experienced a slower recovery in labor force participation. The analysis here uses an approach that allows the COVID-19 shock to have varying effects across states, depending on their pre-COVID opioid exposure. This approach relies on three assumptions: (1) the treatment affects all units (states) simultaneously, (2) the treatment effect depends on initial, predetermined conditions unrelated to the treatment, and (3) these conditions vary across units. The core idea is that states with higher pre-COVID opioid exposure experienced a slower labor force recovery, potentially due to greater opioid availability or a larger population with opioid use experience, which became more salient post-COVID. Importantly, COVID-19 onset is assumed to be independent of initial opioid exposure levels.

This empirical strategy is used by Alpert, Powell and Pacula (2018) to study the effects of OxyContin's reformulation, which made it harder to abuse. The reformulation, an event that affects everyone, is found to lead to greater increases in heroin deaths in states with higher pre-reformulation OxyContin exposure. A similar approach is also used by Beheshti (2023) to assess the impact of hydrocodone rescheduling by the Drug Enforcement Agency (DEA) that made it harder to prescribe by doctors. The areas with higher initial hydrocodone prescriptions are found to have more significant improvements in labor force participation and employment.

The empirical approach uses a dynamic two-way fixed effects model, with labor force participation as the dependent variable and the interaction between the COVID-19 outbreak (February 2020) and pre-COVID opioid exposure as the key explanatory variable. Two versions of pre-COVID exposure, age-adjusted opioid death rates in 2017, are used. First, a binary variable categorizes states into "high" and "low" exposure groups based on whether they are above or below the median exposure. This method offers straightforward, difference-in-difference-like comparisons but loses detail, as states with similar exposure levels might fall into different groups. For instance, Utah (16 deaths per 100,000) is grouped with high-exposure states like Ohio and West Virginia (39 and 50 per 100,000), while Virginia (15 deaths per 100,000) is in the low-exposure group. The second specification uses death rates as a continuous variable, retaining finer distinctions in exposure. To simplify interpretation, this continuous measure is standardized to have a mean of 0 and a standard deviation of 1.

The event-study analysis is based on the following regression for the binary exposure:

$$Y_{s,t} = \alpha_s + \alpha_t + \sum_{T \neq 2020m2} \beta_T \times \mathbb{1}\{t = T\} \times TREAT_s + \delta X_{s,t} + \varepsilon_{s,t}, \tag{1}$$

where where $Y_{s,t}$ is outcome of interest, the LFP, in state s at time t, and α_s, and α_t are the state and time fixed effects. The variable $TREAT_s$ takes the value of one if pre-COVID opioid exposure is higher than a certain threshold and 0 otherwise. The variable $X_{s,t}$ are time-varying controls. The regression equation with a continuous exposure variable is given by:

$$Y_{s,t} = \alpha_s + \alpha_t + \sum_{T \neq 2020m2} \beta_T \times \mathbb{1}\{t = T\} \times Op.\ Exp_s + \delta X_{s,t} + \varepsilon_{s,t}, \tag{2}$$

where $Op.Exp_s$ is the pre-event opioid exposure of state s.

The coefficient of interest in equations (1) and (2) is β_T, with $\beta_{Feb.2020}$ being normalized to 0. These coefficients indicate changes in the outcome variable Y relative to the month before COVID-19 between states with different levels of the prior opioid exposure variable. For the binary exposure, for example, $\beta_{March.2020} = -0.1$ implies that compared to low exposure states, LFP was 10 percentage points lower in March 2020 in high exposure states. For the continuous exposure, on the other hand, $\beta_{March.2020}$ measures the difference in LFP associated with a unit increase in the pre-COVID exposure measure, which, since the measure has been standardized, corresponds to a one standard deviation increase in the age-adjusted opioid death rate in 2017.

As control variables in $X_{s,t}$, the monthly deaths due to COVID-19 (set to 0 in the pre-COVID period and after March 2022) are included to capture the severity of the COVID-19 epidemic across states. The Stringency and Economic Support indexes, which summarize policies enacted by states throughout COVID-19, are also added, as they are likely to affect the extent of economic activity affected by COVID-19 and labor supply incentives. Finally, a Bartik-style control variable is included to account for differences in industrial structure across states. This control is constructed as

$$B_{st} = \sum_k \phi_{s,k,\tau} \frac{\nu_{-s,k,t} - \nu_{-s,k,t-1}}{\nu_{-s,k,t-1}}, \tag{3}$$

where $\nu_{-s,k,t}$ are the national employment shares in industry k at time t computed by excluding the state $-s$. Meanwhile, $\phi_{s,k,\tau}$ is the employment share in industry k, in state s at fixed time $\tau = 2017$. Hence, while national employment has declined everywhere, states with larger employment in certain sectors, such as tourism, might be more intensely affected.

The specifications in equation (1) and (2) assume that before the COVID-19 epidemic, high and low exposure states had parallel trends in LFP. The assumption of parallel trends allows differences in the post-COVID period to be interpreted as difference-in-difference outcomes. As a result, the estimated values for β_T should be close to 0 for the pre-COVID period. Yet, the assumption of parallel trends might be too strong and violated in the data. Following Beheshti (2023) and Dobkin et al. (2018), a more flexible specification, which allows for preexisting differential linear time trends across states, is also considered, given by:

$$Y_{s,t} = \alpha_s + \alpha_t + \sum_{T>2020m2} \theta_T \mathbb{1}\{t = T\} TREAT_s + \sum_S \phi_S \mathbb{1}\{s = S\} t + \delta X_{s,t} + \varepsilon_{s,t}, \qquad (4)$$

for the binary exposure and

$$Y_{s,t} = \alpha_s + \alpha_t + \sum_{T>2020m2} \theta_T \mathbb{1}\{t = T\} Op.\ Exp_s + \sum_S \phi_S \mathbb{1}\{s = S\} t + \delta X_{s,t} + \varepsilon_{s,t}, \qquad (5)$$

for the continuous exposure, where the term $\sum_S \phi_S \mathbb{1}\{s = S\} t$ allows for state-specific linear time trends.

The identifying assumption now does not require parallel trends across states. Instead, similar deviations from potentially different linear trends in different states are needed. Furthermore, the coefficients θ_T are estimated only for the post-COVID period. However, the estimates for β_T obtained in equation (1) can be used to obtain estimates of θ_T for the pre-COVID period (Dobkin et al., 2018). If these constructed estimates for the pre-COVID period are close to 0, the linear trend assumption provides a good representation of the data. Following Beheshti (2023), equations (1) and (2) are referred to as the non-parametric event-study specifications, while equations (4) and (5) are referred as the parametric event-study specifications.

An alternative parametric event study is also suggested by Alpert, Powell and Pacula (2018). This alternative specification allows for a linear preexisting trend in labor force participation, a shift in its level, and a trend-break, i.e., a different linear trend after the onset of COVID-19, given by

$$
\begin{aligned}
LFPR_{i,t} = \alpha_i + \alpha_t + \delta_1[t \times Op.\ Exp_i] + \delta_2[Post_t \times Op.\ Exp_i] \\
+ \delta_3[Post_t \times (t - 2020\text{m}2)] + \delta X_{i,t} + \varepsilon_{i,t},
\end{aligned}
\tag{6}
$$

where $Post_t$ is a dummy variable that takes the value of one for the period after February 2020, and t denotes the date. The linear preexisting trend is given by the expression in square brackets after δ_1, the shift in level is given by the expression in square brackets after δ_2, and the trend-break is the expression in square brackets after δ_3. $X_{i,t}$ again represents the time-varying controls.

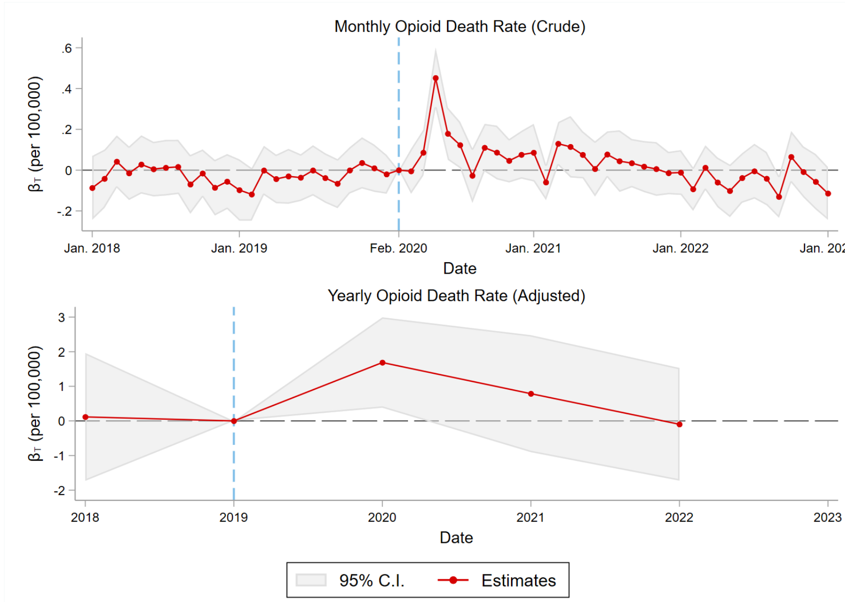
4 Results

The empirical strategy assumes that the age-adjusted opioid overdose death rate is a reliable indicator of opioid exposure. If differences in labor force participation across states are indeed linked to pre-COVID opioid exposure, then states with higher exposure should also show higher opioid death rates following the COVID-19 shock. This "first-stage" effect is studied by estimating equation (2) with opioid death rates as the dependent variable, $Y_{s,t}$. Only the non-parametric event study results are presented since the estimated coefficients β_T for the pre-COVID period do not suggest the existence of any pre-trends. The results are shown in Figure 5. A one standard deviation increase in initial opioid exposure is linked to a 0.4 increase in the monthly opioid death rate by May 2020 and a 2-point increase in the yearly rate for 2020. This effect is significant, representing 35% of the monthly and 13% of the yearly pre-pandemic death rates.[11]

Next, the results for labor force participation are presented. The β_T estimates from the non-parametric event study are shown in Figure 6. The upper panel illustrates the results from equation (1) using a binary exposure measure, dividing states into those above and below the median age-adjusted death rate in 2017. The lower panel shows results from equation (2), using 2017 age-adjusted death rates as a continuous measure of opioid exposure. In both binary and continuous cases, the estimated effects are primarily negative, indicating lower labor force participation post-COVID in states with higher pre-COVID opioid

[11] For binary exposure results, where states are divided into those above and below the median age-adjusted death rate in 2017, see Figure B2 in the Appendix.

Figure 5: Non-Parametric Event Study with Continuous Exposure - Opioid Deaths



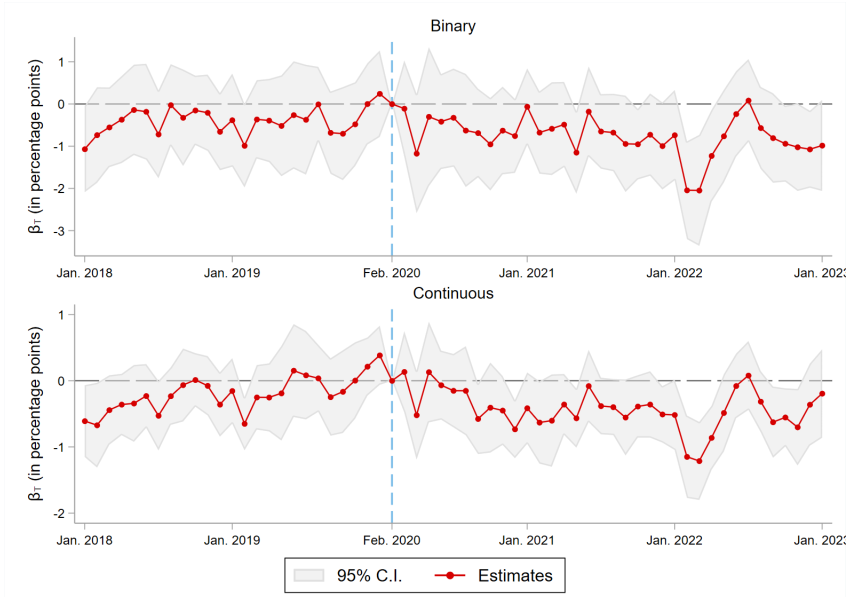
Notes: *The figure shows the non-parametric event-study coefficients β_T and the 95% confidence interval when using opioid-related overdose deaths as the dependent variable. The top panel uses the monthly crude rate, while the bottom uses the yearly age-adjusted rate. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

exposure. However, these estimates are not statistically significant, except for February and March 2022. Additionally, the fact that all the estimated β_T coefficients before COVID-19 are consistently below 0 indicates the existence of pre-trends.

The estimates from the parametric event-study, equations (4) and (5), are shown in Figure 7. The results from the binary measure of opioid exposure are again shown in the upper panel, while results from the continuous exposition are in the lower panel. The estimated coefficients for both specifications before COVID-19 are around 0, supporting the identifying assumption that states experienced similar deviations from linear trends. The estimated θ_T coefficients for the post-COVID period indicate that labor force participation rates in states with higher pre-COVID exposure have consistently fallen below their linear trend compared to less-exposed states.

The gap in labor force participation (LFP) between states with higher and lower opioid exposure emerged immediately after COVID-19. It continued to widen, reaching nearly 1 percentage point by January 2021 and around 2 percentage points by January 2022. The upper panel estimates indicate that from February 2020 to January 2022, LFP in states with

Figure 6: Non-Parametric Event Study, Labor Force Participation

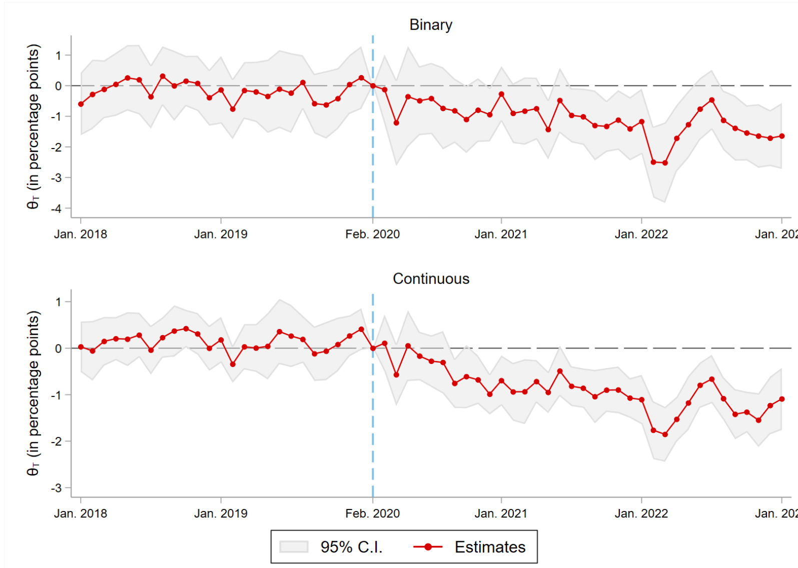


Notes: *The figure shows the non-parametric event-study coefficients* β_T *and the 95% confidence interval when using prime-age LFP as dependent variable. For the top panel, the initial opioid exposure measure has been dichotomized: states with the age-adjusted opioid death rate in 2017 above the median are given a value of 1, and the others a value of 0. For the bottom panel, the initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

above-median opioid exposure was, on average, 1 percentage point below its trend. Similarly, the continuous measure results in the lower panel show that a one-standard-deviation increase in 2017 age-adjusted opioid death rates corresponds to an additional 1 percentage point drop in LFP. This suggests that moving from the 25th percentile of initial opioid exposure (e.g., Minnesota) to the 75th percentile (e.g., Pennsylvania or Michigan) results in an average LFP decline of 1.6 percentage points—a significant effect, considering that the standard deviation in prime-age LFP in January 2022 was 3.3 percentage points.

Finally, the results obtained using equation (6) are presented in Table 3, where the coefficients for δs and the total magnitude after 6, 12 and 24 months, i.e., $\delta_2 + x\delta_3,\ x \in \{6, 12, 24\}$ are reported. The pre-trend coefficient is positive, i.e., as in Figure 6, states with higher opioid exposure had increasing LFP before the onset of COVID-19. The shift and the post-trend are both negative, which indicates that states with higher opioid exposure faced a continuous decrease in LFP with respect to states with lower opioid exposure. The total effect after 6 months (August 2020) is -0.7, which indicates that one standard deviation

Figure 7: Parametric Event Study, Labor Force Participation



Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age LFP as dependent variable. Top panel, the initial opioid exposure measure has been dichotomized: states with the age-adjusted opioid death rate in 2017 above the median are given a value of 1, and the others a value of 0. For the bottom panel, the initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

increase in opioid exposure is associated with a drop of 0.7 percentage points in LFP. The total effect after 24 months (February 2022) is -1.2. The results, both the sign and the magnitudes, align with the results from the previous specification.

4.1 Heterogeneity

The results for different demographic and socioeconomic groups are presented in this section, using the parametric event study with a continuous exposure measure, i.e., equation (5). The effects across gender and age groups are shown in Figure 8. The estimates are very similar for men and women. In contrast, there is a stronger effect among older workers (ages 45–54) than younger workers (ages 25–44). Specifically, for the 45–54 age group, a one standard deviation increase in pre-COVID opioid exposure is associated with a 1.29 percentage point decline in labor force participation (LFP) relative to a linear trend. For the 25–44 age group, the effect is 0.84 percentage points.[12] The effect by educational attainment

[12]The results for age groups 18–24 and 55–64 are presented in Figure B3 in the Appendix; for these groups, the estimates are not significantly different from zero.

Table 3: Alternative Parametric Event Study, Labor Force Participation

	(1)
Pre-trend (δ_1)	0.0248***
	(0.004)
Shift (δ_2)	-0.476*
	(0.052)
Post-trend (δ_3)	-0.0306***
	(0.015)
Effect 6 Months	-0.659***
	(0.003)
Effect 12 Months	-0.842***
	(0.000)
Effect 24 Months	-1.209***
	(0.000)
Adj. R2	0.77

Notes: *The table shows the estimates obtained from the regression equation (6). In parenthesis p-values in parentheses, * p<0.10, ** p<0.05, *** p<0.01. State clustered S.E. used. States have been weighted by their population size. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

is illustrated in Figure 9 and reveals significant differences. The estimates for non-college-educated individuals are significant and imply that one standard deviation increase in pre-COVID opioid exposure is associated with 1.18 percentage points decline in LFP from a linear trend for this group. The estimates for college graduates are not significantly different from zero.

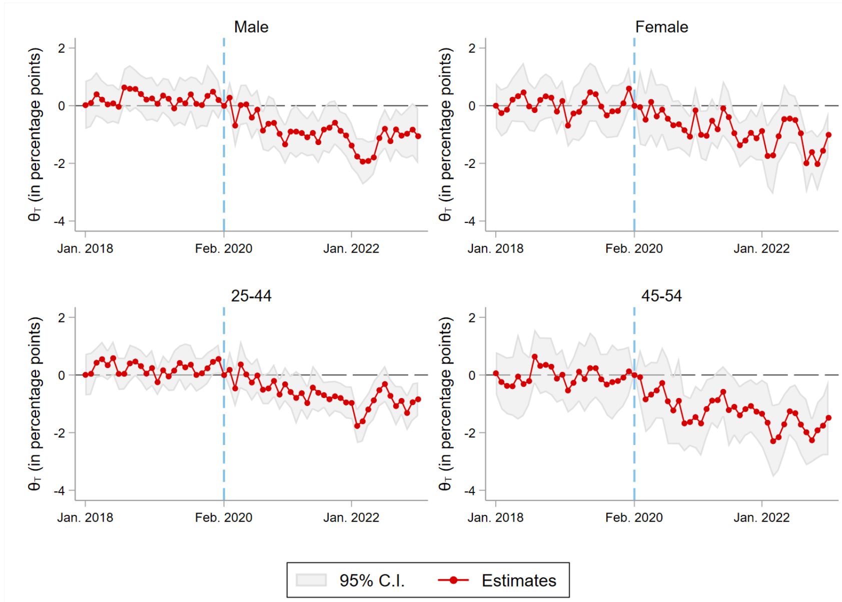
5 Robustness

Several sensitivity and robustness checks are presented in this section. First, results with alternative measures of pre-COVID opioid exposure are presented. Second, a synthetic control method is applied as an alternative empirical approach. Finally, results from a placebo test are presented where the opioid overdose deaths in the pre-COVID period are replaced by other leading causes of death.

Alternative Exposure Measures: In the analysis, the age-adjusted opioid death rates in 2017 are used as a measure of opioid exposure. Using the average age-adjusted opioid death

Figure 8: Parametric Event Study with Continuous Exposure

Labor Force Participation by Gender and Age



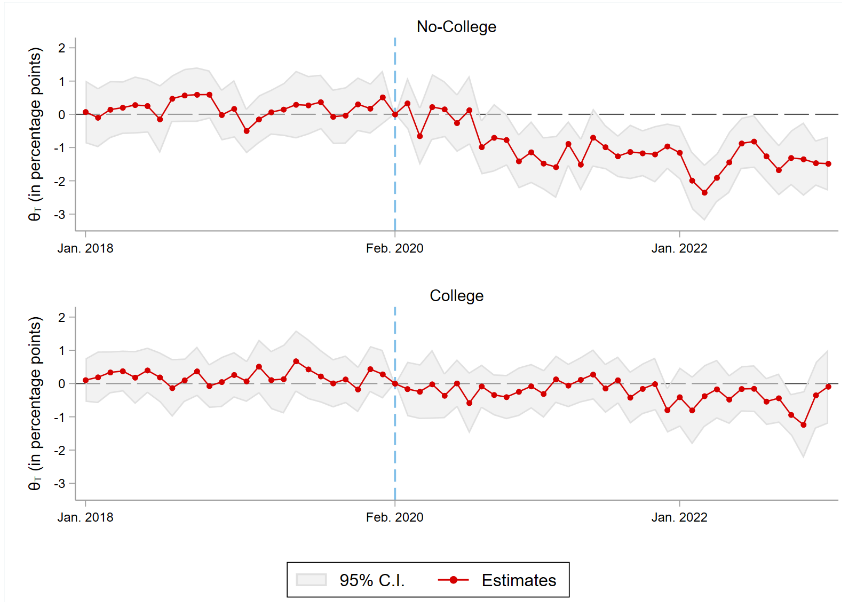
Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using LFP as the dependent variable within a restricted sample. The top panel splits the sample by gender, showing prime-age LFP among males and females. The bottom panels show LFP by age groups, 25-44 in the left panel and 45-54 in the right. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

rates between 2000 and 2017 instead of a single year generates very similar results. Since the distribution of age-adjusted death rates in 2017 is slightly right-skewed, estimates where exposure is measured by the logarithm of death rates are also presented. The results are shown in Figure B4 in the Appendix using a parametric event study with continuous exposure measures. The gap in labor force participation in the post-COVID period closely aligns with the estimates in Figure 7. Again, a one-standard-deviation increase in opioid exposure is associated with about 1 percentage point larger negative deviation from the trend in labor force participation.

Next, results with two alternative measures of the opioid crisis are presented. The first measure is the percentage of individuals above age 12 who are reported to have an opioid use disorder in the NSDUH. The second is the shipment of medicines for the treatment of opioid addiction from ARCOS. The estimates, again with a parametric event study using the continuous exposure measure, are shown in Figure 10. The results are again similar to the ones in Figure 7. States that had one standard deviation higher share of people with

Figure 9: Parametric Event Study with Continuous Exposure

Labor Force Participation by Education

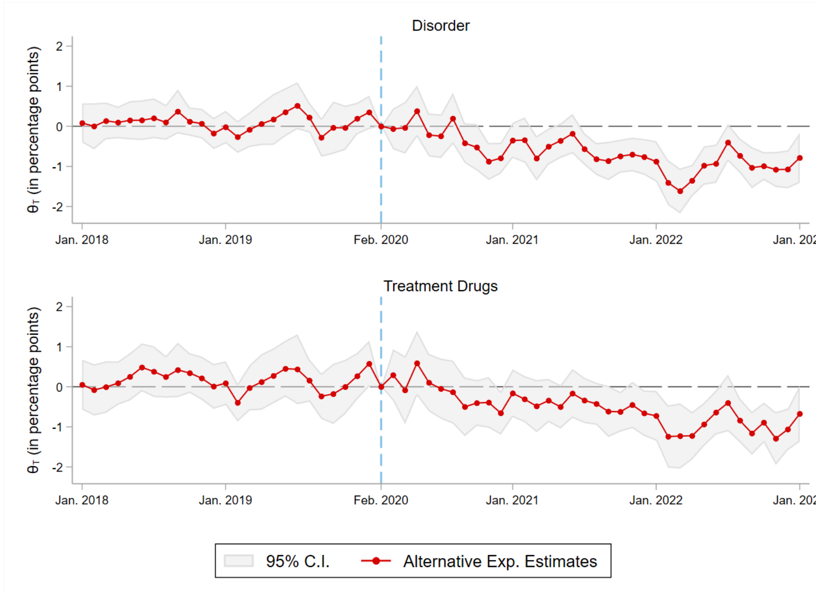


Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age LFP as the dependent variable within a restricted sample. The upper panel uses prime-age LFP focusing on non-college-educated, while the bottom uses college-educated. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

an opioid use disorder or one standard deviation higher per-capita amount of medicines to treat opioid addiction experienced about 1 percentage point larger negative deviation from the trend in labor force participation.

Alternative Empirical Approach: In the parametric event-study approach, it is assumed that states with different initial opioid exposure had similar deviations from their state-specific linear trend. The results with a *synthetic control*, which follow Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010), are presented as an alternative empirical strategy. A synthetic control group is constructed as follows. Imagine states are assigned into treated and untreated groups based on whether they have above or below median pre-COVID exposure. Then, weights are assigned to each state in the untreated group so that the average pre-COVID labor force participation in this synthetic control group follows as closely as possible the one in the treated group. The weights are time-invariant and are obtained by minimizing the difference in labor force participation between the weighted control units and the treated group before COVID-19. Therefore, by construction, the synthetic

Figure 10: Parametric Event Study - Alternative Measures of Opioid Exposure



Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age LFP as dependent. The top panel uses the percentage of people with a substance use disorder in 2017-2018 as a measure of exposure. The bottom panel uses the amount of MME per capita of drugs to treat opioid use disorder distributed to the state in 2017. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

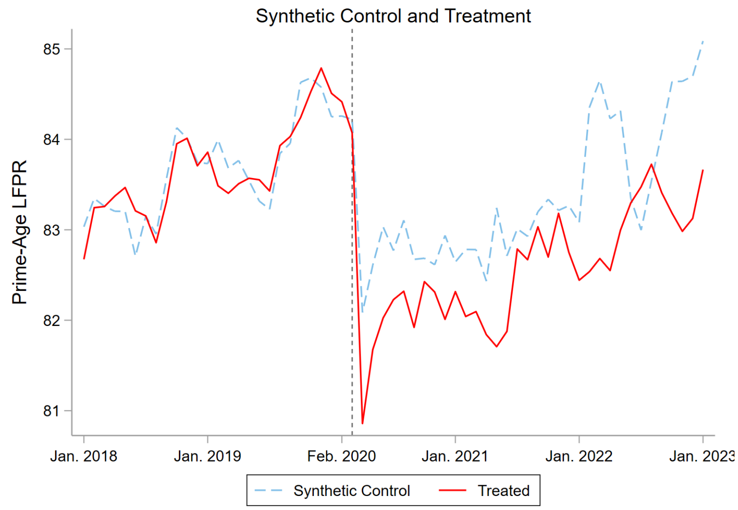
control and the treatment group have a similar trend in labor force participation before the onset of COVID-19. The treatment effect of the intervention is then obtained by comparing the post-intervention outcomes in the treated and in the synthetic control groups by simply comparing the average labor force participation in the treated group and the synthetic control in the post-COVID period.

The average prime-age labor force participation in treated states and in the synthetic control are shown in Figure 11. The labor force participation in these two groups diverged in the post-COVID period, and the treated group, i.e., states with higher opioid exposure, had lower labor force participation. The average treatment effect in the post-COVID period is -0.59 percentage points and significant at a 10 percent level.[13]

Placebo Analysis: Finally, placebo results are presented where the initial pre-COVID

[13]Based on bootstrapped standard errors for the average treatment throughout the period.

Figure 11: Synthetic Control and Treatment Group - LFPR



Notes: *The figure shows the labor force participation in treatment and synthetic control groups. The treatment group includes states with an initial opioid exposure above the median. The LFP of the synthetic control is obtained as a weighted average of the LFP of states with an initial opioid exposure below the median.*

exposure is replaced with the age-adjusted death rates from causes other than opioid overdoses. If the results of this placebo measure of exposure turn out to be significant, the larger drop in labor force participation in states with higher initial opioid exposure might be due to general health conditions in the population or features of the healthcare sector in a state that affects both pre-COVID opioid death and post-COVID labor supply decisions.

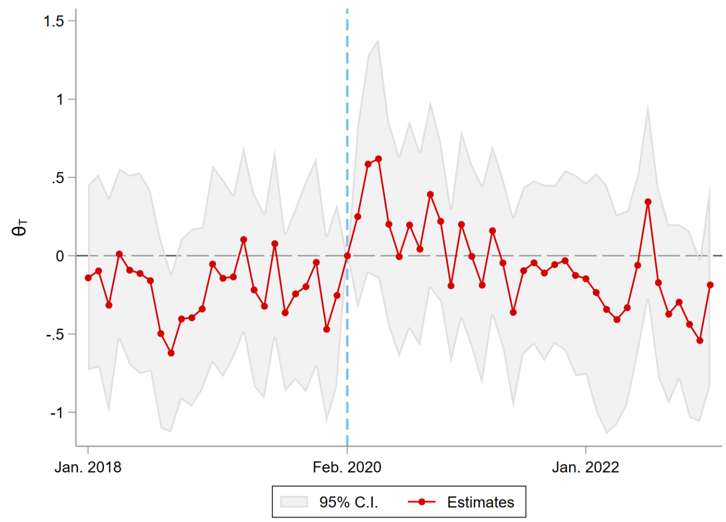
For the placebo analysis, information on the 15 leading causes of death in the US from the CDC Underlying Cause of Death dataset is used.[14] Table B1 shows the 15 leading causes and their age-adjusted death rate in 2017. Deaths due to accidents and intentional self-harm (causes 3 and 8) might also be included in the opioid death rate measure.[15] Figure 12 shows the estimated coefficient of the parametric event with the initial exposure measure of a state given by the total death rate due to the remaining 13 underlying causes. The coefficients, while negative, are not statistically significant for the post-COVID period.[16]

[14] https://wonder.cdc.gov/ucd-icd10.html.

[15] The underlying causes with ICD-10 codes X40-X44 are subcategories included in accidents, while underlying causes with ICD-10 codes X60-X64 are subcategories included in intentional self-harm.

[16] The results when the initial exposure is measured by each of these 13 underlying causes are shown in Figure B5 in Appendix.

Figure 12: Parametric Event Study with Placebo Exposure



Notes: *The figure shows the placebo parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age LFP as dependent. The regression is used as a measure of initial exposure to the total age-adjusted death rate in 2017 due to the top 15 underlying causes of death. The death rate has been normalized to have a standard deviation equal to 1*

6 Mechanisms

The COVID-19 pandemic was associated with an unprecedented rise in opioid overdose deaths, likely due to multiple factors. Pandemic-induced isolation worsened mental health (Panchal et al., 2020, Adams-Prassl et al., 2022*a*). Additionally, disruptions in medical services may have reduced access to medications for opioid use disorder, as documented by Currie et al. (2021*a*) and Russell et al. (2021). This was also a period when opioid consumption was shifting to fentanyl, a potent opioid (Currie et al., 2021*b*). Increased free time, lower drug prices, and government income support during the pandemic may have further exacerbated the issue (Mulligan, 2022). While opioid-related deaths increased nationwide during COVID-19, the impact was most severe in states with higher pre-COVID opioid exposure, as shown in Figure 5. This differential effect may reflect established illegal opioid distribution channels, more lenient prescribing patterns, or a larger opioid-experienced population in highly affected states.

We posit that this higher increase in opioid use, proxied by opioid deaths in states with higher initial opioid exposure, led to a slower LFP recovery in the post-COVID period because opioid users have a lower participation rate and worse health. This can be seen in

Table 4. In 2019, before COVID-19, 15% of individuals aged 24-49 who did not use opioids were out of the labor force.[17] This rate was 20% for those using opioids by prescription and 26% for those with opioid use disorders. Focusing on individuals who report not participating due to a disability, the disparity is even sharper; individuals with opioid disorders are nearly three times as likely to report a disability. Opioid misuse also affects job attendance, with those diagnosed with opioid use disorder missing an average of 3.5 workdays monthly, compared to less than one day among nonusers. Self-reported health outcomes are also poorer for opioid users, as indicated in the lower panel of Table 4, with 27% reporting fair or poor health, compared to 8% among nonusers and 17% among prescription users. Finally, comparing data for 2019 and for the 2021-2022 period, we observe that the labor force participation and disability gaps between nonusers and those with opioid disorders widened in the post-COVID period, as shown in Figure 13.[18]

Table 4: Employment and Health by Opioid Use, Ages 24-49

Panel A: Employment	Out of LF	Disability	Total Skipped Days
Nonuser	15%	11%	0.9
Prescription User	20%	32%	2.0
Disorder	26%	31%	3.5
Panel B: Self Reported Health	Very Good	Good	Fair/Poor
Nonuser	65%	27%	8%
Prescription User	50%	33%	17%
Disorder	36%	37%	27%

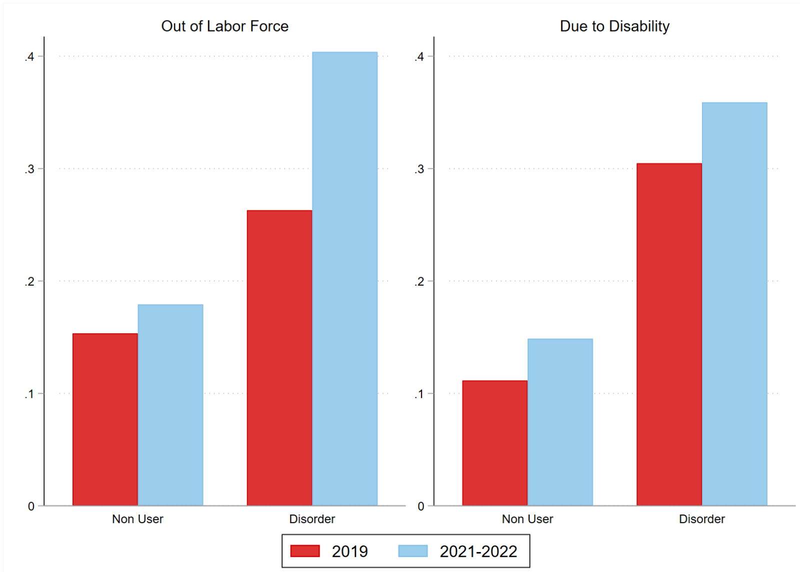
Notes: *The table shows employment-related variables in Panel A, and self-reported health status in Panel B, by type of opioid use in 2019. In Panel A, the first column shows the percentage of people not in the labor force, the second, the percentage not in the labor force due to disability, and the third, the average number of work days missed in the past 30 days due to sickness or other reasons. Self-reported health status is a categorical variable with 4 options: very good, good, fair, and poor. Fair and poor categories are aggregated. The type of opioid use is defined by the NSDUH, as explained in the text. Source: NSDUH.*

The importance of disability as a potential link between opioids and labor force participation is analyzed using again an event study that focuses on the post-COVID trajectory of the share of prime-age individuals who are not working due to disability. In CPS, individuals not participating in the labor force may select "retired," "unable to work" (for medical conditions that prevent work for six months or more), or "other." Those in the "other" category

[17] A different age group than 25-54 is chosen as the age variable is reported in brackets in NSDUH.

[18] Tables B2, and B3 shows employment status and health outcomes by opioid use in 2019 and 2021.

Figure 13: Changes in Labor Force Participation by Opioid Use, Ages 24-49



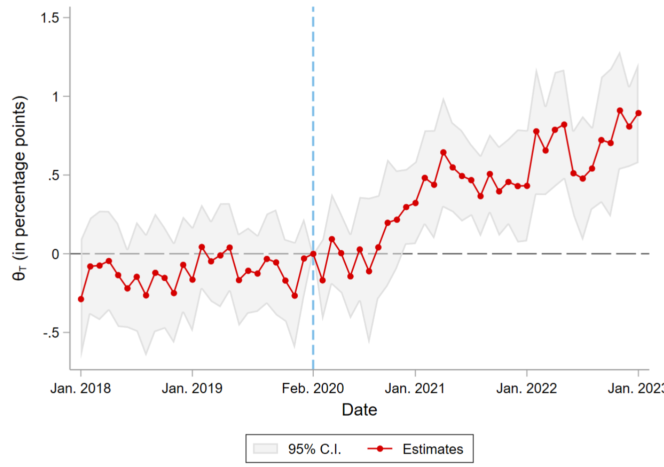
Notes: *The figure shows the share of individuals who are out of the labor force for any reason (left panel) and due to disability (right panel) by type of opioid use in 2019 and 2021-2022. The type of opioid use is defined by the NSDUH, as explained in the text. Source: NSDUH.*

may specify reasons, including disability or illness. The disability rate is calculated from those selecting "unable to work" or "disabled." In 2019, 31% of non-participants reported a disability. The share of prime-age individuals who are out of the labor force due to a disability has been declining since 2014, driven mainly by those without a college degree. The decline, however, stopped with the pandemic. There was a sharp initial increase for non-college, and the share of individuals who are out of the labor force due to a disability has been relatively constant afterward (Figure B6 in the Appendix).

A parametric event study using a continuous initial opioid exposure measure, i.e., equation (5), with the out-of-labor force due to disability rate as the dependent variable, is estimated. Figure 14 presents the estimated coefficients. The results show that pre-COVID states with varying opioid exposure levels displayed similar deviations from their trends. Post-COVID, however, states with higher preexisting opioid exposure deviated more positively from these trends. A standard deviation increase in opioid exposure is correlated with a 0.51 percentage point rise in post-COVID disability.[19]

[19] As was the case for the labor force participation, the results are driven by those non-college educated, as shown in Figure B7 in Appendix.

Figure 14: Parametric Event Study Estimates - Out of LF due to Disability



Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age out of labor force due to disability as the dependent variable. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

7 Conclusions

The COVID-19 pandemic significantly disrupted labor force participation across the United States, with prolonged declines among prime-age individuals, especially those without a college degree. This study reveals that states with higher pre-pandemic opioid exposure faced an even slower recovery in labor force participation, highlighting how public health crises can have compounding effects on labor markets. Our findings suggest that preexisting opioid misuse patterns magnified the labor market challenges posed by COVID-19, likely due to a higher rate of substance abuse exacerbated by pandemic-related factors. The interaction between the COVID-19 and opioid crisis suggests that the labor force impacts of future economic shocks may be similarly moderated by underlying public health challenges.

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Appendix

A Labor Force Participation Trends

To obtain the difference between the actual and predicted prime-age labor force participation shown in Figure 4, we do the following steps. First, we estimate for each state a trend in prime-age LFP for the period January 2010 to February 2020. Second, we use the estimated coefficients to forecast the prime-age LFP for the period March 2020 to December 2022. Lastly, we determine the difference between the observed values and the trend.

To predict the trend we first HP filter the time series for each state for the period January 2010 - February 2020 (default smoothing parameter, 1600 $\times$ 34). Then, we run on the obtained trend the following state-level regression:

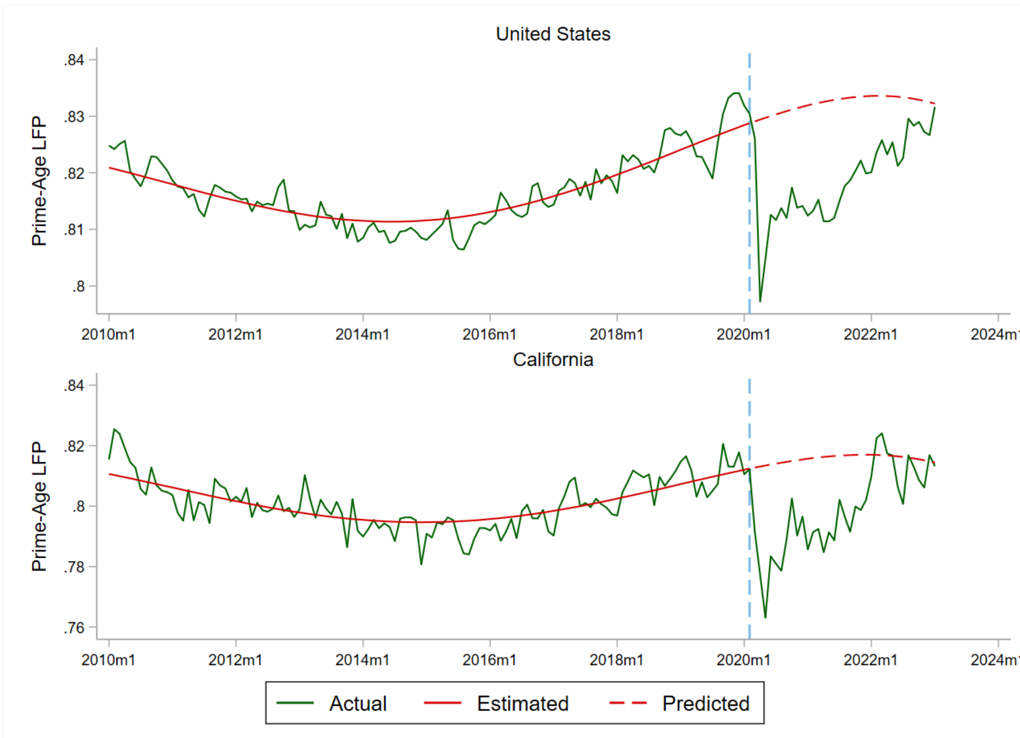
$$LFP_{i,t} = \alpha + \beta_1 t + \beta_2 (t-\tau)^2 + \beta_3 (t-\tau)^3 + \beta_4 (t-\tau)^4 + \gamma_t,$$

where $LFP_{i,t}$ is prime-age Labor Force Participation for state i at date t (monthly). Finally, τ represents the end of the estimation period (February 2020) and γ_t are date fixed effects.

Using the estimated coefficient, we predict for each state the prime-age LFP for the period March 2020 to December 2022, $\widehat{LFP_{i,t}}$. Figure A1 shows the actual (green line), the estimated (solid red line), and the predicted (dashed red line) prime-age LFP for the US and California, as examples.

Then we obtain the difference as $Diff_{i,t} = LFP_{i,t} - \widehat{LFP_{i,t}}$. Negative values imply a lower labor force participation than what has been predicted. To obtain the measure presented on the vertical axis of Figure 4, we average the difference for the period of December 2022.

Figure A1: Estimated and Predicted LFP for the US and California



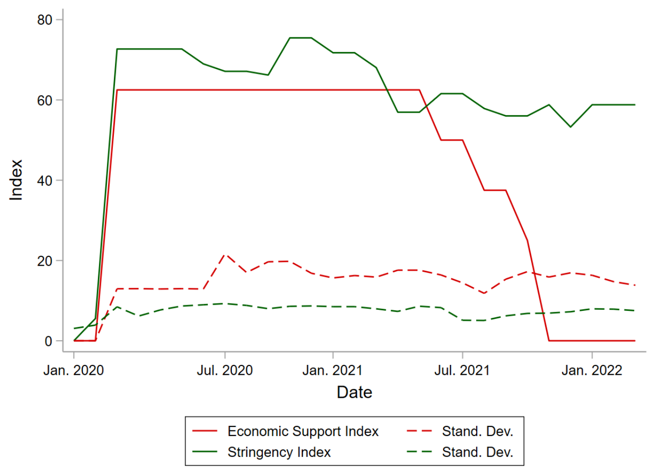
Notes: *The figure shows the actual Prime-Age LFP, the estimated trend (solid red line), and the predicted trend for the post-COVID period (dashed red line). The figure shows the results for the entire United States and the state of California.*

B Heterogeneity and Robustness

B.1 Stringency and Economic Support Index

Figure B1 shows the Stringency and Economic Support index developed by the Oxford Tracker.

Figure B1: Stringency and Economic Support Index

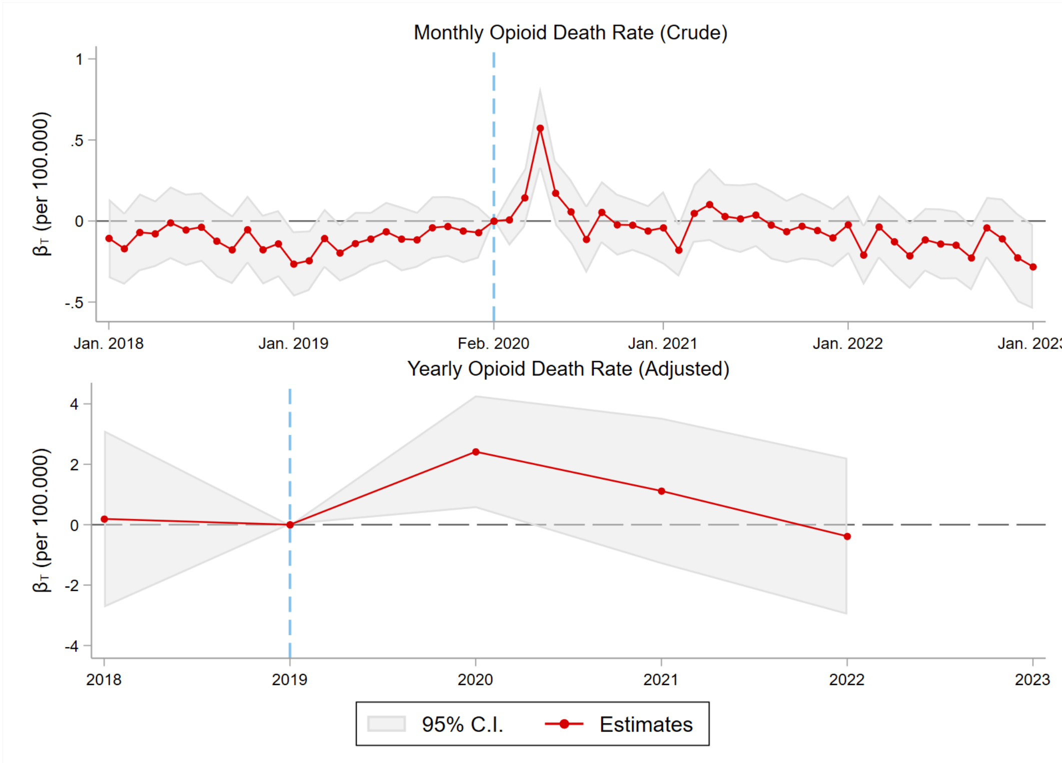


Notes: *The figure shows the summary policy indexes for Stringency and Economic Support reported by the Oxford Tracker for the entire U.S. and the standard deviation of these policy indexes across U.S. states. Source: Oxford Tracker.*

B.2 Non-Parametric Opioids Deaths

Figure B2 shows the results obtained by estimating equation (1) using opioid death rate as the dependent variable. The top panel uses the monthly opioid death rate, and the bottom panel uses the yearly age-adjusted opioid death rate. Exposure is measured as a binary variable.

Figure B2: Non-Parametric Binary Event Study - Opioid Deaths

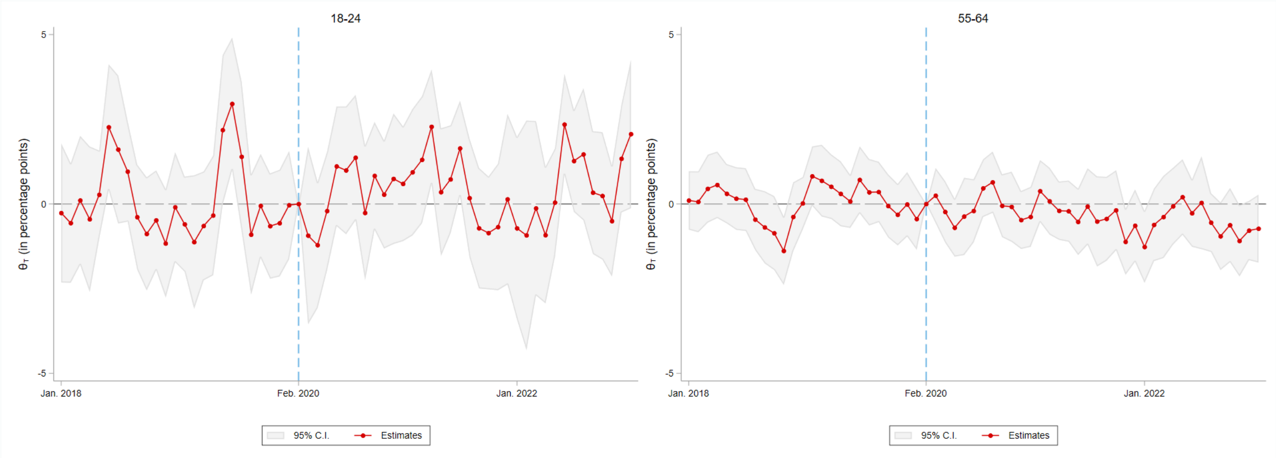


Notes: *The figure shows the non-parametric event-study coefficients β_T and the 95% confidence interval when using opioid-related overdose deaths as the dependent variable. The top panel uses the monthly crude rate, while the bottom uses the yearly age-adjusted rate. The initial opioid exposure measure has been dichotomized: states with the age-adjusted opioid death rate in 2017 above the median are given a value of 1, the others a value of 0.*

B.3 Alternative Age Groups

The main analysis focuses on the labor force participation of prime-age workers, i.e., ages between 25 and 54. Here, the results from the event-study analysis in equation (5) are presented for age groups 18-24 and 55-64.

Figure B3: Parametric Event Study Estimates - Labor Force Across Samples

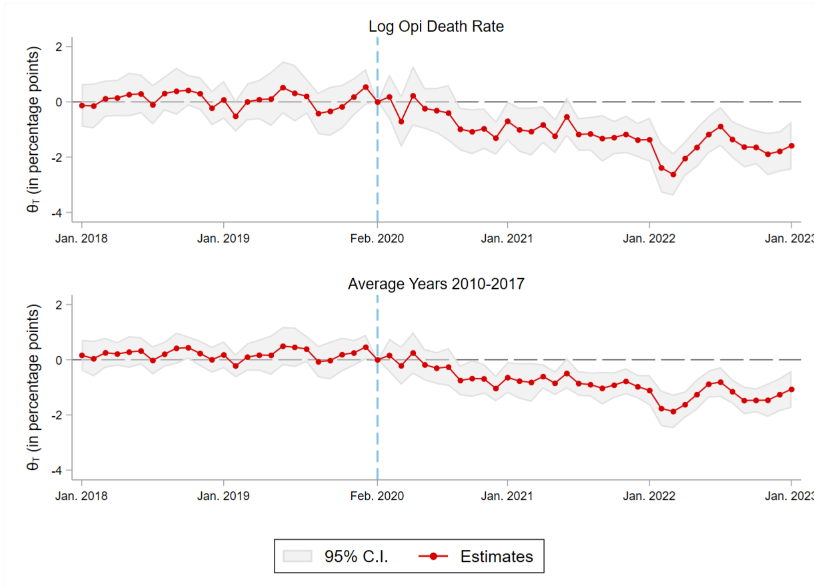


Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using LFP as the dependent variable within a restricted age group. The left panel restricts the sample to individuals aged 18-24, and the right panel to 55-64. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*

B.4 Alternative Exposure Measures

The results with two alternative measures of opioid exposure are presented: the logarithm of the age-adjusted opioid death rate in 2017 and or the average age-adjusted opioid death rate between 2010 and 2017.

Figure B4: Parametric Event Study Estimates - Measures of Opioid Death Rate



Notes: *The figure shows the parametric event-study coefficients* θ_T *and the 95% confidence interval when using prime-age LFP as dependent variable. In the top panel, the log of the opioid-related overdose age-adjusted death rate is used as initial exposure. In the bottom panel, the initial opioid exposure is given by the average opioid-related overdose age-adjusted death rate between 2010 and 2017, normalized to have a standard deviation equal to 1.*

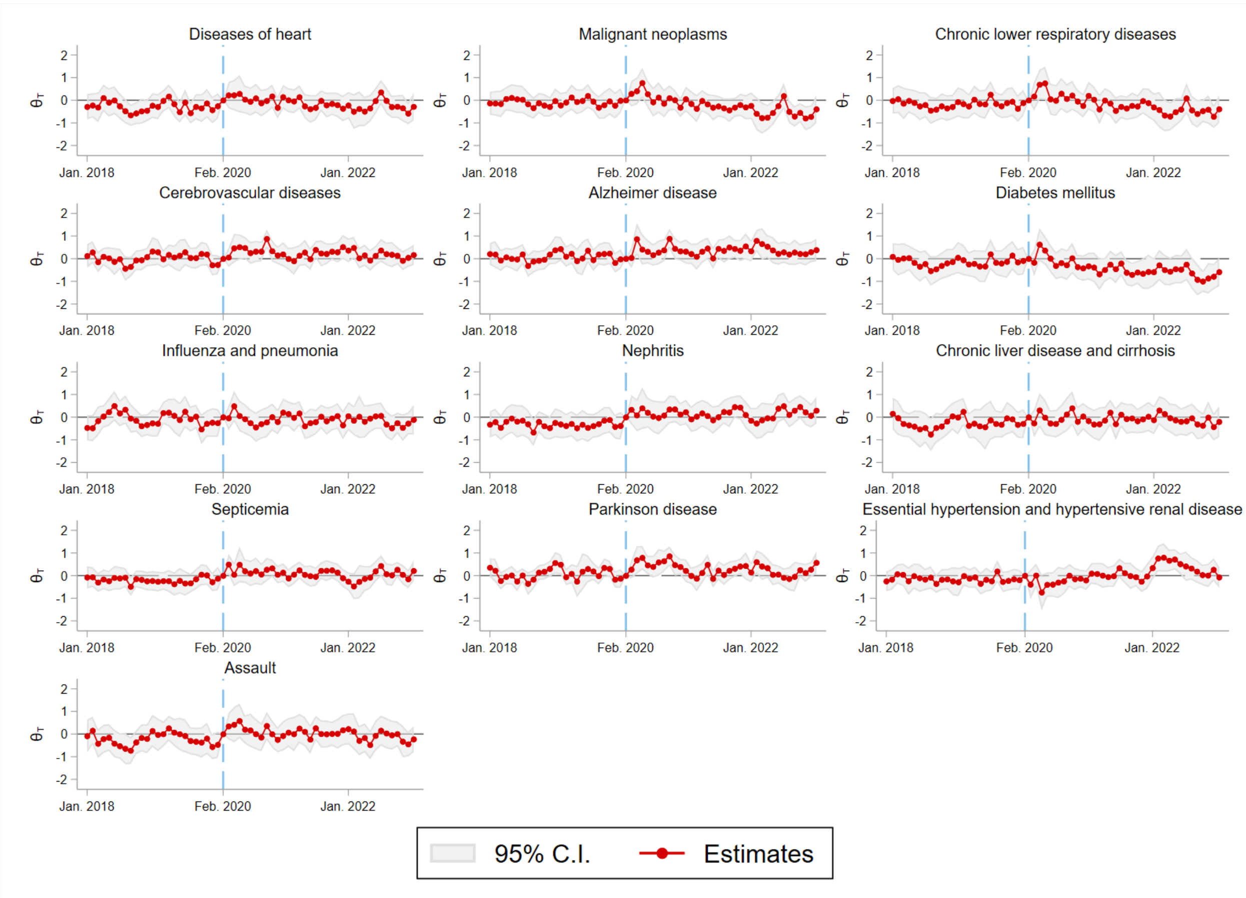
B.5 Placebo Analyis

Table B1: Average Age-Adjusted Death Rate by Cause in 2017

	Death Rate
1. Diseases of heart (I00-I09,I11,I13,I20-I51)	165.99
2. Malignant neoplasms (C00-C97)	155.00
3. Accidents (unintentional injuries) (V01-X59,Y85-Y86)	54.01
4. Chronic lower respiratory diseases (J40-J47)	43.78
5. Cerebrovascular diseases (I60-I69)	37.43
6. Alzheimer disease (G30)	32.07
7. Diabetes mellitus (E10-E14)	21.99
8. Intentional self-harm (suicide) (*U03,X60-X84,Y87.0)	16.50
9. Influenza and pneumonia (J09-J18)	14.90
10. Nephritis (N00-N07,N17-N19,N25-N27)	12.79
11. Chronic liver disease and cirrhosis (K70,K73-K74)	11.30
12. Septicemia (A40-A41)	10.27
13. Parkinson disease (G20-G21)	8.62
14. Essential hypertension and hypertensive renal disease (I10,I12,I15)	8.44
15. Assault (homicide) (*U01-*U02,X85-Y09,Y87.1)	6.69

Notes: *The table shows the age-adjusted death rate in 2017 by the leading causes of death in the US. Source: CDC - Underlying Cause of Death.*

Figure B5: Parametric Event Study Estimates - Placebo



Notes: *The figure shows the placebo parametric event-study coefficients* θ_T *and the 95% confidence interval when using prime-age LFP as the dependent variable. As a measure of initial exposure, the age-adjusted death rate in 2017 due to causes indicated in the title of each panel is used. All death rates have been normalized to have a standard deviation equal to 1.*

C Mechanisms

Table B2: Employment Status by Opioid Use, Ages 24-49

Panel A		**2019**			**2021**	
	Emp.	Unemp.	Out of LF	Emp.	Unemp.	Out of LF
Non User	80.6%	4.1%	15.3%	75.3%	5.9%	18.8%
Disorder	61.1%	12.6%	26.3%	39.5%	21.0%	39.6%
Population	79.0%	4.4%	16.6%	73.6%	6.3%	20.1%
Panel B		**2019**			**2021**	
	Very Good	Good	Fair/Poor	Very Good	Good	Fair/Poor
Non User	65.1%	27.2%	7.7%	60.9%	30.0%	9.1%
Disorder	36.0%	36.6%	27.4%	30.3%	39.0%	30.7%
Population	60.5%	28.9%	10.6%	57.1%	31.0%	11.9%

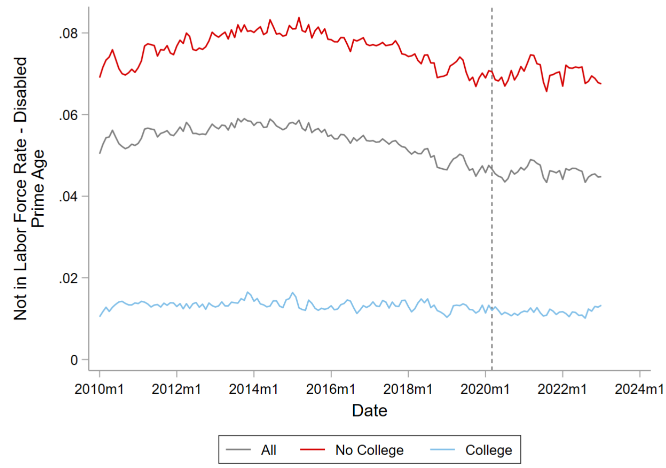
Notes: *The table shows the employment status in Panel A, and self-reported health status in Panel B, by type of opioid use in 2019 and 2021. Self-reported health status is a categorical variable with 4 options: very good, good, fair, and good. Fair and poor categories are aggregated. The type of opioid use is defined by the NSDUH. See the text for further details. Non-user do not use any opioids. For each opioid user type and year, the row sums up to 100. Source: NSDUH.*

Table B3: Opioids And Work Disability, Ages 24-49

	NLF - Disability		Work Days Sick		Work Days Skip	
	2019	**2021**	**2019**	**2021**	**2019**	**2021**
Non User	11.1%	14.8%	0.63	0.77	0.27	0.33
Disorder	30.5%	42.8%	1.75	2.16	1.92	1.19
Population	18.2%	19.5%	0.88	0.98	0.34	0.37

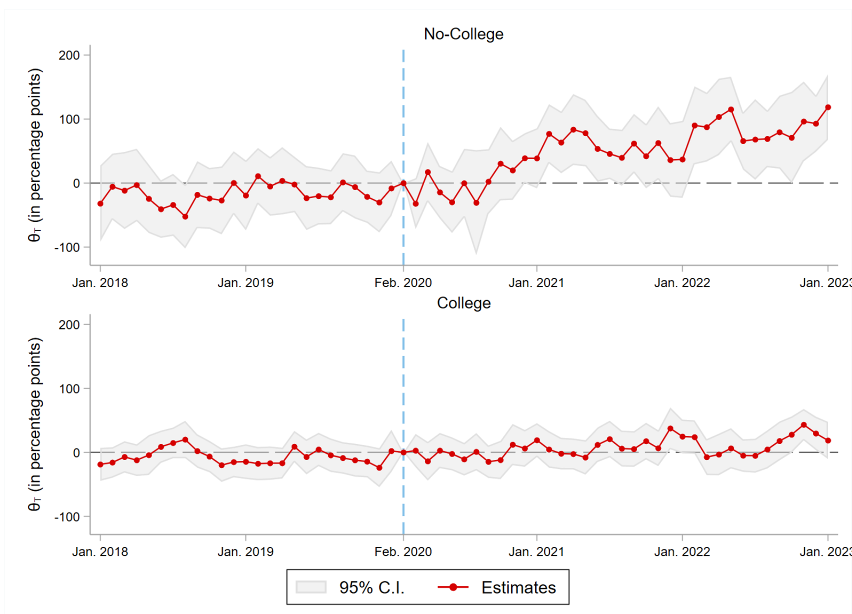
Notes: *The table shows several measures of absence from work by type opioid use in 2019 and 2021. The first two columns show the percentage of people out of the labor force due to a disability. The second two columns show the average number of work days missed in the past 30 days due to sickness. The last two columns show the average number of work days missed for other reasons. The type of opioid use is defined by the NSDUH. See the text for further details. Source: NSDUH*

Figure B6: Not in Labor Force for Disability Rate (NLDR)



Notes: *The figure shows the share of individuals not in the labor force due to disability reasons. This measure includes individuals who report being unable to work and not worked due to disability. Source: CPS*

Figure B7: Parametric Event Study Estimates - Out of LF due to Disability



Notes: *The figure shows the parametric event-study coefficients θ_T and the 95% confidence interval when using prime-age out of labor force due to disability among either non-college-educated (top panel) or college-educated (bottom panel) as the dependent variable. The initial opioid exposure measure has been normalized to have a standard deviation equal to 1.*