Democracy and The Opioid Epidemic

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Abstract

In this paper we estimate the causal effect of the opioid epidemic on political outcomes by exploiting rich geographic variation in exposure to the crisis. We study its effect on the Republican vote share in House Elections from 1982 to 2020. Our results suggest that exposure to the opioid epidemic continuously increased Republican vote share in the house starting in 2006. This higher vote share translated into additional number of seats won by Republicans from 2014 and until 2020.

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I. Introduction

The opioid epidemic is one of the most tragic public health crises in the history of the United States, causing staggering health and socio-economic costs (Arteaga and Barone, 2023 and Maclean et al., 2020). Exposure to the opioid epidemic increased mortality, disability, and poverty and had complex effects on family formation and household composition. In the last two decades, this led communities more exposed to the crisis unto divergent demographic and economic paths. The unfolding of the epidemic coincides with a historical moment of enhanced partisanship and polarization in the United States. Survey data shows that the share of Americans consistently expressing conservative or liberal views doubled between 1994 and 2017 (Doherty et al., 2017). Political elites, particularly members of Congress across parties, increasingly disagree on policy issues (McCarty et al., 2016), and the content of political speech is more polarized (Gentzkow et al., 2019 Card et al., 2022). This raises the question of whether there is a causal relationship between the opioid epidemic and these political changes.

Deteriorating socio-economic conditions and the decline of economic opportunities can both lead to the increase in the demand for opioids (Ruhm, 2019; Currie and Schwandt, 2021) and can fuel anti-establishment and far-right support (Blickle, 2020; Galofré-Vilà et al., 2022). It is a well-established fact that support for Donald Trump in the 2016 presidential election has a strong correlation with stagnated life expectancy and mid-life mortality (Monnat, 2016; Bilal et al., 2018). While there is evidence to suggest that economic inequality translates into ideological polarization (McCarty et al., 2016; Voorheis et al., 2015; Autor et al., 2020), evidence on the relationship between divergent health trends and political outcomes is very scarce.

In this paper, we exploit rich geographic quasi-exogenous variation in the exposure to the opioid epidemic to provide causal evidence of the epidemic's effects on political outcomes. We leverage that at the dawn of the opioid epidemic, marketing efforts were concentrated in the cancer pain market with the plan to quickly expand to the much larger non-cancer pain market in those same geographic areas. Furthermore, the pharmaceutical industry's strategy to disproportionally target top opioid prescribers—those in the highest deciles of the distribution—meant that these initial targets always received more marketing, even when the attention was not on the cancer pain market. This targeting implied that non-cancer physicians and patients in high-cancer areas were disproportionally exposed to the opioid epidemic and the unfortunate chain of events that followed. Following Arteaga and Barone (2023), we use cancer mortality before the unfolding of the epidemic as a measure of exposure.

We collect data from multiple sources and construct a panel of commuting zones covering the United States from 1982 to 2020.[1] We use data from the Drug Enforcement

[1]Commuting zones are geographic areas defined to capture local economic markets. They encompass

Agency (DEA) on the distribution of controlled substances to measure opioid prescriptions at the commuting zone level. We construct cancer and opioid mortality using data from the National Vital Statistics System. To examine political outcomes, we used county-level data from Dave Leip's Atlas of US Elections (Leip, 2022) and the United States Historical Election Returns Series assembled by the Inter-university Consortium for Political and Social Research (ICPSR), which provides information on House and presidential election results. We construct a panel of 625 commuting zones over 20 congressional election years.

We find that the opioid epidemic substantially increased the Republican vote share. We document that the relationship between cancer mortality and Republican vote share started soon after the onset of the opioid epidemic. By 2020, a one-standard-deviation in 1996 cancer mortality increases Republican vote share by 13.8 percentage points in congressional elections. These increases initially did not come from swing districts, and it took several terms in order for these incremental gains to flip election outcomes. We estimate that by 2012, exposure to the opioid epidemic translated into a higher number of seats in house elections for the Republican party. Presidential elections follow a similar pattern in terms of vote share, and we do not find any effects on turnout rates. Finally, we also document that this rise in Republican vote share was accompanied by an increase in conservative views on immigration, abortion, gun control, and ideology in general.

Variation in mid-1990s cancer mortality across locations is not random; it depends on demographic, environmental, and socio-economic variables. Nonetheless, the validity of the identification strategy does not require that cancer be randomly distributed across areas, but rather that in the absence of prescription opioid marketing, areas with higher cancer mortality in the pre-period exhibit the same trend as areas with lower cancer mortality in terms of our outcome variables (Goldsmith-Pinkham et al., 2020). To support this assumption, we present estimates of reduced-form event studies of the relationship between Republican vote share and 1996 cancer mortality and test for differential trends in the pre-period. We show that there is no relationship between our instrument and political outcomes before the introduction of OxyContin and the start of the opioid epidemic. This event-study design also allows for a transparent display of our results. We observe communities drift apart in terms of Republican vote share as a function of their exposure to the opioid epidemic.

We provide several falsification tests that support our empirical strategy. First, we perform an out-of-sample exercise using lagged cancer mortality and repeat our empirical strategy in the pre-period. We do not find any evidence of a relationship between these two variables. Second, we construct placebo mortality rates in 1996 from other unrelated causes of death and replicate our main specification; we show that our results are not

all metropolitan and nonmetropolitan areas in the US. While less granular than counties, they are much more granular than states.

driven by these other health trends that are not connected to the opioid epidemic. Third, we control for economic and political shocks that have been documented to affect political outcomes, such as the exposure to Chinese import competition, economic recessions, and the introduction of Fox News. We find that the correlation between these shocks and our instrument is low, and as a result, our estimates are unaffected when we control for these variables.

We are the first to provide evidence on the effects of the opioid epidemic on political outcomes, specifically on the rise in Republican party support and its consequent effects on polarization. This paper contributes to the literature on the effects of the opioid epidemic. Previous work has documented its effects on mortality, disability, fertility, children's outcomes, and poverty: Alpert et al. (2018); Evans et al. (2019); Park and Powell (2021); Buckles et al. (2022); Arteaga and Barone (2023), among others and see Maclean et al. (2020) for a review.

Second, we contribute to the small literature on health and political outcomes. Voigtländer and Voth (2012); Galofré-Vilà et al. (2022) and Blickle (2020) link extreme health events such as the black death and the 1918 influenza pandemic to increases in out-group polarization and far-right support. Specifically, places hardest hit by the black deaths saw higher surges of anti-semitism. Similarly, places where the influenza pandemic was stronger saw higher support from far-right/nazi parties in Germany and Italy. There is also work at the individual level on the effect of own health changes and political views and the effects of health on political participation (Kavanagh et al., 2021; Ojeda and Pacheco, 2019; Schur et al., 2002). We add to this literature by providing evidence of how one of the major health crises in the United States has contributed to the diverging voting patterns and political preferences.

II. The Opioid Epidemic and the Rise in Polarization

The United States has experienced an unprecedented crisis related to the misuse of and addiction to opioids. As of 2022, over 700,000 lives were lost due to opioid overdoses (CDC, 2023). The number of lives affected by the epidemic through its effects on disability, poverty, fertility, and foster care is orders of magnitude larger. During the last decade, a sizeable body of research has studied the origins of the opioid crisis and the factors that shaped its evolution from prescription to illicit sources. It has been established that the pharmaceutical industry and healthcare providers played a critical role in the origins of the crisis (Miloucheva, 2021; Arteaga and Barone, 2023; Alpert et al., 2022; Eichmeyer and Zhang, 2020). In particular, the aggressive and deceiving marketing of new prescription opioids with high potential for addiction directed to physicians, in a setting with financial incentives to increase prescriptions and weak monitoring, created the perfect platform for a crisis to unfold.

The opioid epidemic began with the introduction of OxyContin to the market in 1996. OxyContin is a prescription opioid manufactured by Purdue Pharma that changed the standard of practice for the treatment of non-terminal pain. Prior to the mid-1990s, pain management focused on cancer and end-of-life pain treatment due to care providers' fears of the risk of severe addiction (Melzack, 1990). MS Contin, a drug produced by Purdue Pharma, was the gold standard for cancer pain treatment, and OxyContin's development was in response to the generic competition expected after MS Contin's patent protection expired in 1996. OxyContin was intended to take over MS Contin's market and gain ground in the non-cancer pain treatment market, in which opioids were almost absent (OxyContin Launch Plan, September 1995). However, establishing the use of OxyContin for moderate and chronic pain faced clear challenges. First, the fear and stigma related to the use of opioids for non-terminal or non-cancer pain. Second, the administrative barriers physicians and pharmacies had to overcome to prescribe and sell Schedule II drugs.[2]

As a result, Purdue focused its marketing efforts on the physicians and pharmacies who faced less stigma around opioids and who knew how to navigate the paperwork related to the distribution of Schedule II drugs: Those in the cancer pain market. On repeated occasions, Purdue states clearly that: *"OxyContin Tablets will be targeted at the cancer pain Market."* (OxyContin Team Meeting, April 1994). *"OxyContin primary market positioning will be for cancer pain."* (OxyContin Team Meeting, March 1995). *"At the time of launch, OxyContin will be marketed for cancer pain."* (OxyContin Launch Plan, September 1995). This, however, was only intended as their entering path to the larger non-cancer pain market: *"The use of OxyContin in cancer patients, initiated by their oncologists and then referred back to FPs/GPs/IMs, will result in a comfort that will enable the expansion of use in chronic non-malignant pain patients also seen by the family practice specialists"* (OxyContin Launch Plan, September 1995).

That is, Purdue exploited its previously established network of cancer patients and their physicians to introduce its newest product to the broader pain market. Purdue Pharma's and its competitors' aggressive marketing of new prescription opioids successfully changed physicians' attitudes around opioid prescribing. Highly addictive opioids became the standard practice in treating moderate and chronic pain.[3] At its peak, opioid prescribing reached 81.3 prescriptions per 100 persons in 2012 (CDC, 2020). Rates of substance use disorder grew by a factor of six between 1999 and 2009 (Paulozzi et al., 2011), and prescription opioid mortality grew by a factor of five (Maclean et al., 2020).

[2]Schedule II drugs are drugs with a high potential for abuse which may lead to severe psychological or physical dependence. Examples of Schedule II narcotics include: hydromorphone (Dilaudid), methadone (Dolophine), meperidine (Demerol), oxycodone (OxyContin, Percocet), and fentanyl (Sublimaze, Duragesic).

[3]See Maclean et al. (2020), Alpert et al. (2022), and Arteaga and Barone (2023) for detailed discussions of the marketing of prescription opioids.

In response to the widespread misuse of prescription opioids and OxyContin, restrictions on prescription were tightened, and Purdue Pharma introduced an abuse deterrent formulation of OxyContin. Unfortunately, Evans et al. (2019) and Alpert et al. (2018) show that the reformulation led many consumers to substitute for a dangerous and inexpensive alternative: heroin. As a result, deaths, poisonings, emergency room visits, and enrollments in treatment programs for heroin abuse increased. In particular, between 2010 and 2013, heroin death rates increased by a factor of four with no reduction of the combined heroin and opioid death rate (Evans et al., 2019).

Beginning in 2013 and until today, the epidemic has been characterized by surging deaths related to the use of synthetic opioids, particularly fentanyl. Fentanyl, an extremely potent synthetic opioid, is more profitable to manufacture and distribute than heroin, and has a higher risk of overdose.[4] Indeed, fentanyl-related deaths explain almost all of the increase in drug overdose mortality between 2014 and 2021.

Over the course of the past 27 years, the opioid epidemic has caused widespread disruption of health and economic outlooks both at the individual and community level. Recent work documents that exposure to the epidemic increased in the share of the population in SNAP and disability programs, fertility, the fraction of children living away from a parent, and raised the rates of child removals (Gihleb et al., 2022; Buckles et al., 2022; Arteaga and Barone, 2023, Park and Powell, 2021). These changes are likely to impact the absolute and relative socio-economic standings of individuals and communities affected by the epidemic. In turn, this can translate into divergent political and policy preferences.

Contemporaneously, political polarization and party tribalism in the United States have increased dramatically, creating divisions in society and stifling policy progress (Boxell et al., 2020; Afrouzi et al., 2022). The share of Americans consistently expressing conservative or liberal views doubled between 1994 and 2017 (Doherty et al., 2017). Political elites, particularly members of Congress across parties, increasingly disagree on policy issues (McCarty et al., 2016), and the content of political speech is more polarized (Gentzkow et al., 2019; Card et al., 2022). Support for partisan leaders has increasingly divided along party lines; the difference in presidential approval ratings across parties was 85 (75) points for President Donald Trump (Barack Obama) relative to approximately 38 points for President George Bush in the early 1990s (Jones, 2021).

These trends stem from multiple factors, including the rise of social media and the segmentation of media exposure, which has reduced the overlap of information viewed by partisans (Di Tella et al., 2021; Levy, 2021; Allcott et al., 2020; Jo, 2017; Barberá et al., 2015), the introduction of widely available decentralized propaganda or "fake news" (Azzimonti and Fernandes, 2018), new internet platforms for leaders to share their ideas,

[4]Heroin is roughly three times as potent as morphine, and fentanyl is 100 to 200 times more potent than morphine, depending on the batch.

and the emergence of new media platforms (DellaVigna and Kaplan, 2007). This paper explores an additional explanation: the drifting trends in health and socio-economic outlooks of communities differentially affected by the opioid epidemic.

III. Data and Descriptive Statistics

Prescription opioids. We digitize historical records from the Automation of Reports and Consolidated Orders System (ARCOS) of the DEA. These reports contain the distribution records of all Schedule II substances by active ingredient (e.g., oxycodone or morphine) at the 3-digit ZIP code level from 1997 to 2020.[5] From these data, we construct a measure of grams of prescription opioids per capita at the commuting-zone level, which includes: oxycodone, codeine, morphine, fentanyl, hydrocodone, hydromorphone, and meperidine. Figure 1 and Table 1 show geographic variation and summary statistics of the level of prescription opioids per capita.

Mortality measures. We use county-level data from the Detailed Multiple Cause of Death files from 1976 to 2020. We compute the 1996 cancer mortality rate to proxy the cancer market served by Purdue Pharma at the time of OxyContin's launch. Panel (a) of Figure 1 shows the distribution of cancer mortality across geographies in 1996.

Prescription opioid mortality includes deaths whose underlying causes are substances usually found in prescription painkillers, e.g., hydrocodone, morphine, and oxycodone. We also consider a broader mortality measure that includes deaths from heroin and synthetic opioids, e.g., fentanyl.[6] Panel (b) of Figure 1 shows the geographic distribution of prescription opioid mortality from 1999 to 2018.

Political outcomes. We obtain data on election outcomes from 1992 to 2020 from Dave Leip's Atlas of US Elections (Leip, 2022). This dataset tracks votes received by Democratic, Republican, and other candidates for the House of Representatives and presidential elections and the number of registered voters at the county level. We collect data for these outcomes from 1982 to 1990 from the United States Historical Election Returns Series developed by ICPSR. Combining these datasets, we construct three main outcomes: the Republican vote share for Congress and presidential elections and voter turnout. Panel (c) of Figure 1 shows the distribution of the Republican vote share in congressional elections in 1996. This figure suggests that there is wide spread variation in the level of support to the Republican party in the mid-nineties. Panel (d) shows changes in the Republican vote share in 2020 relative to 1996.

In sum, our final dataset consists of a panel of 625 commuting zones from 1982 to 2020.[7] We restrict our sample to areas with more than 20,000 residents, this represents

[5]Digitized ARCOS system data are available here. We construct a crosswalk from 3-digit ZIP codes to commuting zones using the geographic correspondence engine powered by the Missouri CDC.

[6]See Arteaga and Barone (2023) for the ICD10 and ICD9 codes used in constructing each variable.

[7]ARCOS data are available since 1997, so analyses using this measure are restricted to a later period.

more than 99% of all opioid deaths and 99% of the total population.

In Table 2 we present regression equations that summarize the correlates of the geographic distribution of these variables at baseline. First, the level of prescription opiods per capita is related to the demographic composition of the commuting zone. A greater share of the white population at the commuting-zone level have a positive correlation with prescription opioids per capita; the share of the Hispanic population and the share of employment in manufacturing have a negative correlation with the opioid supply. In terms of cancer mortality, we find this is strongly related to share of the population over 65, negatively associated with the share of Hispanic population, and positively associated with mortality from other causes of death. There is not, however, a cross-sectional correlation with opioid mortality. Finally, Republican vote share in 1996 is positively correlated with the share of the white population and the employment rate, but is not correlated with cancer or opioid mortality.

IV. Empirical Strategy

IV.a. Causal Effects

To identify the effect of the opioid epidemic on political outcomes, we exploit rich geographic quasi-exogenous variation in the exposure to the opioid epidemic driven by the marketing practices of prescription opioid manufacturers. We proxy the exposure to the epidemic using cancer mortality in the mid-nineties. For each outcome variable, we consider the following specification, which is run over our sample of commuting zones:

$$\Delta\ y_{ct} = \alpha_1 + \sum_{\tau=1982}^{2020} \phi_\tau\ CancerMR_{ct_0}\mathbf{1}(Year = \tau) + \alpha\ \Delta\ X_{ct} + \gamma_{st} + \upsilon_{ct}\ , \qquad (1)$$

where c indexes commuting zones, s indexes states, t indexes years, and t_0 corresponds to 1996, the year of OxyContin's launch. We define Δ as the long-change operator: For any random variable W_{ct}, $\Delta W_{ct} = W_{ct} - W_{ct_0}$. The model includes a vector $\Delta\ X_{ct}$ that represents the long-changes in the time-varying control variables. These are: contemporaneous cancer mortality, shares of the white and female population, the share of population aged 18-29, 30-49, and 50-64, and the share of population under 1 year.

$CancerMR_{ct_0}$ is the cancer mortality rate in commuting zone c in 1996 (t_0) and is interacted with a full set of year dummies indexed by τ. In this specification, the coefficients for the pre-OxyContin period; i.e., ϕ_{1982}, ϕ_{1982}, to ϕ_{1994}, test whether the outcome of interest y_{ct} followed similar trends in higher and lower cancer mortality areas before the launch of OxyContin.

The term γ_{st} represents state times year fixed effects. These fixed effects control for state-specific trends and state-level policy changes which were common during this

period that directly affected the supply of opioids—e.g., the implementation of PDMP, the regulation of "pill mill" clinics, and the availability of naloxone[8]—and also the evolution of our outcome variables.

The validity of our research design relies on two assumptions: (i) cancer mortality in the mid-1990s is a good predictor of the growth in the supply of opioids and tracks opioid mortality, and (ii) in the absence of OxyContin marketing, areas with higher cancer mortality in the pre-OxyContin period exhibit the same *trend* as areas with lower cancer mortality for the outcomes of interest (Goldsmith-Pinkham et al., 2020).

IV.b. Is mid-nineties cancer mortality a good proxy for exposure to the opioid epidemic?

We start by showing the evolution of prescription opioid per capita by cancer mortality in 1996 in Figure 2. Commuting zones in the top quartile of cancer mortality in 1996 saw an increase in oxycodone gm per capita of 2,900%, and areas in the lowest quartile experienced a growth that was one-third of that, even though the two groups started the period with a comparable prevalence of oxycodone. Panel (b) of Figure 2 shows that there is a positive and statistically significant relationship between mid-nineties cancer mortality and shipments of prescription opioids per capita.

The connection between cancer mortality and opioid shipments tracks into opioid-related mortality. Inspecting the raw data, panel (c) of Figure 2 show that areas in the top and bottom quartile of cancer mortality experienced a similar evolution in terms of prescription opioid mortality before the launch of OxyContin. Early in the 2000s, a wedge starts to appear between these areas. Additionally, we find that areas with higher cancer mortality in the mid-nineties were not on a differential trend along opioid related mortality: Estimates of the pre-OxyContin period are indistinguishable from zero. In contrast, after 1996 strong patterns appear and mid-nineties cancer mortality starts to predict opioid-related mortality.

V. Results

V.a. Republican Vote in House Elections

The opioid epidemic caused an increase in the share of votes to the Republican party in congressional elections. We start by showing evidence using raw data. We split commuting zone by quartiles of cancer incidence in 1996. Panel (a) of Figure 3 shows that first, there is no difference in republican vote share before 1996 between high and low cancer places. However, soon after the introduction of OxyContin, there is an increase in the share of Republican votes in high cancer areas accompanied by a reduction in this share

[8]See for example Buchmueller and Carey (2018) and Doleac and Mukherjee (2019)

in low cancer areas. The pattern illustrated in the raw data translates into in a statistically significant increase in the share of votes for the GOP starting in 2006. Our results suggest that a higher exposure to the epidemic—i.e., a one-standard-deviation higher cancer mortality rate—translated into a 13.8 percentage point increase in the share of votes for the Republican party (see panel (b) of Figure 3).

Elections wins and heterogeneity. Whether increases in republican vote share translate into elections wins, depends on how contested districts are and how large are the vote increases. We show that even though republican vote share starts to increase in 2006, it is only until 2012, that there starts to be evidence of an increase in the probability of a republican win (Panel a of Figure 4). This is because the initial increases in vote share were concentrated in communities with low baseline republican vote share (Panel b of Figure 4). Starting in 2014, vote share increases in communities with median level of vote share, and these increases are more likely to flip election results.

V.b. Additional Results

Presidential elections and Turnout. The effects of the epidemic on House elections are also present in Presidential election results. From the raw data, the share of votes for the Republican party in communities in the top and bottom quartile of 1996 cancer distribution trended similarly until the mid-nineties (Figure A1). By the 2000 election there is a wedge in Republican support that widens as time goes on, by 2020, the gap between the share of votes in high relative to low cancer mortality areas is greater than 0.15 points. We estimate that a one standard deviation increase in cancer mortality in the baseline period increased the share of votes for a Republican candidate in presidential elections in 12 percentage points. These increases in vote share are not driven by differential changes in the extensive margins measured by turnout. In Figure A2 we document there are no notable changes along this margin.

V.c. Mechanisms

These changes in voting patterns are not driven by differential migration across commuting zones, but by changes in political views in the incumbent population. We collect data on county-to-county migration flows from the IRS SOI Tax Stats and compute total commuting zone out migration. Figure 5 estimates e.q 1, and shows that exposure to the opioid epidemic is not related to differential migration trends.

Next, we use survey data from the American National Election Study (ANES) and the Cooperative Congressional Election Study (CCES), to document changes in political views and preferences, as a function of the geographic exposure to the opioid epidemic. To maximize power, given the small samples in the ANES, we pooled data from the pre-period, from 1982 to 1994, and look at the relationship between 1996 cancer mortality,

and views on immigration and abortion in Table 3. We do not find any economically or statistically significant correlation between these variables before the onset of the opioid epidemic. On the other hand, when looking at the post period, either pooling years from ANES (1996 to 2020), or using the much larger and richer CCES data for 2020, we find that 1996 cancer mortality predicts more conservative views in terms of immigration, abortion, gun control and ideology.[9] This suggests that the wedge between communities that we document in terms of republican vote share, and that arose as function of their exposure to the opioid epidemic, was also accompanied by a broader polarization in political views.

Finally, we test if these changes in preferences affected the position and views by elected local politicians. We use the data constructed by Card et al. (2022), where for all speeches on immigration given in congress by house members, the *tone* of the speech was computed, in terms of how anti or pro immigrant the speech was. We match house members speeches to commuting zone between 1982 and 2018, the last year available, and reproduce e.q 1. The goal is to asses if 1996 cancer mortality is related to differential trends in the anti-immigrant tone of speeches by house members, and to evaluate if the drifting views in terms of immigration by the general public, translated into views and preferences of elected officials. In Figure A3 we show that there is no pattern between mid-nineties cancer mortality and the pre-period, but also no change in tone when the opioid epidemic begins and develops.

VI. Robustness Checks

In this section, we explore alternative explanations for our findings and test the robustness of our results.

VI.a. Placebo Checks

First, we provide evidence that lagged cancer mortality is not a predictor of future republican vote share in the absence of the opioid epidemic. To do so, we perform an out-of-sample dynamic reduced-form analysis in our pre-period. That is, we run Equation 1 over a sample of commuting zones for the years 1982 to 1994 and estimate if lagged cancer mortality—cancer mortality rate in 1980—predicts our outcome variables. We present the results of this analysis in Panel A of Figure 6. These results demonstrate that before the onset of the opioid epidemic there is no relationship between republican vote and lagged cancer mortality—the estimated coefficients are statistically indistinguishable from zero.

[9] We can not report views on gun control and own ideology in the pre-period as these questions are not available. The CCES starts in 2006 but question are not comparable over the years.

Our identification strategy connects mid-1990s cancer mortality to future exposure to the opioid epidemic. This implies that we can test the validity of our design by estimating event-study regressions for placebo instruments—i.e., mid-1990s mortality from causes unrelated to cancer. Finding a good placebo instrument is challenging, given that the causes that underlie the incidence of cancer and other conditions, such as heart disease are not independent (Chiang, 1991 and Honoré and Lleras-Muney, 2006). As a result, there is substantial overlap across underlying causes and the correlation across measures is very high specially at old age. With this caveat, in panel b of Figure 6 we show placebo instrument regressions for Influenza and diabetes mortality rates under 50, which are less likely to be affected by the previous concern. We find that there is no relationship between these placebo mortality rates and post 1996 republican vote share.

VI.b. Trade shocks, the 2001 Economic Recession & Fox News

In October, 2000, the US Congress passed a bill granting permanent normal trade relations (PNTR) with China. This trade liberalization impact on communities is a function of the importance of the manufacturing industries for local employment, especially in industries subjected to import competition from China. Regions more exposed to Chinese import competition experienced relatively larger declines in employment, a greater uptake of social welfare programs, and increases in fatal drug overdoses (Autor and Dorn, 2013 and Pierce and Schott, 2020). We follow Pierce and Schott (2020) and measure exposure to trade liberalization as the difference between the non-NTR rates to which tariffs could have risen prior to PNTR and the NTR rates that were locked in by the change in policy. A higher NTR gap indicates a larger trade liberalization after the passage of PNTR. Our findings are unaffected by the inclusion of this variable (see Panel a of Figure 7).

Additionally, we asses whether the 2001 economic recession is mediating some of our effects. To do so, we construct a measure of exposure to the recession as the change in the unemployment rate from 2001 to 2000 at the commuting zone. Similar to the china shock, we find that our instrument and this exposure measure have a very low correlation level (ρ=0.03), and that our estimates do not change (see Panel a of Figure 7).

The timing of the opioid epidemic coincides with the introduction of Fox News to cable programming in selected locations in October 1996. DellaVigna and Kaplan (2007) show that initial exposure to Fox News increases republican vote share in the 2000 presidential elections. If Fox News initial coverage is correlated with cancer incidence, it is a possibility that some of the effects we estimate reflect the Fox News effect and not the effects of the opioid epidemic. To investigate this threat, we control for initial Fox News coverage using the data in DellaVigna and Kaplan (2007) and replicate our results. The data in DellaVigna and Kaplan (2007) covers only 60% of commuting zones so there is a substantial loss of sample size which make the results noisy, however, point estimates are

very similar to our baseline specification (see Panel b of Figure 7).

VI.c. Alternative Samples

In our main specification, we restrict our sample to areas with more than 20,000 residents, which represents 99.5% of the total population. We reproduce our analysis using alternative restrictions on the size of commuting zones. We arrive at analogous conclusions to the main analysis; there is a strong and positive relation between mid-nineties cancer mortality and post-1996 republican vote share. Finally, we also test whether the relationship we document is driven by a given state. In Figure A4 we present estimates of the coefficient corresponding to 2020, and show that our results are stable to the exclusion of any state.

VII. Discussion

This paper provides the first evidence of the political effects of the opioid epidemics. We exploit rich geographic quasi-exogenous variation in the exposure to the opioid epidemic to estimate its effect on the republican vote share and polarization. We find that the opioid epidemic substantially increased Republican vote share, and started to flip elections by 2012. By 2020, a one-standard-deviation in 1996 cancer mortality increases Republican vote share by 13.8 percentage points in congressional elections. These rise in Republican support was accompanied by an increase in polarization along immigration, abortion, gun control and own ideology. This paper documents the complex and long-lasting effects of a public health crisis that has touched communities on health, economic and social dimensions; and how it will continue to shape these communities through its effects on political outcomes.

References

Afrouzi, Hassan, Carolina Arteaga, and Emily Weisburst. 2022. "Is it the Message or the Messenger? Examining Movement in Immigration Beliefs."

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow. 2020. "The Welfare Effects of Social Media." *American Economic Review*, 110(3): 629–76.

Alpert, Abby, David Powell, and Rosalie Liccardo Pacula. 2018. "Supply-Side Drug Policy in the Presence of Substitutes: Evidence From the Introduction of Abuse-Deterrent Opioids." *American Economic Journal: Economic Policy*, 10(4): 1–35.

Alpert, Abby, William N Evans, Ethan M J Lieber, and David Powell. 2022. "Origins of the Opioid Crisis and its Enduring Impacts." *The Quarterly Journal of Economics*. qjab043.

Arteaga, Carolina, and Victoria Barone. 2023. "A Manufactured Tragedy: The Origins and Deep Ripples of the Opioid Epidemic." *Working Paper*.

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi. 2020. "Importing political polarization? The electoral consequences of rising trade exposure." *American Economic Review*, 110(10): 3139–3183.

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

Azzimonti, Marina, and Marcos Fernandes. 2018. "Social Media Networks, Fake News, and Polarization." NBER Working Paper.

Barberá, Pablo, John T Jost, Jonathan Nagler, Joshua A Tucker, and Richard Bonneau. 2015. "Tweeting from left to right: Is online political communication more than an echo chamber?" *Psychological Science*, 26(10): 1531–1542.

Bilal, Usama, Emily A Knapp, and Richard S Cooper. 2018. "Swing voting in the 2016 presidential election in counties where midlife mortality has been rising in white non-Hispanic Americans." *Social Science & Medicine*, 197: 33–38.

Blickle, Kristian. 2020. "Pandemics change cities: municipal spending and voter extremism in Germany, 1918-1933." *FRB of New York Staff Report*, , (921).

Boxell, Levi, Matthew Gentzkow, and Jesse M Shapiro. 2020. "Cross-Country Trends in Affective Polarization." NBER Working Paper.

Buchmueller, Thomas C, and Colleen Carey. 2018. "The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare." *American Economic Journal: Economic Policy*, 10(1): 77–112.

Buckles, Kasey, William N Evans, and Ethan MJ Lieber. 2022. "The drug crisis and the living arrangements of children." *Journal of Health Economics*, 102723.

Card, Dallas, Serina Chang, Chris Becker, Julia Mendelsohn, Rob Voigt, Leah Boustan, Ran Abramitzky, and Dan Jurafsky. 2022. "Computational analysis of 140 years of US political speeches reveals more positive but increasingly polarized framing of immigration." *Proceedings of the National Academy of Sciences*, 119(31): e2120510119.

CDC. 2020. "U.S. Opioid Dispensing Rate Maps."

CDC, National Center for Health Statistics. 2023. "Drug Overdose Death Rates."

Chiang, Chin Long. 1991. "Competing risks in mortality analysis." *Annual review of public health*, 12(1): 281–307.

Currie, Janet, and Hannes Schwandt. 2021. "The opioid epidemic was not caused by economic distress but by factors that could be more rapidly addressed." *The ANNALS of the American Academy of Political and Social Science*, 695(1): 276–291.

DellaVigna, Stefano, and Ethan Kaplan. 2007. "The Fox News Effect: Media Bias and Voting." *The Quarterly Journal of Economics*, 122(3): 1187–1234.

Di Tella, Rafael, Ramiro H Gálvez, and Ernesto Schargrodsky. 2021. "Does Social Media Cause Polarization? Evidence from Access to Twitter Echo Chambers during the 2019 Argentine Presidential Debate." NBER Working Paper.

Doherty, Carroll, Jocelyn Kiley, and Bridget Johnson. 2017. "The partisan divide on political values grows even wider. Pew Research Center."

Doleac, Jennifer L, and Anita Mukherjee. 2019. "The moral hazard of lifesaving innovations: naloxone access, opioid abuse, and crime." *Opioid Abuse, and Crime (March 31, 2019).*

Eichmeyer, Sarah, and Jonathan Zhang. 2020. "Can a Single Opioid Prescription Make a Difference? Evidence From Physician Prescribing Variation in Emergency Departments." Working Paper.

Evans, William N., Ethan M.J. Lieber, and Patrick Power. 2019. "How the Reformulation of OxyContin Ignited the Heroin Epidemic." *Review of Economics and Statistics*, 101(1): 1–15.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams. 2018. "What Drives Prescription Opioid Abuse? Evidence From Migration." *Stanford Institute for Economic Policy Research Working Paper*, 18–028.

Galofré-Vilà, Gregori, Martin McKee, María Gómez-León, and David Stuckler. 2022. "The 1918 influenza pandemic and the rise of Italian fascism: a cross-city quantitative and historical text qualitative analysis." *American Journal of Public Health*, 112(2): 242–247.

Gentzkow, Matthew, Jesse M Shapiro, and Matt Taddy. 2019. "Measuring group differences in high-dimensional choices: method and application to congressional speech." *Econometrica*, 87(4): 1307–1340.

Gihleb, Rania, Osea Giuntella, and Ning Zhang. 2022. "The Effect of Mandatory-Access Prescription Drug Monitoring Programs on Foster Care Admissions." *Journal of Human Resources*, 57(1): 217–240.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8): 2586–2624.

Honoré, Bo E, and Adriana Lleras-Muney. 2006. "Bounds in Competing Risks models and The War on Cancer." *Econometrica*, 74(6): 1675–1698.

Jo, Donghee. 2017. "Better the Devil You Know: An Online Field Experiment on News Consumption." Working paper.

Jones, Jeffrey. 2021. "Last Trump Job Approval 34%; Average Is Record-Low 41%." *Gallup*.

Kavanagh, Nolan M, Anil Menon, and Justin E Heinze. 2021. "Does health vulnerability predict voting for right-wing populist parties in Europe?" *American Political Science Review*, 115(3): 1104–1109.

Leip, David. 2022. "Atlas of US elections."

Levy, Ro'ee. 2021. "Social Media, News Consumption, and Polarization: Evidence from a Field Experiment." *American Economic Review*, 111(3): 831–70.

Maclean, Catherine, Justine Mallatt, Christopher J. Ruhm, and Kosali Ilayperuma Simon. 2020. "Review of Economic Studies on the Opioid Crisis." NBER Working Paper No. 28067.

McCarty, Nolan, Keith T Poole, and Howard Rosenthal. 2016. *Polarized America: The dance of ideology and unequal riches.* mit Press.

Melzack, Ronald. 1990. "The tragedy of Needless Pain." *Scientific American*, 262(2): 27–33.

Miloucheva, Boriana. 2021. "Pharmaceutical Promotion, Physician Response, and Opioid Abuse: Identifying the Role of Physicians in the Opioid Crisis." Working Paper.

Monnat, Shannon M. 2016. "Deaths of despair and support for Trump in the 2016 presidential election." *Pennsylvania State University Department of Agricultural Economics Research Brief*, 5: 1–9.

Ojeda, Christopher, and Julianna Pacheco. 2019. "Health and voting in young adulthood." *British Journal of Political Science*, 49(3): 1163–1186.

OxyContin Launch Plan. September 1995. Purdue Pharma.

OxyContin Team Meeting. April 1994. Purdue Pharma.

OxyContin Team Meeting. March 1995. Purdue Pharma.

Park, Sujeong, and David Powell. 2021. "Is the Rise in Illicit Opioids Affecting Labor Supply and Disability Claiming Rates?" *Journal of Health Economics*, 76: 102430.

Paulozzi, Leonard J, Edwin M Kilbourne, and Hema A Desai. 2011. "Prescription drug monitoring programs and death rates from drug overdose." *Pain medicine*, 12(5): 747–754.

Pierce, Justin R, and Peter K Schott. 2020. "Trade Liberalization and Mortality: Evidence from US Counties." *American Economic Review: Insights*, 2(1): 47–64.

Ruhm, Christopher J. 2019. "Drivers of the Fatal Drug Epidemic." *Journal of Health Economics*, 64: 25–42.

Schur, Lisa, Todd Shields, Douglas Kruse, and Kay Schriner. 2002. "Enabling democracy: Disability and voter turnout." *Political Research Quarterly*, 55(1): 167–190.

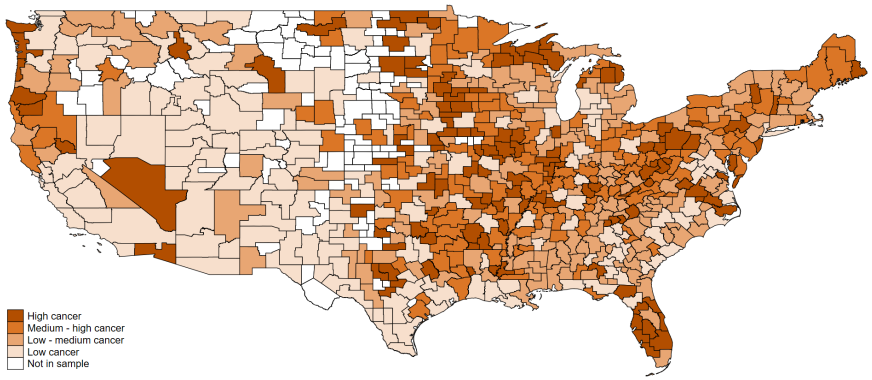
Voigtländer, Nico, and Hans-Joachim Voth. 2012. "Persecution perpetuated: the medieval origins of anti-Semitic violence in Nazi Germany." *The Quarterly Journal of Economics*, 127(3): 1339–1392.

Voorheis, John, Nolan McCarty, and Boris Shor. 2015. "Unequal incomes, ideology and gridlock: How rising inequality increases political polarization." *Ideology and Gridlock: How Rising Inequality Increases Political Polarization (August 21, 2015).*

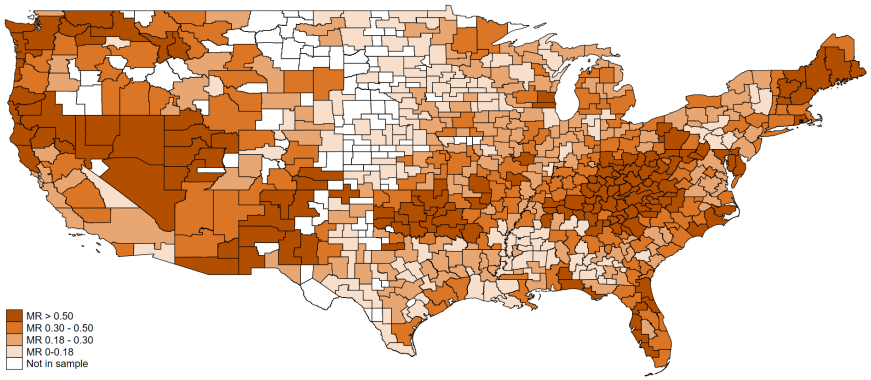
VIII. Figures

Figure 1: Geographical Variation

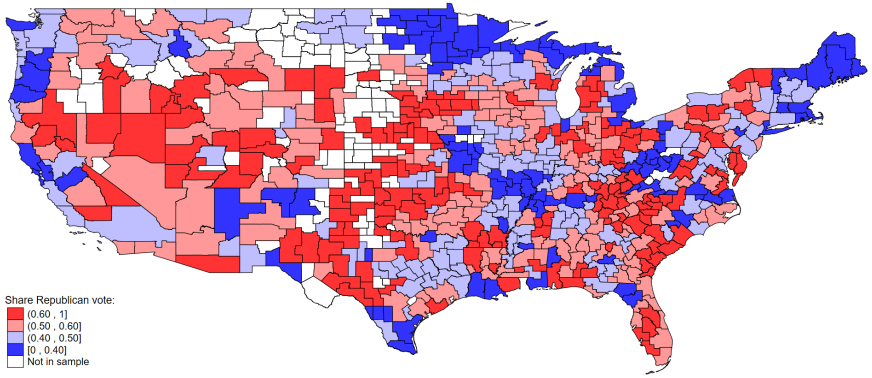
(a) Cancer Mortality Rates 1996



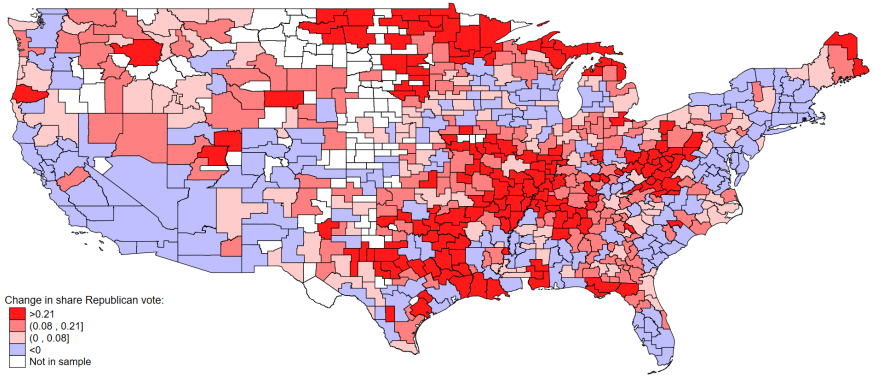
(b) Prescriptions Opioid Mortality Rate 1999 - 2018



(c) Republican Vote Share 1996 - Congressional Elections



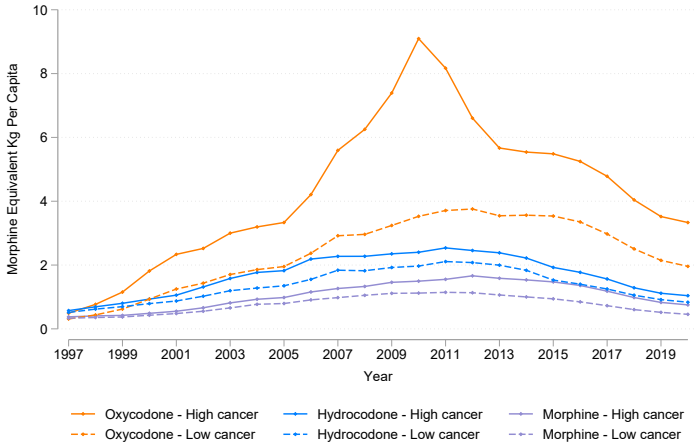
(d) Change in Republican Vote Sh. (2020 - 1996) - Congress



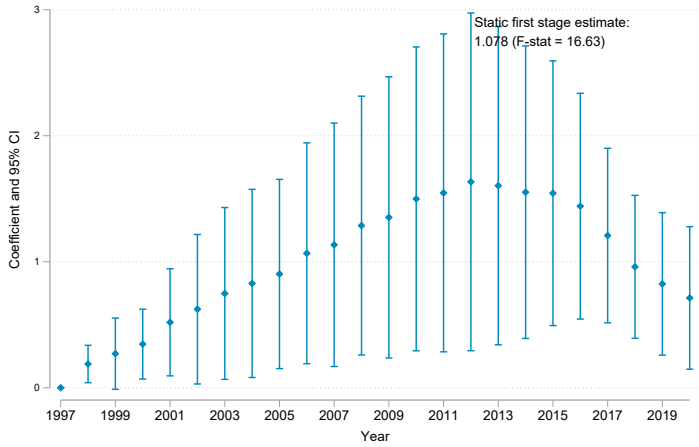
Notes: This figure shows the geographic distribution of our measure of exposure to the opioid epidemic—cancer mortality in 1996—in panel (a) and the distribution of prescription opioid mortality in panel (b). Panels (c) shows the geographic distribution of the Republican vote share in congressional election and panel (c) shoes its evolution between 1996 and 2020. This figure is referenced in Section III.

Figure 2: Effects of Mid-Nineties Cancer-Market Targeting on Opioid Dispensing & Mortality

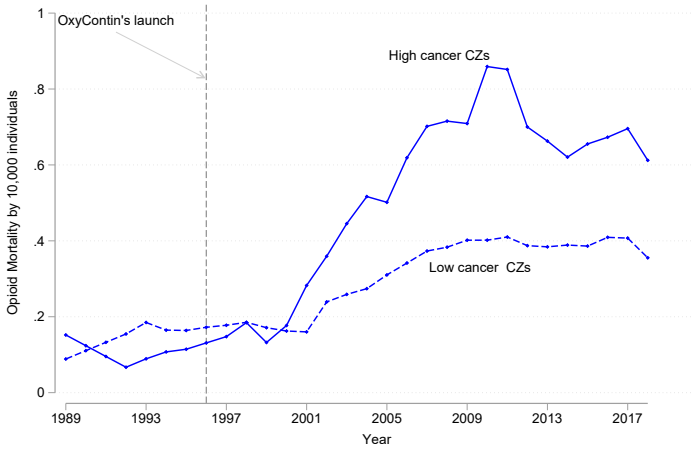
(a) Trends in High versus Low Cancer Mortality CZs



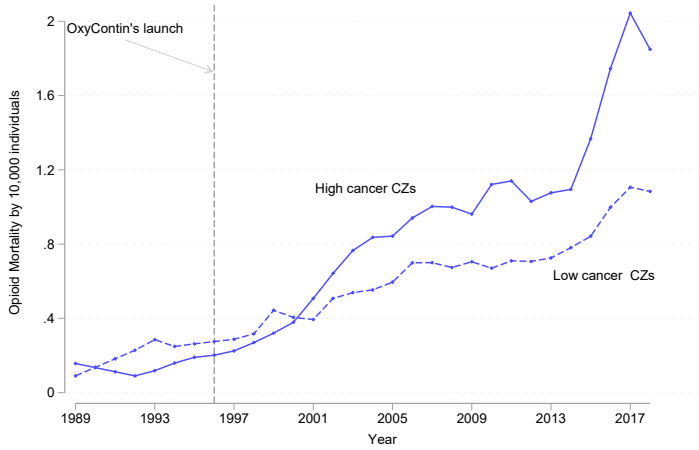
(b) Effects of Mid-Nineties Cancer-Market Targeting



(c) Trends in Prescription Opioid Mortality



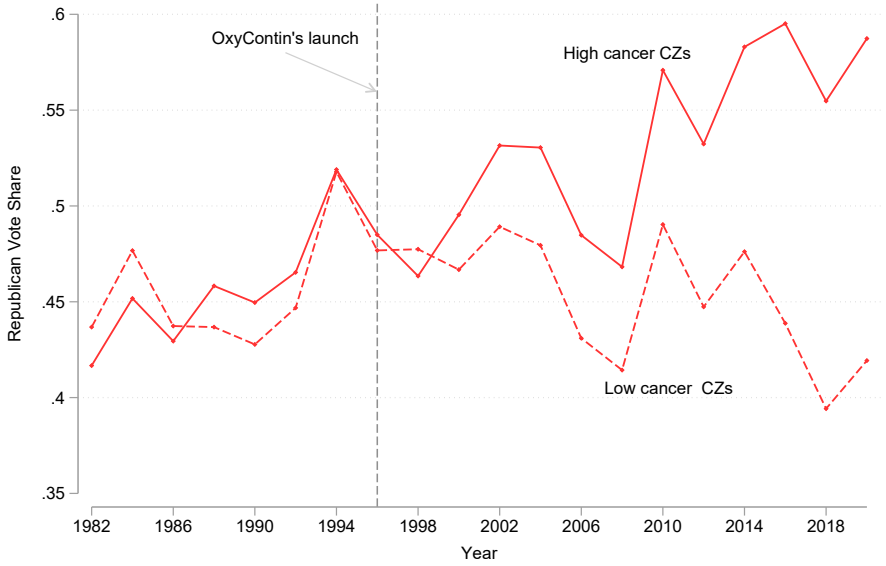
(d) Trends in Any Opioid Mortality



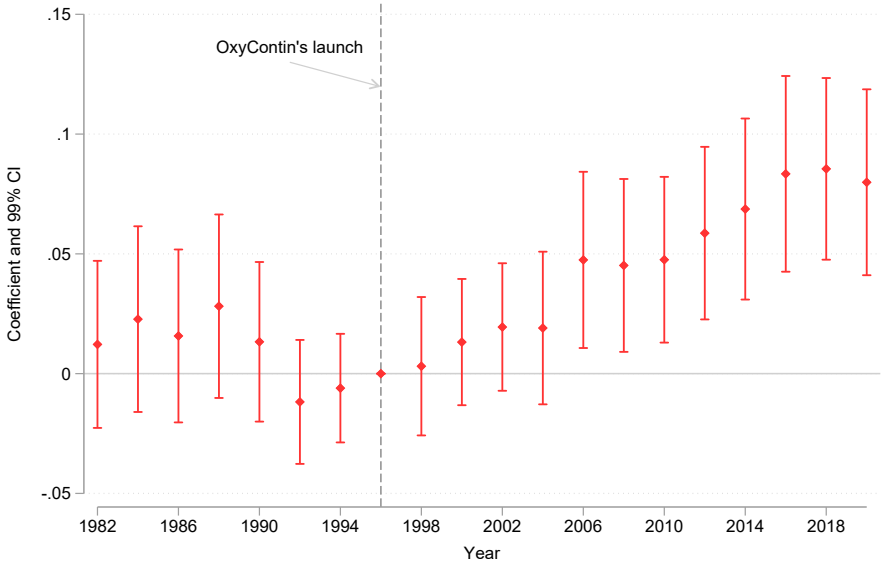
Notes:Panels (a) and (c) show the evolution prescription opioids and mortality in commuting zones in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Oxycodone is OxyContin's active ingredient. Panels (b) and (d) show estimates of the effects of mid-nineties cancer-market targeting on the distribution of prescription opioids and mortality. ARCOS data is available since 1997. We do not reject the null hypothesis that the estimated coefficients before 1996 $(\phi_{1982}, \phi_{1984}, \ldots, \phi_{1994})$ are jointly equal to zero. This figure is referenced in Section IV.b.

Figure 3: Republican Vote Share: Congressional Elections

(a) Trends in High versus Low Cancer Mortality CZs



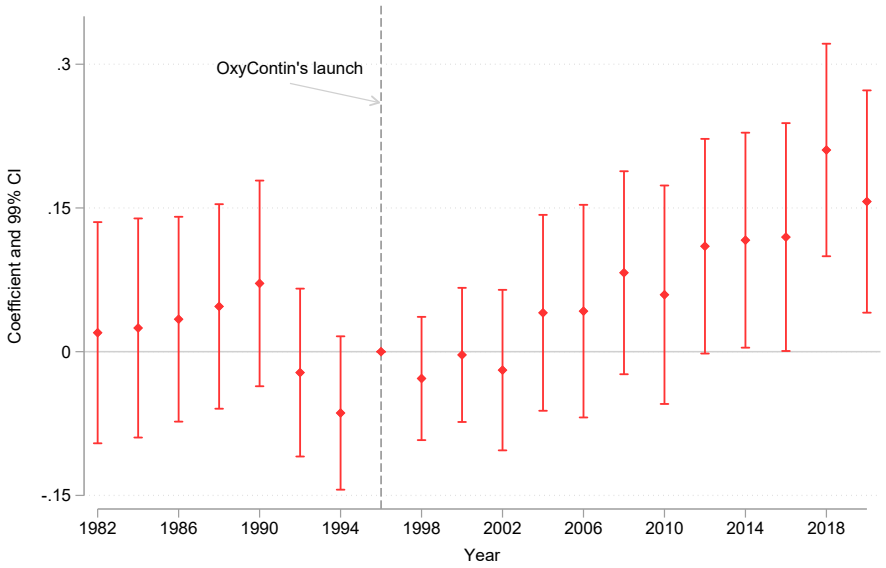
(b) Effects of Mid-Nineties Cancer-Market Targeting



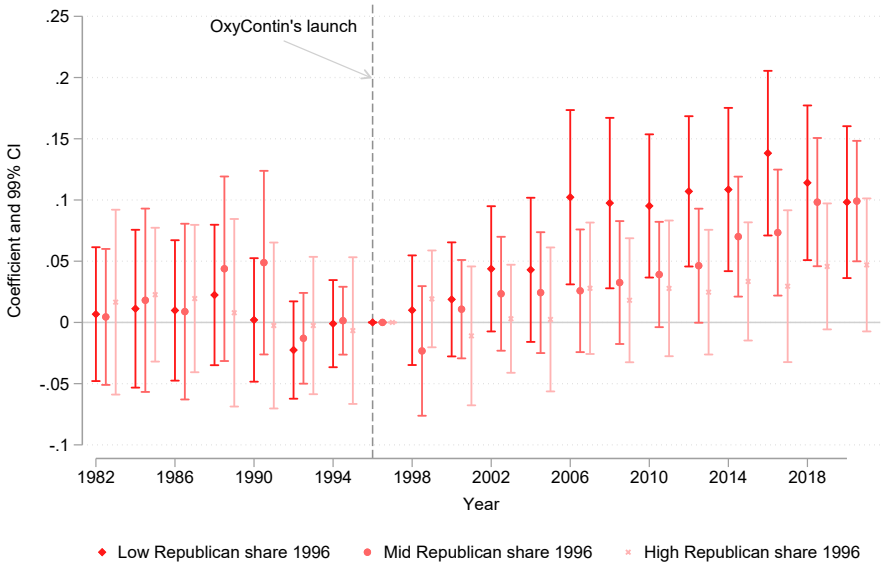
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in congressional elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality, our proxy of exposure to the opioid epidemic. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1976}, \phi_{1977}, \ldots, \phi_{1995}$) are jointly equal to zero. The p value of these tests is presented in the figures. This figure is referenced in Section V.

Figure 4: Congressional Elections: Mechanisms

(a) Republican candidate wins a seat in House elections

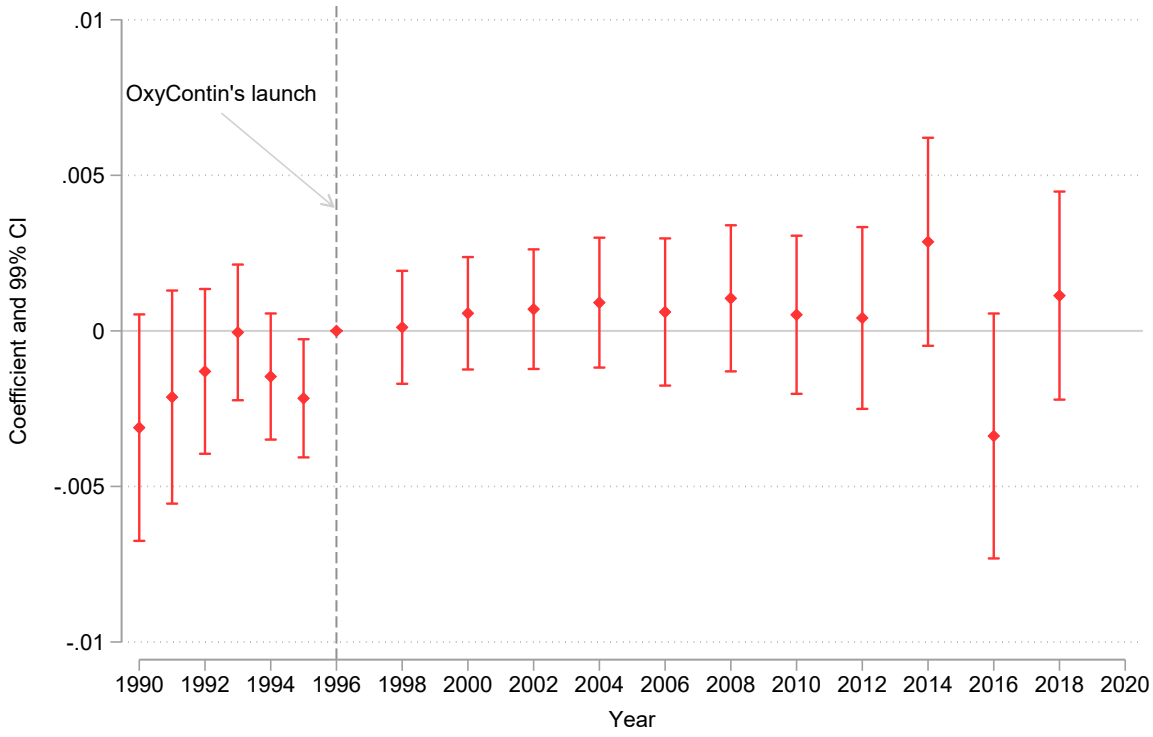


(b) Effects by Tercile of 1996 Republican Vote Share



Notes: Panel (a) presents estimates of the dynamic relationship between the probability that a Republican candidate wins a seat in House elections and cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality by the initial level of Republican support in 1996 house elections. This figure is referenced in Section V.

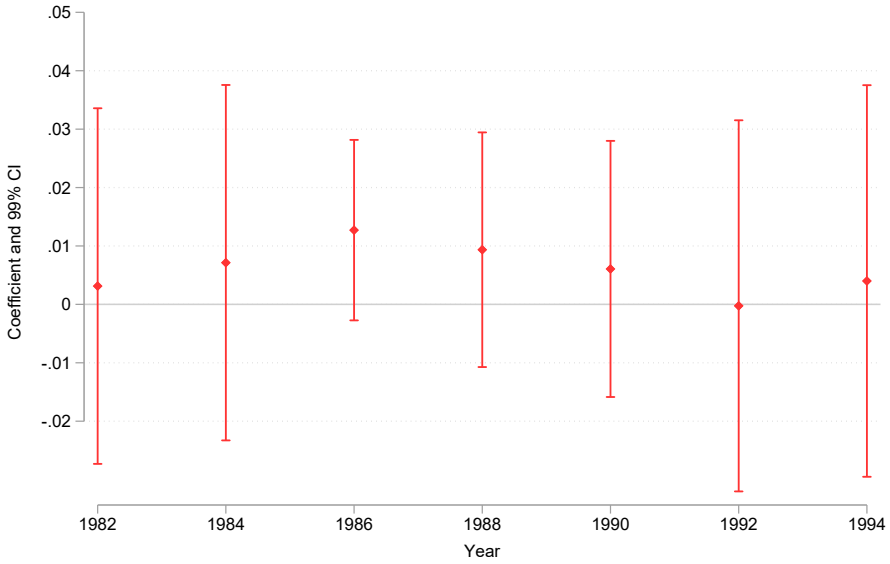
Figure 5: Commuting Zone Out Migration Flows



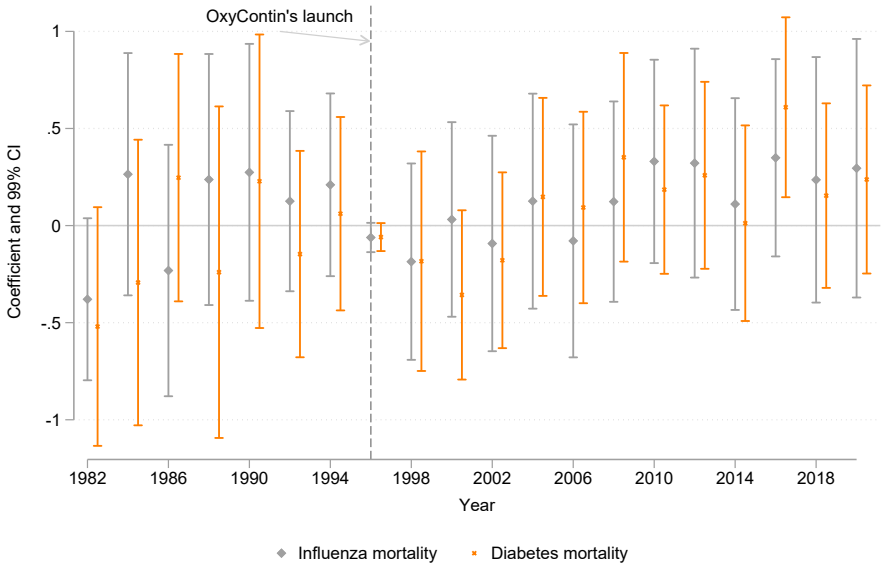
Notes: TBA. This figure is referenced in Section V.

Figure 6: Placebo checks: Out of Sample and Placebo Mortality Rates

(a) Out of Sample Analysis



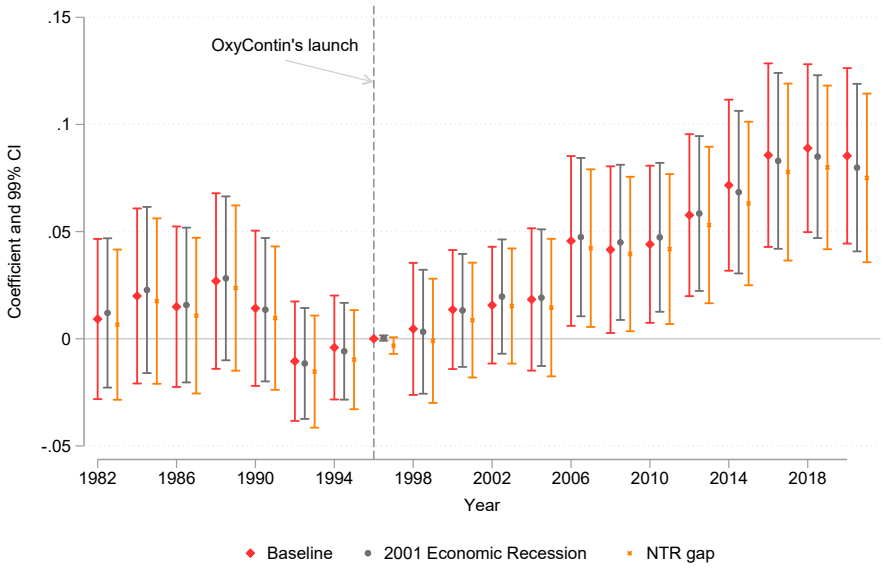
(b) Influenza and Diabetes Mortality



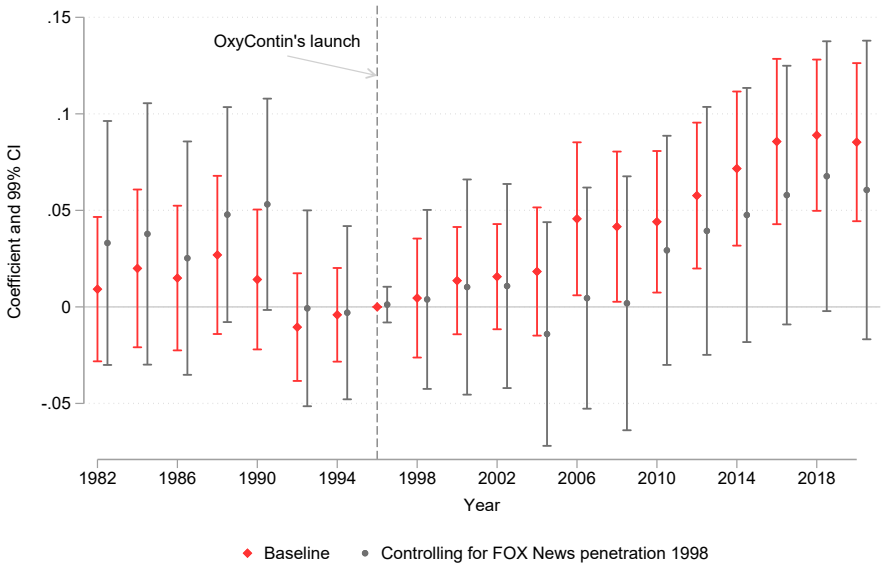
Notes: Panel B presents estimates of the dynamic relationship between Republican vote share and under 50 mortality from influenza or diabetes. This figure is referenced in Section VI.

Figure 7: Robustness Checks - Congressional Elections. Economics Shocks and Introduction of Fox News

(a) Exposure to "China Shock" and 2001 Economic Recession



(b) Introduction of Fox News



Notes: Panel A of this figure presents the baseline estimates of the relation between the share of votes for Republican candidates and cancer mortality along with estimates when we control for exposure to permanent normal trade relations to China—termed the China shock in the trade literature—and the 2001 Economic Recession. We follow Pierce and Schott (2020) and construct a measure of exposure to trade liberalization as the difference between the non-NTR rates to which tariffs could have risen prior to PNTR and the NTR rates that were locked in by the change in policy. A higher NTR gap indicates a larger trade liberalization after the passage of PNTR. We construct a measure of exposure to the recession as the change in the unemployment rate from 2001 to 2000 at the commuting zone. Panel B presents the baseline estimates of the relation between the share of votes for Republican candidates and cancer mortality along with estimates when we control for Fox News initial coverage. This figure is referenced in Section VI.b.

IX. Tables

Table 1: Summary Statistics

	1982 - 1995			1996 - 2020		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
Doses of prescription opioids per capita[(a)]				5.9293	4.9612	4.9227
Cancer mortality per 1,000 (1996)				2.5466	2.5369	0.7606
Cancer mortality per 1,000	2.4185	2.4100	0.5834	2.4846	2.4950	0.5834
Prescription opioids mortality per 10,000[(b)]	0.0652	0.0000	0.1320	0.3488	0.2291	0.4487
Sh. of Republican votes	0.4522	0.4665	0.2131	0.5659	0.5782	0.1798

Notes: This table presents summary statistics the main dependent variables and our measure of exposure to the opioid epidemic for the period before and after the launch of OxyContin. *(a)* data on prescription opioids per capita are available from 1997, *(b)* we construct prescription opioids mortality from 1989. This table is referenced in Section III.

Table 2: Baseline determinants of the level of opioids, Cancer MR & Republican vote share

	Prescription opioids doses (1)	Cancer Mortality (2)	Republican Vote (3)
Sh. of population 50 - 64	41.0454**	4.7878***	-0.5082
	[18.4087]	[1.5183]	[0.3531]
Sh. of population over 66	-26.2889***	3.4932***	0.3088
	[6.561]	[1.3023]	[0.2203]
Sh. White	4.4661***	-0.0889	0.179***
	[0.9896]	[0.1639]	[0.0402]
Sh. Hispanic	-4.1063***	-0.5909***	-0.228***
	[1.0224]	[0.1618]	[0.0454]
Sh. Female	9.2741	0.074	-0.1843
	[10.3161]	[1.2976]	[0.3444]
Opioid mortality	-3.3355	1.1189	-0.0064
	[8.5179]	[1.0779]	[0.2138]
All non-cancer mortality	162.3809	219.0142***	-13.8439***
	[159.1855]	[35.1966]	[3.8794]
Sh. HS diploma or less	-2.8517	-0.466	0.1842**
	[2.1032]	[0.3745]	[0.0762]
Sh. empl in manufacture	-3.3379***	0.2269	-0.0568
	[1.0988]	[0.1591]	[0.0414]
Ln. income	1.1896	0.183	-0.0188
	[0.8234]	[0.1489]	[0.0339]
Employment rate	-7.0423	-1.5961*	0.7307***
	[5.1255]	[0.8786]	[0.2476]
Labor force participation	-5.9111*	-0.8192**	0.2989***
	[3.5619]	[0.3978]	[0.0961]
Cancer mortality rate	0.0707		0.0101
	[0.4097]		[0.0104]
Dep. var mean	2.5333	2.8419	0.4427

Notes: This table presents estimated coefficients from a cross-section regression of the main dependent variables on demographic and economic characteristics and crime and health outcomes at the commuting-zone level. Standard errors are robust to heteroskedasticity. *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Section III.

Table 3: Mid-nineties Cancer Mortality and Preferences

	Immigration	Abortion	Immigration	Abortion
	(1)	(2)	(3)	(4)
Cancer 1996	-1.082	-0.0203	-1.736***	-0.0404*
	[0.806]	[0.0395]	[0.579]	[0.0230]
Obs	39,026	104,475	144,326	190,304
CZ	319	439	615	615
Period	1982-1994	1982-1994	1996-2020	1996-2020
Source	ANES	ANES	ANES	ANES

Post-period	Immigration	Abortion	Gun Control	Own Ideology
	(1)	(2)	(3)	(4)
Cancer 1996	-0.0675***	-0.0460***	-0.0562***	-0.191***
	[0.0139]	[0.0173]	[0.0152]	[0.0517]
Obs	59,390	59,420	59,424	54,777
CZ	610	610	610	607
Period	2020	2020	2020	2020
Source	CCES	CCES	CCES	CCES

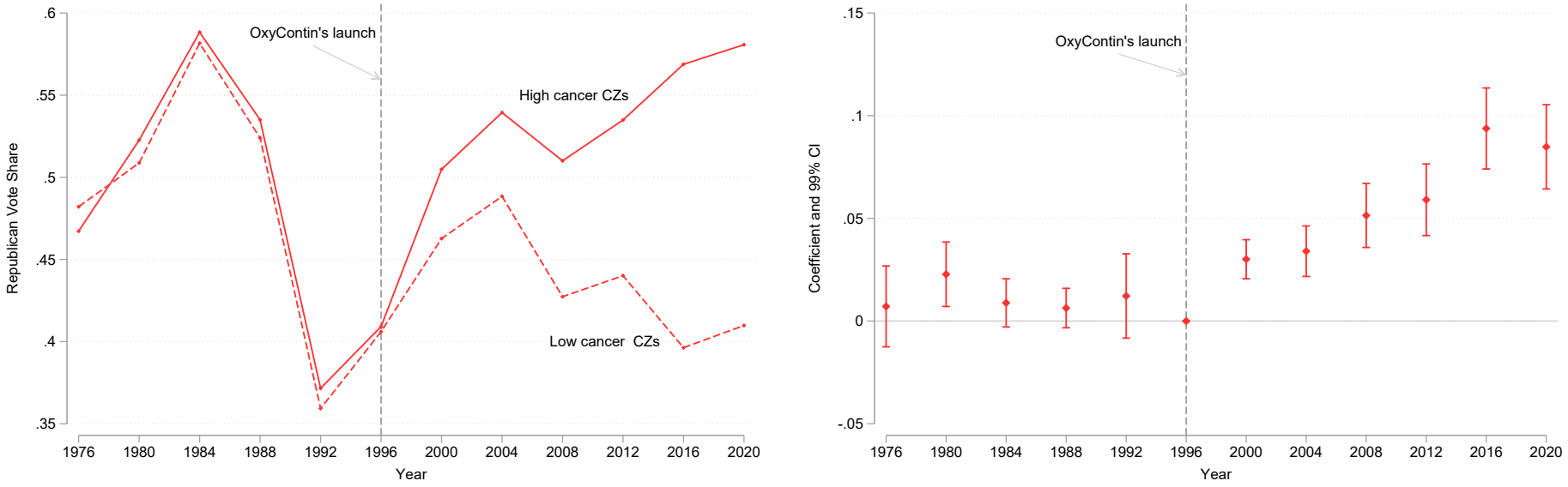
Notes: All variables are coded such that higher variables represent liberal/progressive views. ANES Immigration is the thermometer regarding illegal immigrants. ANES Abortion: By law, when should abortion be allowed? Takes values 1 to 4 where 1 corresponds to: By law, abortion should never be permitted, and 4: By law, a woman should always be able to obtain an abortion as a matter of personal choice. Immigration CCES: Increase the number of border patrols on the US-Mexican Border. 1 Against, 0 Support. Abortion CCES:1= Always allow a woman to obtain an abortion as a matter of choice; 0 otherwise. Gun Control CCES: Ban assault rifles. 1 Support; 0 against. Own ideology CCES. . *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Section III.

A Additional Figures

Figure A1: Republican Vote Share: Presidential Elections

(a) Trends in High versus Low Cancer Mortality CZs

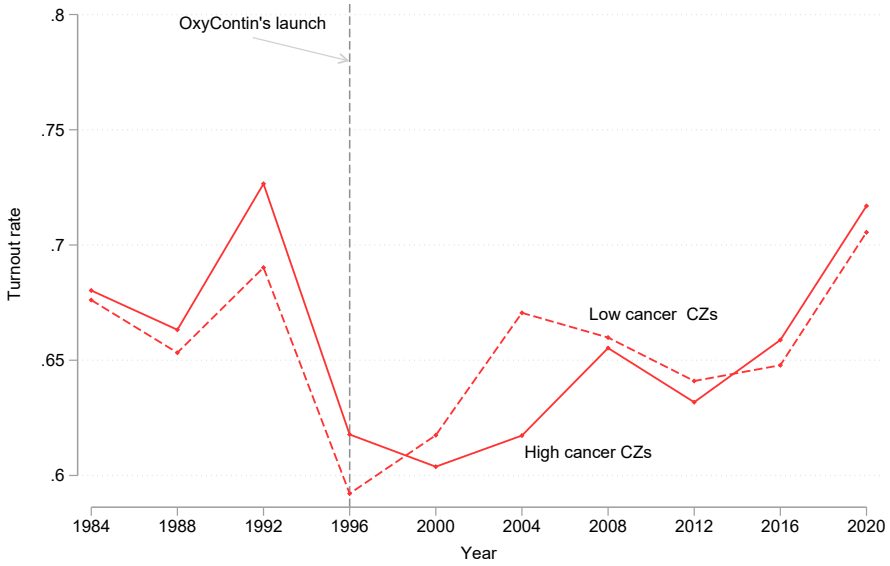
(b) Effects of Mid-Nineties Cancer-Market Targeting



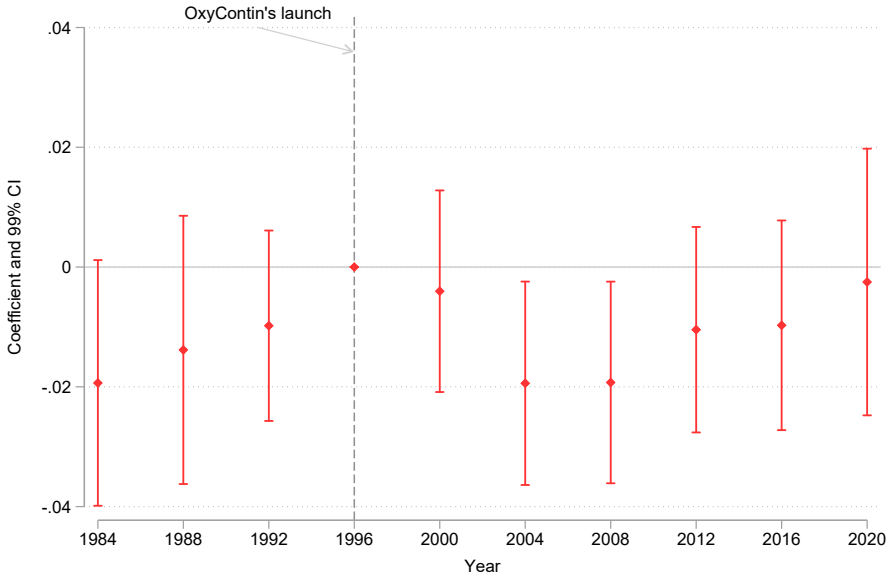
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality, our proxy of exposure to the opioid epidemic. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1976}, \phi_{1977}, \ldots, \phi_{1995}$) are jointly equal to zero. The p value of these tests is presented in the figures. This figure is referenced in Section V.

Figure A2: Turnout Rates

(a) Trends in Turnout.

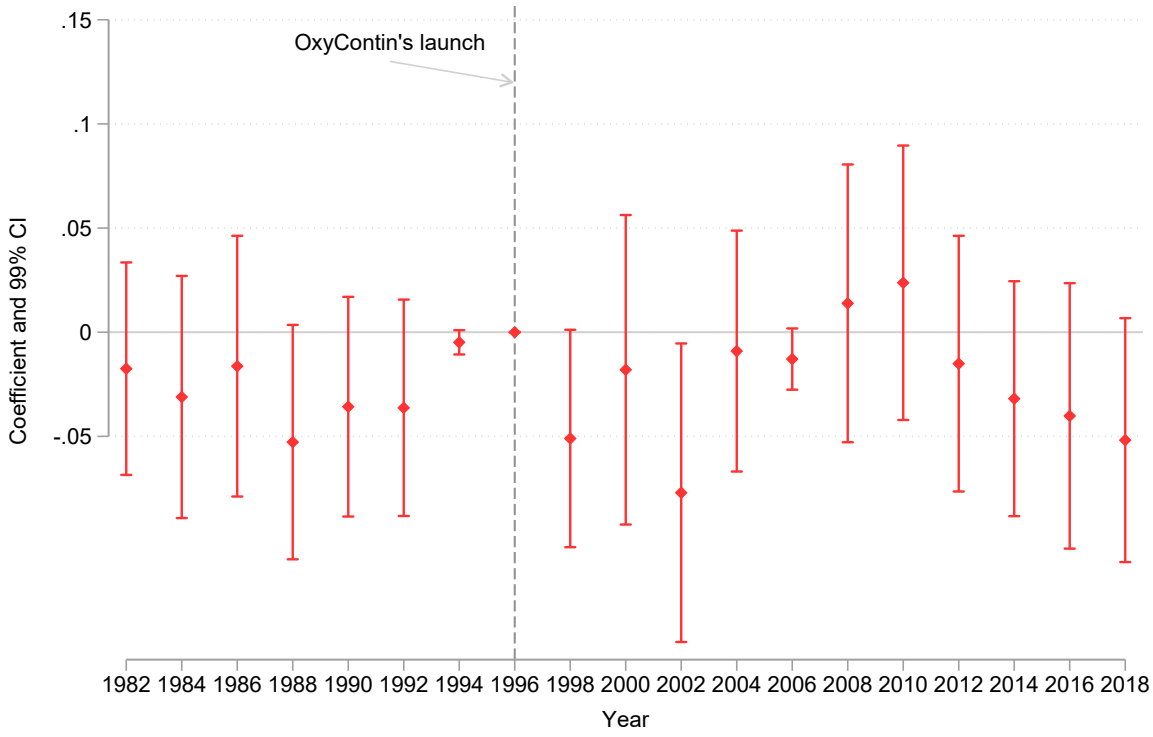


(b) Event Study Approach.



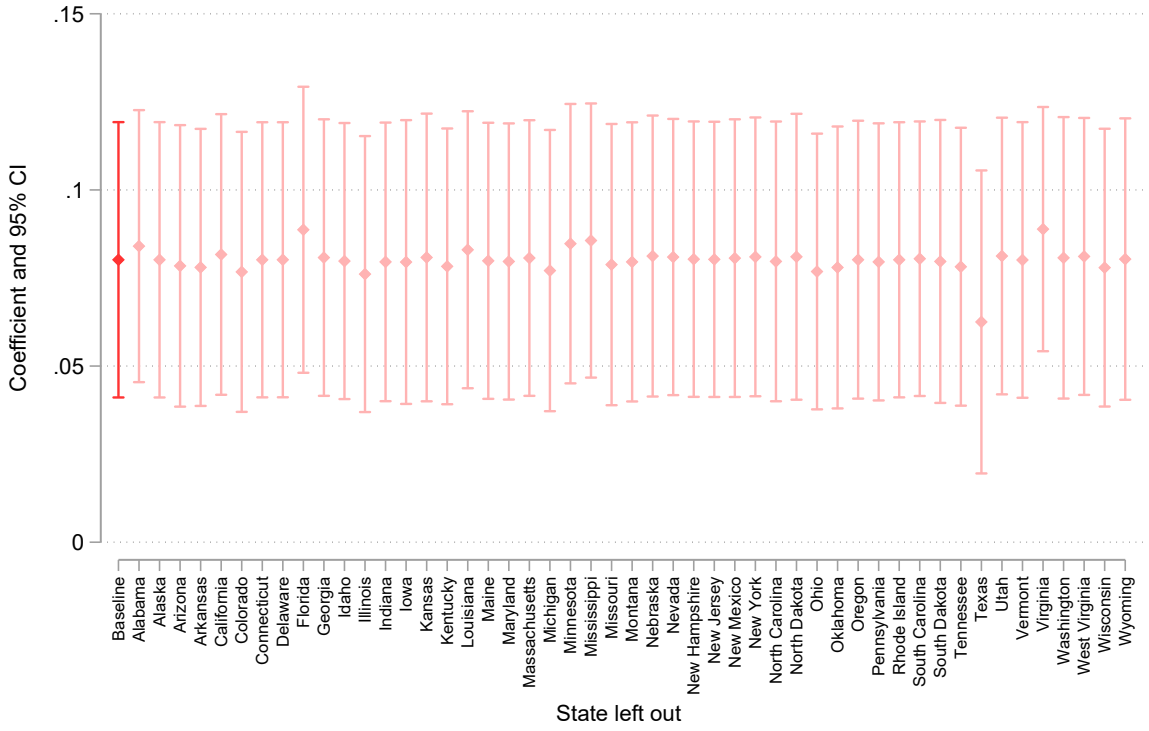
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turn out rates and cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.

Figure A3: Immigration Speeches Tone



Notes: Lower values represent more anti-immigrant tone. This figure is referenced in Section V.

Figure A4: 2020 coefficients: Leave one state out



Notes: This replicates e.q 1 leaving one state out, one at a time.VI.