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Exposure to Deaths of Despair and U.S. Presidential Election Outcomes

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Abstract

This paper evaluates how a community's exposure to deaths from suicide, drug overdose, alcohol poisoning, and liver disease (commonly referred to as "deaths of despair") affects outcomes in U.S. Presidential elections. Using county-level panel data and two-way fixed effects regressions, I find that a standard deviation increase in the deaths of despair mortality rate led to an increase in the Republican (GOP) vote share of 2.36 percentage points. Prior studies have linked voting outcomes to economic trends such as income inequality, import competition, and financial crises, but controlling for these and other economic and demographic factors does not substantially change my estimates. Estimates are larger and only statistically significant in later years (2016-2020), compared to earlier years (2004-2012). There were stronger effects in counties that the GOP candidate won in the previous election, and in counties with higher White population percentages. The results are maintained when using an instrumental variables approach to mitigate endogeneity concerns.

JEL Classification: I18, I1, D72, I38

Keywords: deaths of despair, elections, opioid epidemic, political polarization

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Over the last 20 years, mortality from deaths of despair has been increasing in the United States. Case and Deaton (2015) coined the name 'deaths of despair' and found that increases of this mortality – which comprises of suicides, drug overdoses, alcohol poisoning, and liver disease and cirrhosis – were large enough to offset a previously increasing trend in life expectancy for large portions of the U.S. population. While all of these types of deaths have been rising over this period, there is a notable increase in drug overdoses following the mainstream introduction of Fentanyl in 2014, as seen in Figure 2. Nearly 50,000 deaths in 2019 involved opioids, over six times the rate seen in 1999 (CDC, 2022). With an average of 130 deaths from opioid related drug overdose occurring per day in 2018 and 2019 (HRSA, 2020), many individuals, families, and communities have felt the devastating effects. While the beginning of this epidemic was concentrated in middle-income, non-Hispanic White areas (Case and Deaton, 2015), deaths of despair mortality rates have begun to show a significant increase in non-White areas in more recent years, particularly among Black and Hispanic communities (Drake et al., 2020). As of 2017, the estimated cost of healthcare expenditure in the U.S. due to the opioid epidemic alone was USD 215.7 billion, and an additional USD 8 billion of incurred costs through the criminal justice system (Neville and Foley, 2020). Employers end up covering much of the additional costs including medical expenses, lost productivity and loss of life, which have been estimated to have cost them USD 18 billion (Fuhrmann-Berger, 2018).

Higher rates of drug and alcohol misuse and overdose have affected communities in many ways. These concerning trends impact many dimensions of individual and household welfare, affecting the mental health of both substance users and other household members, increasing their risk of developing substance or opioid use disorder, leading to family dissolution and neglect, and increasing the burden on other caretakers (Winstanley and Stover, 2019; Voss et al., 2023). Local healthcare systems are affected by increased worker burnout (Pike et al., 2019), complications for other conditions with higher rates of comorbidities of SUD (Khayata et al., 2022; Cohen-Mekelburg et al., 2018), and overall increased costs (Neville and Foley, 2020). Areas with greater opioid use see more auto loan defaults, which leads to higher consumer finance rates for all borrowers (Jansen, 2022).

Given the salient effects of the opioid epidemic and related issues, community members in affected areas may seek ways to address the concerning trends. Elections provide an environment where individuals can select candidates and parties most closely aligned with their views on the best approach to the crisis. As drug and alcohol addiction, as well as mental health problems, are still taboo subjects in much of the nation, government responses can greatly vary. While some states (including Connecticut, Massachusetts, and

Indiana) have focused on educating prescribers and patients on the risk of addiction and available resources for treatment, others (including Louisiana, Kansas, and Maryland) have chosen to further criminalize drug possession and usage (Parker et al., 2018).

This paper evaluates citizens' responses to deaths of despair in their communities through partisan voting outcomes. Specifically, I estimate both two-way fixed effects regressions and instrumental variables regressions using county-level data to study how this mortality rate shifts voting behavior in U.S. presidential elections from 2004-2020. I examine how the impacts vary across time, partisan environments, and demographics.

The results show that exposure to deaths of despair is a strong predictor of election outcomes. In the overall sample, a standard deviation increase in this mortality rate was associated with an increase in the GOP vote share of 2.36 percentage points. This could suggest that the Republican policy approach to these deaths is seen as more effective than that of the Democrats'. For example, Republican politicians tend to focus statements about approaches to the opioid epidemic on illicit drug trade, while Democrats point to holding pharmaceutical companies accountable (Stokes et al., 2021).

The impact was stronger in later election years, after the introduction of Fentanyl, compared to earlier years, with 2016-2020 seeing an effect of 2.78 percentage points, compared to only 0.289 for 2004-2012. Counties that had voted for the GOP candidate in the previous election saw a 2.72 percentage point increase for the GOP, compared to only 1.46 percentage point change in counties that voted for the Democratic candidate. Finally, results show that this impact was stronger in Whiter counties, where the effect for a county with a one standard deviation higher White population share was 1.12 percentage points larger. The heterogeneous impacts across partisan and demographic groups indicate how existing community level beliefs and preferences alter the responses to these deaths.

As the two-way fixed effects regressions may face endogeneity concerns, I also implement an instrumental variables strategy. First, an interaction instrument composed of baseline deaths of despair mortality interacted with annual state level Fentanyl seizures is constructed. This instrument is based on the idea that increases in Fentanyl supply and use should yield larger increases in deaths of despair in areas that may have been more susceptible to this type of mortality at baseline. The remaining two instruments are based on existing literature that has identified areas that were more heavily targeted by Purdue Pharma for the introduction of Oxycontin, specifically those with higher cancer rates and more lenient prescription laws, and therefore experienced larger increases in deaths of despair mortality (Arteaga and Barone, 2023a; Alpert et al., 2019).

Across all four specifications, the coefficients on the instrumented deaths of despair mortality remain positive and significant.

This paper contributes to the literature on deaths of despair and the opioid epidemic in the United States. A large literature focuses on how economic shocks affect deaths of despair, including poor economic conditions (Case and Deaton, 2017) and economic uncertainty (Knapp et al., 2019). Less is known about how health and healthcare-related issues may affect these outcomes, but some recent work provides evidence that these increases may be in part due to targeted marketing of OxyContin from Purdue Pharma based on lenient laws around prescriptions (Alpert et al., 2019) and high rates of cancer mortality (Arteaga and Barone, 2023a). Additionally, increased legal imports exploited for smuggling led to an external supply increase (Hansen et al., 2020). Researchers have also investigated whether trade competition with China increased deaths of despair, and evidence is somewhat mixed (Pierce and Schott, 2020; Ruhm, 2019)[1].

While most of these studies aim to identify the reasons behind recent increases in opioid and alcohol related deaths, this paper begins to look at the effects of living in a highly impacted community. The economic literature evaluating the impacts of high deaths of despair mortality rates in a community is sparse, particularly for political outcomes. In research conducted contemporaneously with this paper, Arteaga and Barone (2023b) uses the relationship between 1990s cancer rates and later opioid outcomes (first documented in Arteaga and Barone (2023a)) as a natural experiment to estimate the effects of exposure to the opioid epidemic on House of Representative election outcomes. They use the 1996 cancer mortality rate as a proxy measure of later opioid prescriptions, addiction, and deaths. In contrast, my paper focuses on all deaths of despair, including opioid deaths, and focuses on presidential elections. In one of several instrumental variables approaches conducted to alleviate concerns about endogeneity, I use the findings of Arteaga and Barone (2023a) to construct an instrument for deaths of despair mortality.

Additionally, this paper contributes to the wide body of literature studying how various health, economic, and social issues impact elections. Historically, times of economic and social hardship tend to aid in the rise of right-wing populist movements (Hutchings and Valentino, 2004; Inglehart and Norris, 2016; Algan et al., 2018). Che et al. (2020) and Autor et al. (2020) found that exposure to increased trade with China led to an overall rightward shift in election outcomes. For the 2020 election, community deaths due to the COVID-19

[1]Pierce and Schott (2020) found that the trade shock of China's entrance into the WTO positively and significantly impacted deaths of despair mortality in areas with high trade competition. On the other hand, Ruhm (2019) found that this impact was very small and possibly not significantly different from zero. Both of these papers focused on 10-15 years after the shock, at which point the economy is estimated to have adjusted to the shock (Bloom et al., 2019).

pandemic were positively correlated with votes for President Trump, but this may have been more so related to political beliefs that led to higher mortality than the deaths leading to increased support (Lake and Nie, 2022). Interestingly, the researchers found that swing states with large expansions in health insurance uptake were less likely to vote for Trump, potentially due to his policy platform of repealing the ACA (Lake and Nie, 2022).

1 Data

1.1 Data Sources

1.1.1 Mortality Data

The mortality data is from the CDC Wonder Database Mortality Files. The causes of death used to measure deaths of despair, following Case and Deaton (2015), include suicide, drug overdose, alcohol poisoning, and liver disease and cirrhosis, with corresponding ICD10 codes: K70, K73-74, X60-84, Y87.0, X40-45, Y10-15, Y45, Y47, Y49. Values less than ten are suppressed for privacy. Counties with mortality below that level are not included in the main results. To limit the number of counties that are dropped, three years of mortality rates are combined and averaged, allowing for over 85% of counties to be used in this analysis. The mortality rate attributed to each election in year t is from years $t-2$ to t (i.e. 2018-2020 for 2020). The CDC's cause-of-death classification system changed in 1999 to the current measurements. Thus, the first election year with three years of the new data structure available is 2004.

The deaths of despair mortality rate per 10,000 people for county c in year t is calculated as follows:

$$Deaths\ of\ Despair_{ct} = \frac{Total\ Deaths\ of\ Despair_{ct}}{Total\ Population_{ct}} * 10,000. \tag{1}$$

The CDC provides a crude mortality rate in their data release; however, they deem 1,559 observations (representing 401 counties) in the requested sample unreliable measures. To avoid losing observations, mortality rates are calculated manually as shown above. Using the variable constructed by the CDC or the manually calculated measure does not greatly impact the value or statistical significance of any estimates in this paper.

1.1.2 Election Data

The county level election data for U.S. Presidential elections from 2004 to 2020 are from the MIT Election Data + Science Lab. The dependent variable used is the two party GOP vote share for each election, calculated in each county as the votes for the GOP candidate divided by the total votes cast for either the Republican or Democratic candidate in the election.

1.1.3 Instrumental Variables Data

As described in the next section, I will use an instrumental variables strategy to identify the causal effect of deaths of despair. First, I generate an interaction instrument composed of baseline mortality and state level Fentanyl seizures to capture variation in deaths of despair mortality due to increased Fentanyl supply (which should have larger effects on areas with high baseline mortality rates from deaths of despair). The state level Fentanyl seizures data are from the National Forensic Laboratory Information System (NFLIS), a part of the U.S. Department of Justice Drug Enforcement Administration Diversion Control Division. The NFLIS Public Data Query System provides annual state level data on forensic analyses of seized drugs. The category used for this report are for those classified as "Fentanyl and Fentanyl-related." I first use only drugs categorized as pure Fentanyl, and then also aggregate pure and any Fentanyl-related drug. (NFLIS, 2023)

The next two instruments are based on prior studies which focus on identifying the determinants of increased deaths of despair. Specifically, I use the finding that Purdue Pharma heavily targeted areas with higher cancer rates and more lenient prescription laws for the introduction of Oxycontin (Arteaga and Barone, 2023a; Alpert et al., 2019). CDC Wonder Database Mortality Files are used to calculate the state level cancer mortality rates from 1994-1996, used in these IV regressions. Cancer mortality are marked as "Neoplasms" in the data base with corresponding ICD-9 codes: 140-239.

1.1.4 Import Competition Data

Import competition is an important control in the regressions discussed below, given previous literature pointing to its impact on election outcomes (Autor et al., 2020). Annual national import value data separated by 4-digit NAICS industry codes is from the United Nations Comtrade Database. A pre-sample 4-digit NAICS industry employment proportion for each county is taken from the U.S. Census County Business Partners Database. The selected pre-sample year is 2000, as the largest import shock from this time was the Permanent

Normal Trade Relations with China, beginning in 2001 (Pierce and Schott, 2016). The advantages of using the pre-shock employment is that it eliminates potential endogeneity of imports impacting the prominent industries in an area and that it can illuminate where labor may have previously been, rather than where workers now are.

In a similar style to Autor et al. (2013), the import competition exposure variable is the value of import exposure to each worker in a region, apportioned to each county by their national share of an industry:

$$ImportCompetition_{ct} = \sum_{n} \frac{empl_{cn2000}}{empl_{n2000}} * imports_{nt} \quad (2)$$

Import competition exposure in county c in year t is equal to the county's pre-sample national share of employment in industry n multiplied by national imports value of industry n in year t, summed across all 4-digit NAICS industries. In general terms, the import competition exposure variable is the value of imports in each industry n assigned to counties by the pre-sample proportion of that industry's workers in each county, and then summed for all industries within each county. Import values are measured in 1,000's of U.S. dollars.[2] Following Autor et al. (2013), import competition is instrumented using the above calculation with lagged values of other developed nation's import value to assess U.S. import competition based on Chinese expansion and not other endogenous reasons. Following the mortality measure, this variable is averaged from years $t-2$ to t for each election year t.

1.1.5 Other Data

Additional variables are included to control for confounding factors that may vary across time and geography, and would thus not be accounted for in the use of fixed effects. County-level labor force participation rates from the USDA County Level Databases and county-level GDP per capita from the U.S. Bureau of Economic Analysis (BEA) are implemented as economic controls. As counties drastically vary in population and demographics, the data to control for county population, gender composition, age groups and race proportions are from the U.S. Census Bureau's County Population by Characteristics data sets. To retain consistency, all controls are lagged and averaged from $t-2$ to t for each election year t.

[2]This measure deviates slightly from Autor et al. (2013). Rather than measuring this value per worker by dividing by total workers in each year t, the value used in the regression is per capita by dividing by year t's county population. Labor force participation rates are found to be more important indicators than unemployment; thus, the per capita measure is a better indicator for this analysis than only those in the labor force.

1.2 Summary Statistics

Summary statistics are presented in Table 1, where each variable, excluding GOP vote share, are averaged for the three years before the election ($t-2$ through t). The variables are unweighted in columns (1)-(5) and weighted by the 2000 county population in columns (6)-(7). The means for deaths of despair, GOP vote share, import competition, and White percent of the population are higher when unweighted, showing that less populated counties tend to have higher values for these variables.

Figure 2 shows the mortality rates of deaths of despair in the 2004 and 2020 election periods, respectively. The maps show that earlier impacted areas appear to have higher mortality rates in 2020, and that the concerning trend also expanded into new areas. Figure 3 shows the change in the GOP vote share over this time period. While the general liberal and conservative areas remain somewhat similar, there is a striking decrease in moderate areas (purple and lighter shaded regions).

2 Empirical Strategy

2.1 Two-Way Fixed Effects Regression

First, I estimate a two-way fixed effects regression at the election year and county level, regressing the GOP vote share onto the deaths of despair mortality rate and controlling for economic and demographic county characteristics. The following specification is used:

$$GOPvs_{ct} = \beta_0 + \beta_1 DoD_{c(t-2:t)} + X'_{c(t-2:t)}\beta_2 + \gamma_c + \lambda_t + \epsilon_{ct} \tag{3}$$

Where $GOPvs_{ct}$ represents the GOP vote share in county c in year t. $DoD_{c(t-2:t)}$ is the average deaths of despair mortality per 10,000 in county c in years $t-2$ through t. The economic and demographic controls in county c in years $t-2$ to year t are depicted as $X'_{c(t-2:t)}$, which include the Autor et al. (2013) import competition per capita measure, GDP per capita, labor force participation rate, percent female, percent White, and percents aged 18-65 and over 65. Finally, γ_c and λ_t are county and year fixed effects, respectively.

The model is estimated using data from U.S. Presidential elections from 2004 to 2020. Each observation is weighted by the county population. Standard errors are clustered at the county level.

2.2 Instrumental Variable Regressions

As the two-way fixed effects strategy will not control for any potential unobservable, time-varying, and county-specific factors that could be correlated with both the outcome and independent variable, I use an instrumental variable approach to mitigate concerns of endogeneity.

Counties which had higher prevalence of deaths of despair prior to the study period may have been predisposed to larger increases in response to supply shocks. Similar to the shift-share labor literature (Bartik, 1991), I create a variable using the pre-period (2001) mortality rate in each county and interact it with the state-level reported Fentanyl seizures. This exploits variation in deaths of despair in a given year driven by the base level susceptibility and increases in supply. The first version of this instrument uses only reports of pure Fentanyl, denoted as $DoD_{c,2001} * Fent_{st}$, where $DoD_{c,2001}$ represents Death of Despair mortality rate in 2001 for county c and $Fent_{st}$ is the amount of pure-Fentanyl seizures in state s in year t. The second uses any drug categorized as Fentanyl-related, represented by $DoD_{c,2001} * FentAll_{st}$, with $FentAll_{st}$ is the amount of any Fentanyl related seizures in state s in year t . Table 2 reports the first stage regressions for these instruments (where the outcome variable is the deaths of despair mortality rates), with columns (1)-(2) using this interaction term. Given the positive and significant coefficients and high F statistics, these instruments are strong predictors for deaths of despair. Both measures of this estimate are assumed to follow the Assumption 1 (relevancy) and Assumption 2 (strict exogeneity) for shift-share instrumental variables as described in Goldsmith-Pinkham et al. (2020).

Using documents released during litigation against Purdue Pharma, prior studies found that the pharmaceutical company's strategy focused on areas where health providers would be more likely to prescribe OxyContin to their patients, which was linked later to higher prescription rates and opioid related deaths (Arteaga and Barone, 2023a; Alpert et al., 2019). Arteaga and Barone (2023a) evaluated the transition of OxyContin from its use for pain in cancer patients to general use. The unsealed documents showed that Purdue felt that areas with higher cancer rates had already been using their product for pain management and thus, would be more likely to prescribe it to other patients as well. Arteaga and Barone (2023a) found this to be true, and further analysis showed the effects led to more opioid deaths and decreased quality of life. I use this connection by creating a variable composed of the state-level cancer mortality rate during this transition (1994-1996) interacted with year fixed effects. This is represented as

$CancerMortality_{s(1994:1996)} * \sum_t 1(Year = t)$, where $CancerMortality_{s(1994:1996)}$ is the state s cancer mortality rate in 1994-1994.

A further finding of this unsealed litigation, and a growing topic in the economics literature, is the importance of triplicate prescription laws. These laws required doctors to file triplicate records of any opioids they prescribed, a rather tedious task which involved more oversight. States with these laws were less targeted by Purdue Pharma and later had lower prescription rates, lower rates of opioid addiction, and fewer opioid deaths (Alpert et al., 2019). The states with these laws at the time of OxyContin's transition to general use were: California, Idaho, Illinois, New York, and Texas. I create an instrumental variable based on this by interacting an indicator equal to one if a state did not have these triplicate prescription laws in the mid-1990s and year fixed effects. This is denoted as $NonTriplicate_{s(1994:1996)} * \sum_t 1(Year = t)$, where $NonTriplicate_{s(1994:1996)}$ is a binary variable equal to one in states that did not have such triplicate prescription laws. Columns (3) and (4) of Table 2 report the first stage results for these two instruments. Both variables have positive and significant impacts on the mortality rate, with increasing magnitude throughout the period. The F statistics for both estimations are higher than the required threshold, indicating strong instruments.

Based on these prior findings, four instrumental variable estimations are implemented. The first stage of the IV models predict deaths of despair based on the instrumental variables and the other economic and demographic controls, as shown below:

$$\widetilde{DoD}_{c(t-2:t)} = \alpha_0 + \alpha_1 IV_{ct} + X'_{c(t-2:t)}\alpha_2 + \gamma_c + \lambda_t + \epsilon_{ct} \tag{4}$$

$\widetilde{DoD}_{c(t-2:t)}$ represents the expected deaths of despair mortality per 10,000 in county c in years $t-2$ through t. IV_{ct} represents one of four instrumental variables described above. The first two instruments are interaction terms using county c's pre-period 2001 deaths of despair mortality rate interacted with the annual state-level Fentanyl seizure measure. The first variable uses only pure Fentanyl reports in state s and year t ($DoD_{c,2001} * Fent_{st}$), while the second uses both pure and all Fentanyl-related drugs in state s and year t ($DoD_{c,2001} * AllFent_{st}$). The third and fourth instruments are based on proxy measures for Purdue Pharma's targeted marketing of OxyContin from 1994-1996. The third IV is the state s 1994-1996 cancer mortality rate interacted with a dummy for each year ($CancerMortality_{s(1994:1996)} * \sum_t 1(Year = t)$). The final instrumental variable uses an indicator of the non-triplicate prescription status for state

s in the mid-1990s, equal to one if the state did not have such policy, multiplied by year fixed effects ($NonTriplicate_{s(1994:1996)} * \sum_t 1(Year = t)$).

The instrumented deaths of despair, $\widetilde{DoD}_{c(t-2:t)}$, is used as the main explanatory variable in equation 3. The coefficient β_1 will now report the relationship between the mortality rate and the election outcome based only on the variation due to each instrumental variable used.

3 Results

3.1 Two-way Fixed Effects Results

Table 3 presents the results of the regression as described in Equation 3. Column (1) uses the baseline model exactly as described, while column (2) separately estimates the mortality coefficient in early (2004-2012) and later (2016-2020) years, which also corresponds to before and after the large rise of Fentanyl in 2014. Columns (3)-(4) include interactions between the mortality measure and county characteristics, where column (3) interacts the mortality rate with an indicator equal to one for counties the GOP candidate won the previous presidential election and column (4) uses the percent of the population that is White. All regressions include fixed effects for the year and county and are weighted by pre-period county population in 2000. All independent variables are averaged for the three years prior to the election and standardized.

Focusing on column (1), the coefficient for deaths of despair shows that a standard deviation increase in the mortality rate is correlated with a 2.36 percentage point higher vote share for the GOP candidate. This is approximately 1.22 times the impact of a standard deviation increase in exposure to manufacturing automation (Frey et al., 2018), and 1.13 times the impact for a standard deviation increase in COVID-19 cases in the 2020 election (Baccini et al., 2021) .

Similar to Autor et al. (2020), I find the impact of import competition on GOP vote share is positive and significant. Additional economic control variables show that higher labor force participation and GDP per capita are correlated with lower support for Republican candidates. The demographic control variables show increased support for Republicans in Whiter and more male counties.

As deaths of despair are increasing throughout this period, we might expect larger effects when mortality rates were highest. One of the main drivers of the increases in deaths of despair mortality was increased overdose from synthetic opioids, particularly Fentanyl, beginning around 2014 (CDC, 2022). To estimate the impact before and after the introduction of Fentanyl, the sample is split into "earlier" years (2004, 2008, and 2012) and "later" years (2016 and 2020). These results are shown in column (2). While the effect is positive in earlier years, it is not significantly different from zero and a much smaller magnitude than in the overall sample and in later years. The coefficient for later years shows that the GOP vote share is expected to be 2.78 percentage points higher with a standard deviation increase in the mortality rate. These results are consistent with the fact that the introduction of Fentanyl increased this mortality rate and led to the opioid epidemic being more widely discussed across the nation, and more prevalent in health policies and elections (Centers for Disease Control and Prevention, 2022).

The makeup of each county can provide additional insight into the impact of deaths of despair on election outcomes, as differing characteristics are likely to result in varying responses. More conservative and Whiter areas may differ compared to more liberal and more diverse or non-White areas. To study this, the mortality rate is interacted first with a dummy variable equaling 1 if the GOP candidate in the previous election won more than 50% of the vote share. Next, the mortality is interacted with the percent of the population that is White.

Column (3) of Table 3 shows the results with the dummy for the Republican winning the last election. The sum of the interaction coefficient and the main effect of mortality indicates that a standard deviation increase in mortality in a county that voted for the Republican candidate in the previous election, is associated with a 2.72 percentage point higher GOP vote share. The coefficient on the mortality alone shows that this same increase in a county where the Republican candidate lost the last election would still be accompanied by a 1.46 percentage point higher GOP vote share. This indicates an overall rightward shift in the election outcomes that increases already right-leaning counties even further.

Column (4) shows the results of interacting the percent of the population that is White with the mortality rate. The sum of the interaction and the main effect of mortality show that a standard deviation increase in mortality in a county that is a standard deviation Whiter than the mean will have a 3.65 percentage point higher GOP vote share. The interaction coefficient shows that this is a 1.12 percentage point increase over less White counties.

3.2 IV Regression Results

As the two-way fixed effects regressions cannot control for any potential endogeneity issues arising from time-varying county-specific unobservables, an IV regression is used. The results using the instrumental variable models corresponding to column (1) of Table 3 are shown in Table 4 and the interactions corresponding to Table 3's columns (3) and (4) are shown in Tables 5 and 6. Columns (1) of Tables 4, 5, and 6 use the interaction between county level pre-period deaths of despair mortality rate in 2001 and the state's annual Fentanyl seizures as an instrument, with the following column for each table using the same measure but for all Fentanyl-related drugs. Column (3) of Tables 4, 5, and 6 use the IV interacting the 1994-1996 state cancer mortality rate with year dummies. Finally, column (4) of Tables 4, 5, and 6 use the IV of non-triplicate law status of each state in the mid 1990's multiplied by a year dummies as an instrument.

Across specifications, the coefficients on deaths of despair maintain their positive sign and statistical significance. Columns (1) and (2) of Table 4, using the variation in the mortality based on the interaction IV with base level mortality and Fentanyl supply, show around a 5.1 percentage point higher GOP vote share for a standard deviation increase in deaths of despair mortality. This estimate is just over double the magnitude of the two-way fixed effects result. The OLS estimation may be downward biased due to endogeneity or measurement error. Alternatively, as these estimates rely on variation driven by relatively higher rates of mortality in early years and a larger Fentanyl supply, these coefficients suggest that the "complier" counties may have experienced a larger effect on voting outcomes, which may have been due to the earlier and more severe period of increasing deaths in their communities.

The models using IVs related to Purdue Pharma's Oxycontin marketing show similar trends in columns (3) and (4). The larger magnitudes than the two-way fixed effects results indicate a stronger response in "complier" counties whose deaths of despair were affected by the targeted marketing.

Tables 5 and 6 show the persistence of the finding that effects were larger in more Republican and Whiter counties. For most IV specifications (reported in Table 5), the effect was around 50% stronger in these Republican counties. Table 6 shows that the mortality effects in Whiter areas were about 0.8-1.6 percentage points larger for each standard deviation increase in White proportions, similar to the two-way fixed effects results.

I also report the reduced form results in Table 7. All instruments show positive and significant impacts on the GOP vote share. Columns (1) and (2), which use the baseline deaths of despair mortality and annual drug seizures, show similar results, with pure Fentanyl seizures having a slightly higher magnitude than all Fentanyl related drugs. Columns (3) and (4), which use the targeted Purdue Pharma marketing strategies, show positive and significant impacts with all year dummies, and a notable increase in magnitude following 2014 when Fentanyl became more mainstream. Column (3) presents similar results to those in Arteaga and

Barone (2023a), which found a standard deviation increase in the 1996 cancer rate corresponded with a 12 percentage point higher vote share for Republican candidates, while I find that a standard deviation increase in the mid-1990s cancer rate saw a 7.47 percentage point higher GOP vote share (calculated by multiplying the coefficient in column 3 for 2020 and standard deviation of the variable from Table 1).

4 Robustness Checks

I run additional regressions to ensure that the response to deaths of despair is due to these types of deaths specifically, rather than to any form of mortality. I estimate the two-way fixed effects regression as described in Equation 3 with mortality rates for other leading causes of death: Diabetes Mellitus, Heart disease, and Chronic lower respiratory disease (CLRD). The results are presented in Table 8, with column (1) showing the result using deaths of despair as seen in Table 3, column (2) using Diabetes deaths, column (3) heart disease, and column (4) for CLRD. All coefficients in columns (2)-(4) show much smaller magnitudes and lower significance than that for deaths of despair. Only Diabetes deaths yield a statistically significant coefficient (at the 10% level), but a very small magnitude.

To ensure that the results are driven by a change in votes rather than the composition of voters, I estimate the regressions shown in Table 3 using turnout as the outcome rather than GOP vote share. These results are shown in Table 9. All regressions indicate a negative and significant impact on election turnout from increased deaths of despair; however, the magnitudes are all very small – around 1% of mean turnout in columns 1 and 2. The small changes in turnout are unlikely to be driving the effects on Republican vote shares documented above, which range from 4.3 to 94.2 percentage points.

5 Discussion

The results show a significant and positive impact of higher exposure to deaths of despair on support for the Republican candidate. While this result alone has implications for elections and voter decision making, examining potential mechanisms behind the effect and explanations for the heterogeneous results are needed to provide a broader understanding.

That voting behavior was affected is not surprising given how people were greatly affected by these deaths and the surrounding opioid epidemic. The wide-reaching household, healthcare, and economic impacts show the salience and effects on these communities. Households with members with opioid misuse or OUD are more likely to experience dissolution and worse outcomes for children (Winstanley and Stover, 2019), with further impacts on family members who may have to become caretakers, notably grandparents, for children no longer able to stay with their parents (Voss et al., 2023). Healthcare systems experience more burnout among workers (Pike et al., 2019), complications with other treatments when patients have comorbidities of SUD or OUD (Cohen-Mekelburg et al., 2018; Khayata et al., 2022), and overall higher expenditures on healthcare (Neville and Foley, 2020). Employers have higher costs related to medical expenses and lost productivity (Fuhrmann-Berger, 2018), and individuals face higher consumer finance rates in affected areas (Jansen, 2022). More directly, a survey analysis compared respondents perceptions of whether the area they lived in was below-, at-, or above- average in terms of overdose deaths and the actual ranking of where they live; there was a significant correlation between their perceived rankings and reality (Gollust and Haselswerdt, 2021). There is also a high correlation between the number of opioid related posts state legislators put on social media and the state's overdose mortality rate (Stokes et al., 2021).

This evidence suggests people are both aware of these deaths in their communities and face many impacts, but what remains an open question is why this would lead to increased support of Republican Presidential candidates. This may be due to an average preference for the GOP policies regarding addiction and the opioid epidemic. While both Democratic and Republican politicians acknowledge addiction and the opioid epidemic to be a serious issue that needs intervention, their approaches are not the same. Surveys have shown that while most Americans across parties support treatment to be offered to those suffering from addiction, they are not willing to host nor pay for treatment facilities in their communities (Benedictis-Kessner and Hankison, 2019; Schneider et al., 2021). Conservative states tend to commit less funds towards treatment and resources, which aligns with the preferences just described[3]. As the surveys highlight, many citizens do not want to be paying more for other's treatment, which aligns with the Republican policy. Additionally, Republican state legislators are more likely to express on social media the need to curb the illicit drug trade when discussing opioids, while Democratic legislators focus on holding pharmaceutical companies responsible (Stokes et al., 2021).

As the results show that the net effect of these deaths does match the hypothesis that there is an average policy preference for the Republican platform, they also highlight notable heterogeneity across partisan and demographic identities. Counties that voted for the Republican candidate in the previous election had an

[3]Republicans tended to respond to the issue primarily through small expansions of Medicaid, compared to Democratic areas which adopt the much larger ACA medicaid expansion (Grogan et al., 2019).

effect around double that of Democratic voting areas. Surveys throughout this period found that self-identified Republicans or conservatives were less likely to support any type of investment into treatment for addiction (Benedictis-Kessner and Hankison, 2019), and less likely to support additional COVID-19 resources for drug users (Schneider et al., 2021). As the increasing deaths of despair mortality rate heightened the level of salience and discussion of these deaths, already Republican areas with these preferences were likely to shift further in their support in order to align with this increasingly important stance. The deaths of despair effect on elections was also higher in Whiter counties. The first research and media reports on the opioid epidemic focused on middle income, White individuals (Case and Deaton, 2015). Research suggests this may have made White citizens more aware and invested in the epidemic as White survey respondents had a closer perception of how their local area compared to others regarding overdose death rates (Gollust and Haselswerdt, 2021). Being more aware of the situation likely increased the responsiveness to and prioritization of the addiction problem among Whiter populations.

6 Conclusion

This paper sought to evaluate the impacts of exposure to deaths of despair mortality in a community on U.S. Presidential election outcomes. These deaths have significant effects on elections, with increases leading to more support for the Republican Party. The impacts of deaths of despair are stronger in later years during the period, following the increased prevalence of Fentanyl overdoses. Additionally, stronger impacts were seen in counties that had voted for the Republican candidate in the previous election and in Whiter areas.

I use instrumental variable estimations to mitigate endogeneity concerns regarding deaths of despair. The results maintain the positive and significant effects estimated in the two-way fixed effects regressions. These estimates take advantage of variation in deaths of despair driven by changes in Fentanyl supply affecting areas with higher baseline mortality, and then due to targeted marketing by Purdue Pharma during the introduction of OxyContin.

My results, in conjunction with prior studies' findings, suggest that an average preference for Republican policies related to addiction treatment and the opioid epidemic might explain these results, and different preferences across counties might explain the heterogeneous impacts. Further research is needed to better understand the mechanisms driving these results.

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A Tables

Table 1: Summary Statistics

	Unweighted Sample					Weighted by 2000 Population	
	mean	count	sd	min	max	mean	sd
GOP vote share	60.90	12422	14.76	4.30	94.17	47.71	16.17
Deaths of Despair per 10,000	13.12	12422	5.87	2.51	83.54	11.38	4.71
Pre-period DoD * State Fentanyl supply	5.49	12422	16.57	0.00	242.69	7.50	19.51
Pre-period DoD * State Fentanyl supply (All)	6.83	12422	20.72	0.00	318.80	9.52	24.51
Mid 1990s Cancer Rate	39.99	12417	82.58	0.00	262.79	40.76	82.80
Mid 1990s Non-triplicate Prescription Law	0.16	12422	0.37	0.00	1.00	0.14	0.34
Per capita IC	2.03	12328	29.77	0.00	1879.39	0.63	9.92
Per capita IC - other countries	0.19	12328	1.54	0.00	70.20	0.08	0.63
Percent pop. white	78.75	12422	19.11	2.52	99.39	64.96	22.04
Percent pop. female	50.25	12422	1.88	33.10	57.20	50.86	1.21
Percent pop. age 18-65	60.31	12422	3.18	37.30	77.66	61.97	2.88
Percent pop. over age 65	14.89	12422	4.05	1.67	55.27	12.82	3.58
LFPR	47.67	12422	6.15	16.48	100.00	49.84	4.74
GDP per capita	38.96	12127	36.33	8.22	1988.30	51.75	30.32

Statistics for 2,539 U.S. counties where data for all variables was available. Data includes years corresponding to US Presidential elections in 2004-2020. Import competition and GDP are reported per capita in thousands of US dollars. All variables, except for GOP vote share and IVs are for the three year average in the years before the election.

Table 2: IV First Stage Results

VARIABLES	(1) Pre-period DoD * Fent Supply	(2) Pre-period DoD * Fent Supply (all)	(3) Mid 90s Cancer Rate year trend	(4) Mid 90s Nontriplcate Law Status year trend
2001 DoD per 10,000 * Annual State Fentanyl Seizures (1000's)	0.00712***			
	(0.000518)			
2001 DoD per 10,000 * Annual State All Fentanyl Like Seizures (1000's)		0.00559***		
		(0.000401)		
1994-1996 Cancer Mortality rate * 2008			0.000862**	
			(0.000339)	
1994-1996 Cancer Mortality rate * 2012			0.00133**	
			(0.000555)	
1994-1996 Cancer Mortality rate * 2016			0.00514***	
			(0.000764)	
1994-1996 Cancer Mortality rate * 2020			0.00791***	
			(0.000823)	
1994-1996 Non-Triplicate State Laws * 2008				0.0694***
				(0.0243)
1994-1996 Non-Triplicate State Laws * 2012				0.135***
				(0.0429)
1994-1996 Non-Triplicate State Laws * 2016				0.331***
				(0.0523)
1994-1996 Non-Triplicate State Laws * 2020				0.478***
				(0.0617)
Per capita IC - other countries (3 Year average, standardized)	0.100	0.0970	0.0978	0.0653
	(0.0727)	(0.0735)	(0.0705)	(0.0724)
LFPR (3 Year average, standardized)	0.0133	0.0178	-0.0399	0.00817
	(0.0541)	(0.0545)	(0.0591)	(0.0483)
Percent pop. female (3 Year average, standardized)	-0.342***	-0.350***	-0.216***	-0.276***
	(0.0880)	(0.0900)	(0.0712)	(0.0755)
Percent pop. age 18-65 (3 Year average, standardized)	-0.131	-0.139	0.0320	0.0669
	(0.107)	(0.111)	(0.0770)	(0.0777)
Percent pop. over age 65 (3 Year average, standardized)	0.0686	0.0672	0.161**	0.119
	(0.0828)	(0.0845)	(0.0732)	(0.0744)
GDP per capita (3 Year average, standardized)	-1.993***	-2.063***	-1.274**	-1.144***
	(0.534)	(0.547)	(0.572)	(0.422)
Percent pop. white (3 Year average, standardized)	0.577***	0.575***	0.540***	0.536***
	(0.158)	(0.159)	(0.167)	(0.142)
Dependent variable mean	-0.181	-0.181	-0.181	-0.181
Observations	12,036	12,036	12,036	12,036
R-squared	0.729	0.728	0.726	0.719
F-test	95.07	98.01	24.72	13.92

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for Deaths-of-Despair in election years for U.S. Presidential elections in 2004-2020. All variables are averaged for the three years before the election and standardized, except for excluded instruments.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Two-way Fixed Effects Results

VARIABLES	(1) Base model	(2) Early vs. late years	(3) Interaction: GOP won last election	(4) Interaction: % White
Deaths of Despair per 10,000 (standardized)	2.362***		1.460***	2.523***
	(0.260)		(0.323)	(0.258)
Deaths of Despair per 10,000, 2004-2012		0.289		
		(0.272)		
Deaths of Despair per 10,000, 2016-2020		2.781***		
		(0.299)		
DoD * GOP won last election			1.262***	
			(0.270)	
DoD * % pop. white				1.123***
				(0.172)
County voted GOP last election			3.378***	
			(0.350)	
Percent pop. white (3 Year average, standardized)	15.25***	14.72***	13.37***	15.01***
	(1.599)	(1.510)	(1.532)	(1.570)
Per capita IC (3 Year average, standardized)	7.471***	8.395***	7.047***	5.908***
	(2.258)	(2.479)	(2.176)	(1.941)
LFPR (3 Year average, standardized)	-1.163	-0.889	-1.007	-0.950
	(0.757)	(0.778)	(0.724)	(0.708)
Percent pop. female (3 Year average, standardized)	-9.950***	-9.595***	-9.011***	-8.744***
	(0.878)	(0.860)	(0.860)	(0.857)
Percent pop. age 18-65 (3 Year average, standardized)	-5.327***	-4.698***	-4.263***	-4.274***
	(0.737)	(0.742)	(0.845)	(0.721)
Percent pop. over age 65 (3 Year average, standardized)	-1.410*	-1.288	-1.033	-1.759**
	(0.773)	(0.784)	(0.731)	(0.737)
GDP per capita (3 Year average, standardized)	-16.83***	-13.53***	-15.35***	-17.07***
	(5.597)	(4.975)	(5.141)	(5.271)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.416	0.434	0.453	0.440
Number of FIPS	2,539	2,539	2,539	2,539
DoD + Interaction			2.721***	3.646***
SE			(0.238)	(0.307)

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004-2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: IV Second Stage Results

VARIABLES	(1) Pre-period DoD * Fent Supply	(2) Pre-period DoD * Fent Supply (all)	(3) Mid 90s Cancer Rate year trend	(4) Mid 90s Nontriplcate Law Status year trend
Deaths of Despair per 10,000 (standardized)	5.109***	5.146***	11.54***	4.965***
	(1.112)	(1.138)	(1.513)	(1.396)
Per capita IC (3 Year average, standardized)	6.796***	6.787***	5.629**	6.883***
	(2.219)	(2.220)	(2.445)	(2.231)
LFPR (3 Year average, standardized)	-1.223*	-1.224*	-1.363*	-1.220*
	(0.708)	(0.708)	(0.721)	(0.710)
Percent pop. female (3 Year average, standardized)	-8.826***	-8.811***	-6.181***	-8.883***
	(0.849)	(0.853)	(1.012)	(1.020)
Percent pop. age 18-65 (3 Year average, standardized)	-5.029***	-5.025***	-4.327***	-5.044***
	(0.632)	(0.629)	(0.855)	(0.635)
Percent pop. over age 65 (3 Year average, standardized)	-1.590**	-1.593**	-2.017**	-1.581**
	(0.751)	(0.752)	(0.976)	(0.757)
GDP per capita (3 Year average, standardized)	-11.05**	-10.97**	2.509	-11.35**
	(5.177)	(5.214)	(4.734)	(5.370)
Percent pop. white (3 Year average, standardized)	13.67***	13.65***	9.943***	13.75***
	(1.718)	(1.706)	(2.288)	(1.841)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.379	0.378	-0.026	0.382
Number of Counties	2,539	2,539	2,539	2,539

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004-2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: IV Second Stage - Previous Election Interaction Results

VARIABLES	(1) Pre-period DoD * Fent Supply	(2) Pre-period DoD * Fent Supply (all)	(3) Mid 90s Cancer Rate year trend	(4) Mid 90s Nontriplcate Law Status year trend
Deaths of Despair per 10,000 (standardized)	3.845***	4.000***	9.297***	2.495**
	(1.082)	(1.115)	(1.454)	(1.190)
DoD * GOP won last election	1.765***	1.723***	2.619***	2.438***
	(0.598)	(0.590)	(0.549)	(0.442)
County voted GOP last election	3.233***	3.211***	2.851***	3.480***
	(0.392)	(0.398)	(0.468)	(0.354)
Per capita IC (3 Year average, standardized)	6.266***	6.245***	4.513**	6.584***
	(2.134)	(2.136)	(2.248)	(2.179)
LFPR (3 Year average, standardized)	-0.977	-0.987	-0.955	-0.844
	(0.658)	(0.658)	(0.616)	(0.647)
Percent pop. female (3 Year average, standardized)	-7.916***	-7.872***	-5.524***	-8.182***
	(0.849)	(0.841)	(0.902)	(0.951)
Percent pop. age 18-65 (3 Year average, standardized)	-3.777***	-3.784***	-2.822***	-3.545***
	(0.780)	(0.769)	(0.796)	(0.764)
Percent pop. over age 65 (3 Year average, standardized)	-1.235*	-1.245*	-1.682*	-1.160*
	(0.685)	(0.687)	(0.862)	(0.702)
GDP per capita (3 Year average, standardized)	-9.635**	-9.381**	2.956	-11.33**
	(4.537)	(4.544)	(4.266)	(4.837)
Percent pop. white (3 Year average, standardized)	11.86***	11.80***	8.569***	12.21***
	(1.609)	(1.595)	(2.044)	(1.694)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.417	0.413	0.058	0.433
Number of Counties	2,539	2,539	2,539	2,539
DoD + Interaction	5.609***	5.723***	11.916***	4.933***
SE	1.084	1.091	1.339	1.213

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004-2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: IV Second Stage - White Percentage Interaction Results

VARIABLES	(1) Pre-period DoD * Fent Supply	(2) Pre-period DoD * Fent Supply (all)	(3) Mid 90s Cancer Rate year trend	(4) Mid 90s Nontriplcate Law Status year trend
Deaths of Despair per 10,000 (standardized)	5.284***	5.334***	7.192***	6.664***
	(1.051)	(1.068)	(2.743)	(1.179)
DoD * % pop. white	0.903**	0.818**	4.894***	1.697***
	(0.384)	(0.408)	(1.883)	(0.252)
Per capita IC (3 Year average, standardized)	5.528***	5.631***	-0.0417	4.419**
	(2.052)	(2.079)	(2.613)	(1.895)
LFPR (3 Year average, standardized)	-1.053	-1.071	-0.326	-0.930
	(0.674)	(0.677)	(0.687)	(0.629)
Percent pop. female (3 Year average, standardized)	-7.837***	-7.903***	-2.994**	-6.457***
	(0.918)	(0.923)	(1.470)	(0.866)
Percent pop. age 18-65 (3 Year average, standardized)	-4.177***	-4.250***	-0.286	-3.292***
	(0.700)	(0.717)	(1.753)	(0.614)
Percent pop. over age 65 (3 Year average, standardized)	-1.874***	-1.851**	-3.206***	-2.208***
	(0.718)	(0.720)	(0.881)	(0.724)
GDP per capita (3 Year average, standardized)	-11.15**	-11.00**	-9.201	-8.640*
	(4.915)	(4.963)	(7.623)	(4.580)
Percent pop. white (3 Year average, standardized)	13.45***	13.43***	11.80***	12.53***
	(1.647)	(1.636)	(2.255)	(1.822)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.399	0.396	0.161	0.352
Number of Counties	2,539	2,539	2,539	2,539
DoD + Interaction	6.187***	6.152***	12.086***	8.361***
SE	(1.001)	(1.000)	(1.618)	(1.134)

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004-2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: IV Reduced Form

VARIABLES	(1) Pre-period DoD * Fent Supply	(2) Pre-period DoD * Fent Supply (all)	(3) Mid 90s Cancer Rate year trend	(4) Mid 90s Nontriplcate Law Status year trend
2001 DoD per 10,000 * Annual State Fentanyl Seizures (1000's)	0.0363***			
	(0.00786)			
2001 DoD per 10,000 * Annual State All Fentanyl Like Seizures (1000's)		0.0287***		
		(0.00622)		
1994-1996 Cancer Mortality rate * 2008			0.0364***	
			(0.00491)	
1994-1996 Cancer Mortality rate * 2012			0.0320***	
			(0.00676)	
1994-1996 Cancer Mortality rate * 2016			0.105***	
			(0.00907)	
1994-1996 Cancer Mortality rate * 2020			0.0905***	
			(0.00910)	
1994-1996 Non-Triplicate State Laws * 2008				0.952***
				(0.308)
1994-1996 Non-Triplicate State Laws * 2012				1.316***
				(0.410)
1994-1996 Non-Triplicate State Laws * 2016				4.105***
				(0.760)
1994-1996 Non-Triplicate State Laws * 2020				1.786***
				(0.683)
Per capita IC - other countries (3 Year average, standardized)	4.176***	4.157***	3.711***	3.889***
	(1.230)	(1.229)	(1.131)	(1.171)
LFPR (3 Year average, standardized)	-1.181	-1.158	-1.959**	-0.964
	(0.823)	(0.822)	(0.942)	(0.776)
Percent pop. female (3 Year average, standardized)	-10.78***	-10.82***	-8.447***	-10.23***
	(0.962)	(0.967)	(0.779)	(0.953)
Percent pop. age 18-65 (3 Year average, standardized)	-5.792***	-5.833***	-4.152***	-4.765***
	(0.913)	(0.929)	(0.664)	(0.765)
Percent pop. over age 65 (3 Year average, standardized)	-1.182	-1.189	-0.0460	-0.885
	(0.857)	(0.862)	(0.711)	(0.812)
GDP per capita (3 Year average, standardized)	-21.78***	-22.13***	-12.59*	-18.13***
	(6.526)	(6.592)	(7.060)	(6.017)
Percent pop. white (3 Year average, standardized)	16.83***	16.82***	16.20***	16.50***
	(1.672)	(1.681)	(1.450)	(1.642)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.412	0.412	0.476	0.421
Number of FIPS	2,539	2,539	2,539	2,539

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004-2020. All independent variables are averaged for the three years before the election and standardized, excluding instrumental variables.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Check: Alternate Mortality Rates

VARIABLES	(1) Deaths of Despair	(2) Diabetes	(3) Heart Disease	(4) CLRD
Deaths of Despair per 10,000 (standardized)	2.362***			
	(0.260)			
Deaths from Diabetes per 10,000 (standardized)		0.159*		
		(0.0630)		
Deaths from Heart Disease per 10,000 (standardized)			0.239	
			(0.523)	
Deaths from Chronic Lower Respiratory diseases per 10,000 (standardized)				-0.257
				(0.212)
Percent pop. white (3 Year average, standardized)	15.25***	16.59***	16.61***	16.53***
	(1.599)	(1.726)	(1.728)	(1.723)
Per capita IC (3 Year average, standardized)	7.471***	8.041***	8.004***	8.099***
	(2.258)	(2.358)	(2.356)	(2.377)
LFPR (3 Year average, standardized)	-1.163	-1.043	-1.086	-1.102
	(0.757)	(0.809)	(0.813)	(0.815)
Percent pop. female (3 Year average, standardized)	-9.950***	-10.96***	-10.94***	-10.86***
	(0.878)	(1.006)	(1.001)	(1.004)
Percent pop. age 18-65 (3 Year average, standardized)	-5.327***	-5.621***	-5.578***	-5.545***
	(0.737)	(0.920)	(0.909)	(0.908)
Percent pop. over age 65 (3 Year average, standardized)	-1.410*	-1.355	-1.351	-1.157
	(0.773)	(0.862)	(0.879)	(0.875)
GDP per capita (3 Year average, standardized)	-16.83***	-21.69***	-21.70***	-21.92***
	(5.597)	(6.459)	(6.497)	(6.525)
Observations	11,931	11,931	11,931	11,931
R-squared	0.416	0.384	0.383	0.383
Number of FIPS	2,539	2,539	2,539	2,539
Dependent variable mean	48.02	48.02	48.02	48.02

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for coefficients onto GOP vote shares in U.S. Presidential elections from 2004 - 2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness Check: Alternate Outcome - Turnout

VARIABLES	Base model	Early vs. late years	Interaction: GOP won last election	Interaction: % White
Deaths of Despair per 10,000 (standardized)	-0.601***		-0.946***	-0.575***
	(0.128)		(0.169)	(0.123)
Deaths of Despair per 10,000, 2004-2012		-0.652***		
		(0.106)		
Deaths of Despair per 10,000, 2016-2020		-0.656***		
		(0.148)		
DoD * GOP won last election			0.608***	
			(0.147)	
DoD * % pop. white				0.179**
				(0.0815)
County voted GOP last election			-0.0516	
			(0.162)	
Percent pop. white (3 Year average, standardized)	-1.074*	-1.119**	-1.104*	-1.113**
	(0.559)	(0.562)	(0.565)	(0.556)
Per capita IC (3 Year average, standardized)	-1.403**	-1.324**	-1.559**	-1.652**
	(0.669)	(0.638)	(0.679)	(0.722)
LFPR (3 Year average, standardized)	0.719**	0.742**	0.823***	0.753**
	(0.298)	(0.297)	(0.295)	(0.299)
Percent pop. female (3 Year average, standardized)	1.372***	1.403***	1.407***	1.565***
	(0.388)	(0.389)	(0.383)	(0.362)
Percent pop. age 18-65 (3 Year average, standardized)	3.406***	3.460***	3.663***	3.574***
	(0.405)	(0.411)	(0.393)	(0.391)
Percent pop. over age 65 (3 Year average, standardized)	5.520***	5.531***	5.503***	5.465***
	(0.372)	(0.373)	(0.367)	(0.371)
GDP per capita (3 Year average, standardized)	-1.045	-0.763	-0.873	-1.084
	(2.060)	(2.075)	(1.994)	(2.016)
Dependent variable mean	48.02	48.02	48.02	48.02
Observations	11,931	11,931	11,931	11,931
R-squared	0.742	0.742	0.745	0.742
Number of FIPS	2,539	2,539	2,539	2,539
Joint			-0.338***	-0.396***
SE			(0.114)	(0.142)

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for U.S. Presidential elections in 2004 -2020. All independent variables are averaged for the three years before the election and standardized.
*** p<0.01, ** p<0.05, * p<0.1

B Figures

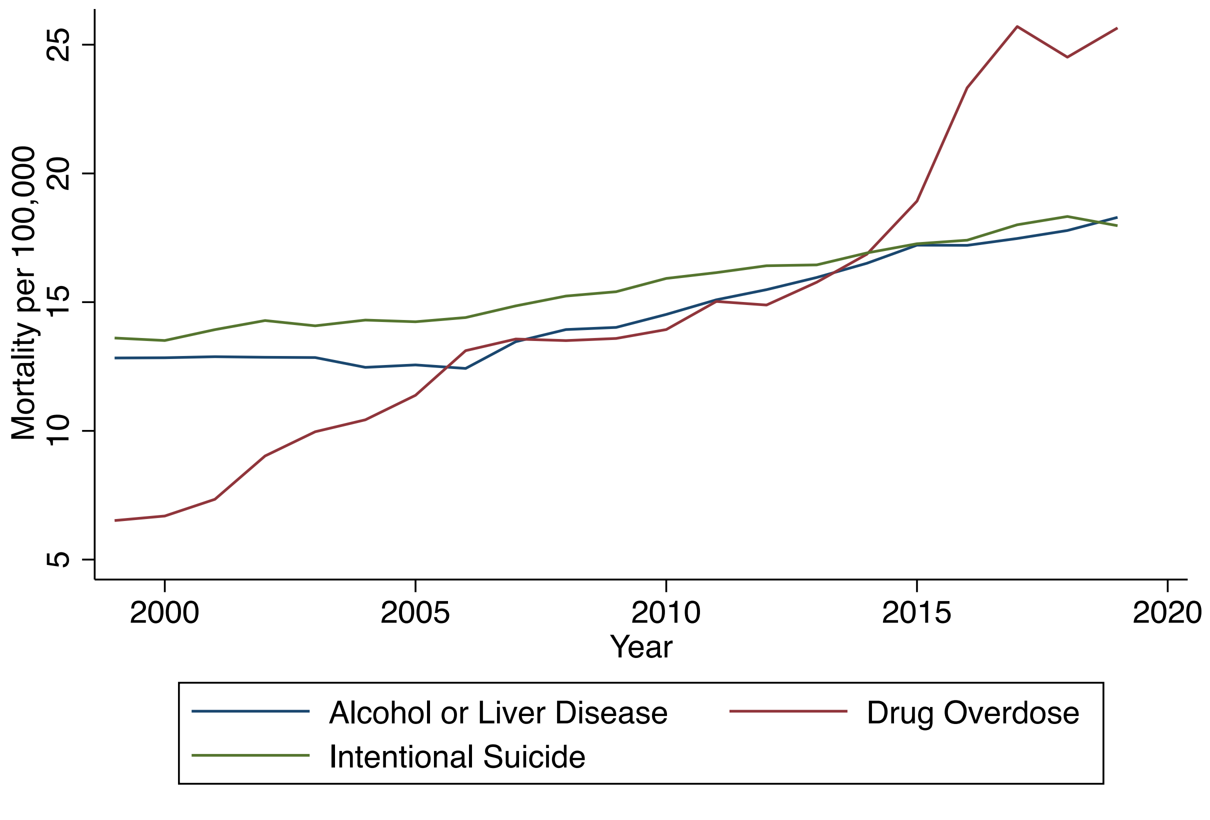

Figure 1: Components of deaths of despair over study period. Mortality rates are shown per 100,000 and are from the CDC Mortality Files. The three categories combined comprise the overall deaths of despair measure used throughout the paper.

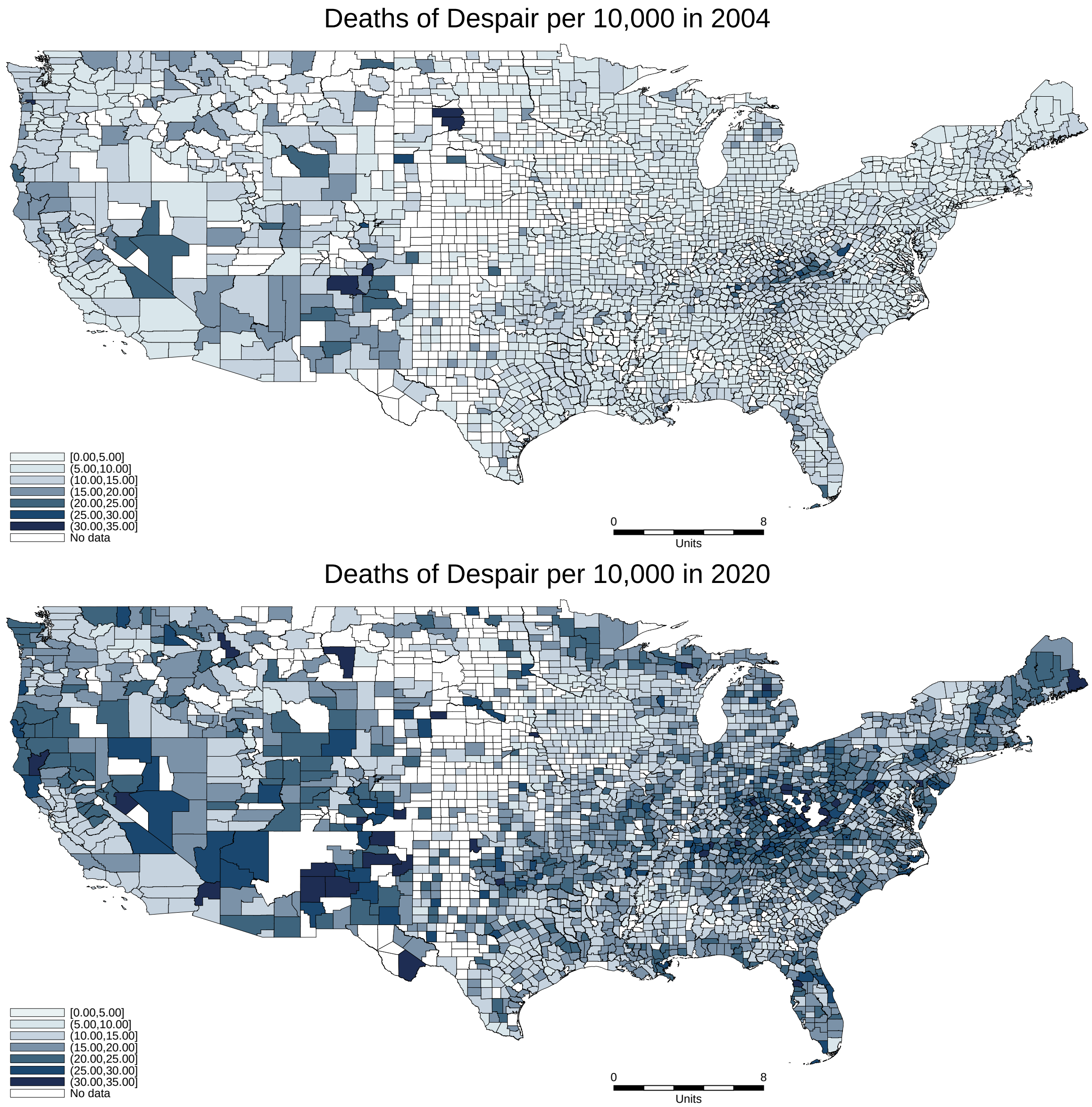

Figure 2: Deaths of despair per 10,000 in each U.S. county in 2004 and in 2020.

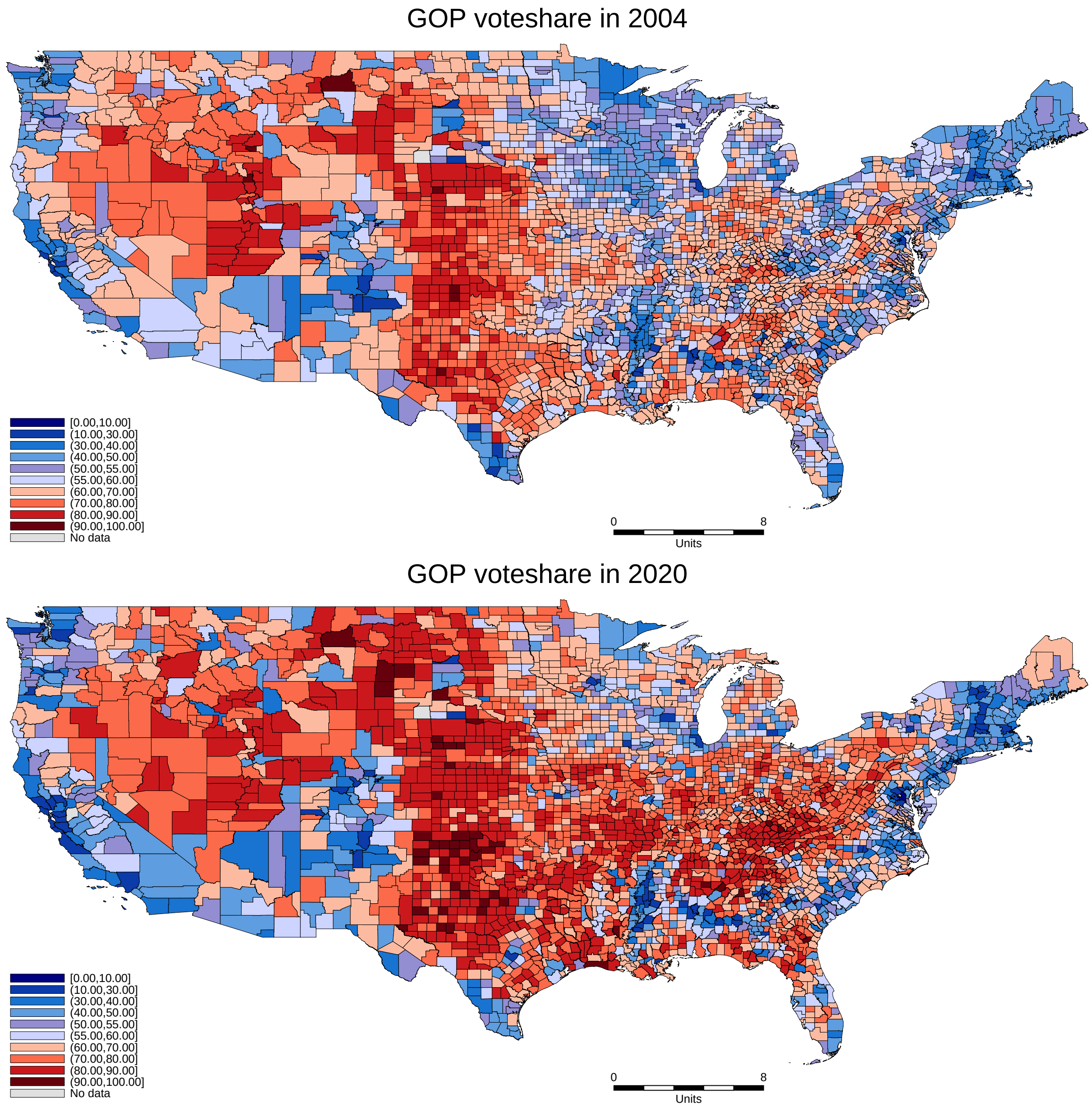

Figure 3: GOP two party vote share in each U.S. county in 2004 and in 2020.

A Appendix

Table A1: IV First Stage - Previous Election Interaction Results

VARIABLES	(1) DoD	(2) DoD*GOP lag	(3) DoD	(4) DoD*GOP lag	(5) DoD	(6) DoD*GOP lag	(7) DoD	(8) DoD*GOP lag
Pre-period DoD * State Fentanyl supply	0.00784***	-0.00566***						
	(0.000672)	(0.000725)						
GOP lag * (Pre-period DoD * State Fentanyl supply)	-1.63e-06**	1.79e-05***						
	(8.12e-07)	(8.71e-07)						
Pre-period DoD * State Fentanyl supply (All)			0.00599***	-0.00456***				
			(0.000531)	(0.000589)				
GOP lag * (Pre-period DoD * State Fentanyl supply - all)			-9.70e-07	1.44e-05***				
			(6.64e-07)	(7.00e-07)				
1994-1996 Cancer Mortality rate * 2008					0.000794**	0.000692**		
					(0.000324)	(0.000343)		
1994-1996 Cancer Mortality rate * 2012					0.00104*	0.000457		
					(0.000535)	(0.000339)		
1994-1996 Cancer Mortality rate * 2016					0.00487***	0.000577		
					(0.000761)	(0.000426)		
1994-1996 Cancer Mortality rate * 2020					0.00798***	0.00100**		
					(0.000904)	(0.000501)		
GOP lag * (1994-1996 Cancer Mortality rate * 2008)					0.000253**	0.00119***		
					(0.000104)	(7.96e-05)		
GOP lag * (1994-1996 Cancer Mortality rate * 2012)					0.000617***	0.00241***		
					(0.000167)	(9.94e-05)		
GOP lag * (1994-1996 Cancer Mortality rate * 2016)					0.000536***	0.00425***		
					(0.000207)	(0.000120)		
GOP lag * (1994-1996 Cancer Mortality rate * 2020)					0.000104	0.00650***		
					(0.000272)	(0.000151)		
1994-1996 Non-Triplicate State Laws * 2008							0.0285	-0.0375**
							(0.0259)	(0.0168)
1994-1996 Non-Triplicate State Laws * 2012							0.0817*	-0.126***
							(0.0446)	(0.0295)
1994-1996 Non-Triplicate State Laws * 2016							0.302***	-0.239***
							(0.0571)	(0.0354)
1994-1996 Non-Triplicate State Laws * 2020							0.502***	-0.328***
							(0.0717)	(0.0466)
GOP lag * (1994-1996 Non-Triplicate State Laws * 2008)							0.0703***	0.227***
							(0.0245)	(0.0257)
GOP lag * (1994-1996 Non-Triplicate State Laws * 2012)							0.105***	0.446***
							(0.0285)	(0.0308)
GOP lag * (1994-1996 Non-Triplicate State Laws * 2016)							0.0405	0.846***
							(0.0395)	(0.0353)
GOP lag * (1994-1996 Non-Triplicate State Laws * 2020)							-0.0619	1.341***
							(0.0566)	(0.0419)
Per capita IC - other countries (3 Year average, standardized)	0.107	0.124	0.102	0.114	0.0741	-0.0385	0.0706	0.00996
	(0.0708)	(0.0932)	(0.0714)	(0.0948)	(0.0688)	(0.100)	(0.0707)	(0.0931)
County voted GOP last election	0.0800***	-0.300***	0.0802***	-0.302***	-0.0245	-0.715***	0.0377	-0.489***
	(0.0284)	(0.0421)	(0.0288)	(0.0425)	(0.0389)	(0.0391)	(0.0316)	(0.0366)
LFPR (3 Year average, standardized)	0.00785	-0.113**	0.0134	-0.111**	-0.0292	0.0282	2.93e-05	-0.0468
	(0.0540)	(0.0557)	(0.0542)	(0.0550)	(0.0552)	(0.0314)	(0.0481)	(0.0448)
Percent pop. female (3 Year average, standardized)	-0.328***	-0.296***	-0.335***	-0.292***	-0.198***	-0.102**	-0.267***	-0.234***
	(0.0904)	(0.0635)	(0.0923)	(0.0630)	(0.0691)	(0.0417)	(0.0763)	(0.0542)
Percent pop. age 18-65 (3 Year average, standardized)	-0.135	-0.369***	-0.139	-0.365***	0.0558	-0.0429	0.0668	-0.213***
	(0.111)	(0.0689)	(0.114)	(0.0673)	(0.0772)	(0.0410)	(0.0802)	(0.0598)
Percent pop. over age 65 (3 Year average, standardized)	0.0814	-0.0142	0.0789	-0.0110	0.164**	0.0937**	0.125*	0.0398
	(0.0848)	(0.0648)	(0.0866)	(0.0643)	(0.0736)	(0.0454)	(0.0752)	(0.0535)
GDP per capita (3 Year average, standardized)	-2.019***	-0.957**	-2.077***	-0.938**	-1.296**	-0.105	-1.170***	-0.658*
	(0.548)	(0.461)	(0.559)	(0.450)	(0.557)	(0.174)	(0.431)	(0.364)
Percent pop. white (3 Year average, standardized)	0.552***	0.384***	0.545***	0.378***	0.527***	0.179***	0.540***	0.0592
	(0.159)	(0.117)	(0.161)	(0.117)	(0.171)	(0.0659)	(0.146)	(0.0830)
Observations	11,931	11,931	11,931	11,931	11,931	11,931	11,931	11,931
R-squared	0.730	0.552	0.729	0.552	0.728	0.651	0.722	0.613
Number of FIPS	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for Deaths-of-Despair in election years for U.S. Presidential elections in 2004-2020. All variables are averaged for the three years before the election and standardized, except for excluded instruments.

*** p<0.01, ** p<0.05, * p<0.1

Table A2: IV First Stage - White Percentage Interaction Results

VARIABLES	(1) DoD	(2) DoD*White %	(3) DoD	(4) DoD*White %	(5) DoD	(6) DoD*White %	(7) DoD	(8) DoD*White %
Pre-period DoD * State Fentanyl supply	0.00745***	0.00515***						
	(0.000509)	(0.000818)						
White % * (Pre-period DoD * State Fentanyl supply)	8.66e-07	1.72e-05***						
	(5.82e-07)	(8.20e-07)						
Pre-period DoD * State Fentanyl supply (All)			0.00592***	0.00379***				
			(0.000400)	(0.000645)				
White % * (Pre-period DoD * State Fentanyl supply - all)			8.86e-07*	1.33e-05***				
			(4.76e-07)	(8.13e-07)				
1994-1996 Cancer Mortality rate * 2008					0.000164	0.000473		
					(0.000295)	(0.000412)		
1994-1996 Cancer Mortality rate * 2012					-0.000256	0.00244***		
					(0.000393)	(0.000645)		
1994-1996 Cancer Mortality rate * 2016					0.00319***	0.00183*		
					(0.000559)	(0.000991)		
1994-1996 Cancer Mortality rate * 2020					0.00695***	0.000145		
					(0.000824)	(0.00152)		
White % * (1994-1996 Cancer Mortality rate * 2008)					0.000317***	0.000681***		
					(4.86e-05)	(0.000105)		
White % * (1994-1996 Cancer Mortality rate * 2012)					0.000765***	0.00119***		
					(7.85e-05)	(0.000179)		
White % * (1994-1996 Cancer Mortality rate * 2016)					0.00102***	0.00270***		
					(0.000109)	(0.000251)		
White % * (1994-1996 Cancer Mortality rate * 2020)					0.000691***	0.00537***		
					(0.000158)	(0.000350)		
1994-1996 Non-Triplicate State Laws * 2008							0.0843***	0.113***
							(0.0247)	(0.0253)
1994-1996 Non-Triplicate State Laws * 2012							0.182***	0.229***
							(0.0434)	(0.0475)
1994-1996 Non-Triplicate State Laws * 2016							0.410***	0.500***
							(0.0532)	(0.0565)
1994-1996 Non-Triplicate State Laws * 2020							0.524***	1.100***
							(0.0631)	(0.102)
White % * (1994-1996 Non-Triplicate State Laws * 2008)							0.0424***	0.171***
							(0.0126)	(0.0285)
White % * (1994-1996 Non-Triplicate State Laws * 2012)							0.108***	0.331***
							(0.0164)	(0.0428)
White % * (1994-1996 Non-Triplicate State Laws * 2016)							0.156***	0.692***
							(0.0237)	(0.0631)
White % * (1994-1996 Non-Triplicate State Laws * 2020)							0.0576*	1.297***
							(0.0345)	(0.0808)
Per capita IC - other countries (3 Year average, standardized)	0.0875	0.480***	0.0794	0.475***	-0.0178	0.167***	0.0189	0.215***
	(0.0723)	(0.114)	(0.0731)	(0.114)	(0.0724)	(0.0632)	(0.0737)	(0.0715)
LFPR (3 Year average, standardized)	0.0180	-0.103*	0.0239	-0.105*	0.0465	0.0469	0.0182	-0.133**
	(0.0530)	(0.0622)	(0.0529)	(0.0632)	(0.0415)	(0.0608)	(0.0452)	(0.0665)
Percent pop. female (3 Year average, standardized)	-0.319***	-0.617***	-0.319***	-0.615***	-0.0738	-0.00711	-0.220***	-0.236*
	(0.0830)	(0.114)	(0.0825)	(0.117)	(0.0588)	(0.113)	(0.0709)	(0.122)
Percent pop. age 18-65 (3 Year average, standardized)	-0.104	-0.418***	-0.103	-0.402***	0.146**	-0.129	0.0975	-0.460***
	(0.100)	(0.106)	(0.0998)	(0.112)	(0.0643)	(0.131)	(0.0785)	(0.0951)
Percent pop. over age 65 (3 Year average, standardized)	0.0671	0.282***	0.0652	0.284***	0.106*	0.0392	0.0983	0.0729
	(0.0815)	(0.0932)	(0.0823)	(0.0973)	(0.0628)	(0.106)	(0.0720)	(0.100)
GDP per capita (3 Year average, standardized)	-1.935***	1.522**	-1.975***	1.718***	-1.281***	2.261***	-1.189***	0.863
	(0.516)	(0.638)	(0.520)	(0.659)	(0.441)	(0.742)	(0.407)	(0.558)
Percent pop. white (3 Year average, standardized)	0.551***	-0.328	0.542***	-0.313	0.322**	-0.913***	0.424***	-1.023***
	(0.159)	(0.235)	(0.160)	(0.241)	(0.162)	(0.291)	(0.149)	(0.242)
Observations	11,931	11,931	11,931	11,931	11,931	11,931	11,931	11,931
R-squared	0.729	0.492	0.729	0.489	0.739	0.642	0.724	0.593
Number of FIPS	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539

Standard errors in parentheses, clustered at the county level. All regressions include year and county fixed effects. Observations are weighted by county population in 2000. Estimates for Deaths-of-Despair in election years for U.S. Presidential elections in 2004-2020. All variables are averaged for the three years before the election and standardized, except for excluded instruments.

*** p<0.01, ** p<0.05, * p<0.1