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Democracy and The Opioid Epidemic

By Carolina Arteaga, Victoria Barone

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Carolina Arteaga*
Victoria Barone†

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Abstract

This paper estimates the effects of the opioid epidemic on political outcomes by leveraging rich geographic variation in exposure to the crisis. We study its effect on the Republican vote share in House and presidential elections from 1982 to 2020. Our results suggest that greater exposure to the opioid epidemic continuously increased the Republican vote share, starting in the early 2000s. This higher vote share translated into additional seats won by Republicans in the House from 2014 until 2020, as well as House members holding more conservative views. These effects are explained by voters changing their views rather than by compositional changes.

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*Department of Economics, University of Toronto (carolina.arteaga@utoronto.ca).
†Department of Economics, University of Notre Dame (mbarone2@nd.edu).
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I. Introduction

The opioid epidemic stands as one of the most tragic public health crises in the United States over the past century, resulting in staggering health and socioeconomic costs (Cutler and Glaeser, 2021; Maclean et al., 2020). Since its onset in 1996, exposure to the epidemic has led to increased mortality, disability, and poverty, triggering changes in family formation and household composition. In the last two decades, this has set communities more exposed to the crisis onto divergent demographic and socio-economic paths (Arteaga and Barone, 2023). The unfolding of the epidemic coincides with a historical moment of enhanced partisanship and polarization in the United States. Survey data show 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).

Historical and contemporaneous evidence shows that communities experiencing deteriorating health and rising death rates are more likely to support radical political views, turn to right-leaning candidates and to experience increases in out-group anymosity. For example, worsening mortality rates in Germany in the early 1930s are associated with increasing votes for the Nazi Party (Galofré-Vilà et al., 2021). Voigtländer and Voth (2012) document persistent anti-Semitic attitudes and behaviors in towns and cities more affected by the Black Death. More recently, support for Donald Trump in the 2016 presidential election has been shown to strongly correlate with stagnated life expectancy and mid-life mortality (Monnat, 2016; Bilal et al., 2018; Goodwin et al., 2018; Bor, 2017, and Siegal, 2023). This paper addresses the question of whether there is a causal relationship between the opioid epidemic and the increase in polarization and Republican support in the last two decades.

Establishing this causal relationship is challenging since deteriorating socioeconomic conditions can both lead to an increase in demand for opioids (Ruhm, 2019; Currie and Schwandt, 2021) and can fuel anti-establishment sentiment and support for the far right (Blickle, 2020). To overcome this challenge, we exploit rich geographic quasi-exogenous variation in the exposure to the opioid epidemic to provide causal evidence of its effects on political outcomes. Our approach exploits detailed features of the initial marketing of prescription opioids, which we obtained from unsealed court records drawn from litigation against Purdue Pharma, the manufacturer of OxyContin —a prescription opioid at the center of the epidemic. Those records show OxyContin that at the dawn of the opioid epidemic in 1996, pharmaceutical marketing efforts were concentrated in the cancer pain market with a plan to quickly expand to the much larger non–cancer pain market in those *same* geographic areas. Furthermore, the pharmaceutical industry's later strategy to target top opioid prescribers—those in the highest deciles of the distribution—meant that these initial targets always received more marketing even when attention was not on the cancer pain market. This targeting implied that noncancer patients in high-cancer areas were disproportionately exposed to the opioid epidemic and the unfortunate chain of events that followed. Our identification assumptions is that areas with higher cancer mortality in 1996 would have exhibited the same trends in political outcomes as areas with lower cancer mortality. As in Arteaga and Barone (2023), we use cancer mortality in 1996, before the unfolding of the epidemic as a measure of exposure. This, and work that followed show that mid-nineties cancer mortality captures the impacts on opioid prescriptions and opioid-related mortality.[1]

To estimate the causal effects of the exposure to the opioid epidemic on political outcomes, we collect data from multiple sources and construct a panel of commuting zones covering the United States from 1982 to 2020.[2] We use county-level data on political outcomes 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 combine these data with two surveys on political views, the American National Election Survey (ANES) and the Cooperative Congressional Election Study(CCES). To measure opioid prescriptions at the commuting zone level, we use data from the DEA on the distribution of controlled substances. Finally, we construct cancer and opioids mortality from the National Vital Statistics System (NVSS).

We find that exposure to the opioid epidemic substantially increased the Republican vote share in congressional and presidential elections. We document that the relationship between cancer mortality and Republican vote share emerged soon after the onset of the opioid epidemic. After continuous years of increase, by the 2020 congressional elections, a rise of one standard deviation in the 1996 cancer mortality rate corresponds to an increase in the Republican vote share of 13.8 percentage points. Using survey data, we document that this shift towards the Republican party and away from the Democrat party, was similar across age, gender, and education levels. These increases were initially concentrated in communities with relatively low support for Republicans, and it took several terms for the incremental gains to change election outcomes. We estimate that greater initial exposure to the opioid epidemic translated by 2012 into a higher number of seats in House elections for the Republican party. These changes increased the conservative leaning of the House of Representatives, measured by legislative roll-call voting by members of Congress. We also observe a positive wedge in favor of the Republican party in terms of the number of individual House campaign donations. This difference is the

[1] See Buckles et al. (2022); Siegal (2023); Cohle and Ortega (2023); Olvera et al. (2023), among others.

[2] Commuting zones are geographic areas defined to capture local economic markets. They encompass all metropolitan and nonmetropolitan areas in the US. While less granular than counties, they are much more granular than states.

result of the decline in donations to Democrat candidates, with no effects observed for Republicans. Presidential elections follow a similar pattern in terms of vote share. We do not find any effects on turnout rates.

Next we investigate what are the mechanism behind these changes in voting patterns. First, we explore changes in population composition. Exploiting migration flow data, we document that areas with high versus low exposure to the opioid epidemic did not exhibit differential trends in terms of inflow or outflow migration. Second, we also reject that our results are mechanically driven by the direct mortality effects. Back-of-the-envelope calculations suggest that by 2020, the vote share for Republicans would have changed at most by 0.22 percentage points. Instead, we find evidence that supports the hypothesis that voting patterns result from changes in views and political preferences. We use survey data from CCES and ANES to measure this ideological realignment. Specifically, we estimate that exposure to the epidemic translated into an increase in affective polarization and a rise in conservative views across the board, measured as views on immigration, abortion, gun control, self-declared ideology, and Fox News viewership.[3]

What explains these changes in views? First, work in psychology—particularly the social identity and intergroup threat theories—propose that shared experiences of hardship strengthen in-group identity, alter the perceived distance between groups, and increase affective polarization, which indeed we observe in our findings.[4] Second, when these experiences are the result of "relative deprivation"—i.e., the discrepancy between what people think they deserve and what they think they actually receive—outgroup antagonism and hostility increase (Gurr, 2015). The opioid epidemic is an example of such shared hardship, which, to some extent, resulted from the negligent and criminal behavior of physicians, pharmaceutical companies, and public institutions.[5] Shared hardship and relative deprivation have the potential to influence shifts in political preferences. In fact, studies by Mian et al. (2014) and De Bromhead et al. (2013) establish a connection between adverse economic shocks and the rise of polarization and far-right support.

The validity of the identification strategy requires that in the absence of prescription opioid marketing, areas with higher cancer mortality in 1996 would have exhibited the same trend as areas with lower cancer mortality in terms of our outcome variables. To support this assumption, we present estimates of reduced-form event studies of the relationship between the Republican vote share and 1996 cancer mortality and test for differential trends in the pre-period. We find no relationship between our instrument and political outcomes from 1982 to 1994, the period before the introduction of OxyContin and the start of the opioid epidemic. However, soon after, communities started to drift

[3]Affective polarization refers to the extent to which citizens feel more negatively toward other political parties than toward their own (Iyengar et al., 2019).

[4]See Struch and Schwartz (1989); Brewer (2001); Bastian et al. (2014); and Nugent (2020).

[5]Former government officials have been implicated in cases of corruption and negligence around the opioid epidemic Quinones (2015).

apart in terms of Republican vote share as a function of their exposure to the opioid epidemic. This event study design also allows a transparent display of our results.

In addition we provide several falsification tests that support our empirical strategy. First, we perform an out-of-sample exercise using 1980 cancer mortality and reproduced our empirical strategy in the pre-period from 1982 to 1994. We do not find any evidence of a relationship between lagged cancer mortality and future Republican support. Second, we construct placebo mortality rates in 1996 from unrelated causes of death and replicate our main specification; we show that our results are not driven by these other health trends that are not connected to the opioid epidemic. Third, we control for concurrent economic and political shocks that have been documented to affect political outcomes, such as exposure to Chinese import competition, economic recessions, unionization rates and the introduction of Fox News. Our estimates are robust to the inclusion of these variables as controls.

This paper creates a bridge between a literature in political economy and in health economics, to connect two of the most salient social developments in the the United States over the past three decades: the rise in polarization and the change in the political landscape, and the aftermath of the opiod epidemic. We contribute to the literature on the socio-economic determinants of political preferences and ideological views. Previous work has studied the effects of economic conditions, globalization, trade, automation and immigration in political ideology and polarization (Brunner et al., 2011; Voorheis et al., 2015; McCarty et al., 2016; Margalit, 2019; Autor et al., 2020; Rodrik, 2021; Che et al., 2022; Guriev and Papaioannou, 2022; among others). Closer to our work is the 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 outgroup polarization and support for the far right. We provide evidence on the effects of the opioid epidemic on political outcomes and views, specifically on the rise in Republican party support and its consequent effects on polarization and ideology. This paper shows how the disparate community effects of a major public health crisis in the United States translated into divergent political preferences, increased affective polarization, and strengthened the distance along conservative-liberal lines between the more and less exposed communities. Finally, this paper also contributes to the literature on the community-level effects of the opioid epidemic. Previous work has documented its effects on poverty, disability, employment, crime, municipal finances, house prices, fertility, and children's outcomes: see, for example, Park and Powell (2021); Buckles et al. (2022); Arteaga and Barone (2023); Ouimet et al. (2020); Cornaggia et al. (2022); Custodio et al. (2023), among others, and Maclean et al. (2020) for a review.

II. Background: Opioid Epidemic & Political Landscape

This section discusses the causes and the community-level impacts of the opioid epidemic and it links the former to the rationale behind our empirical strategy. It also presents the main trends in political expressions and partisanship in the United States that took place concurrently with the opioid epidemic.

II.a. The Unfolding of the Opioid Epidemic

The United States has experienced an unprecedented crisis related to the misuse of and addiction to opioids. As of 2022, over 700,000 lives had been lost to opioid overdoses (CDC, 2023). During the last decade, a sizeable body of research has studied the origins of the opioid crisis and the factors that shaped its evolution and propagation. This literature has established that the pharmaceutical industry and healthcare providers played a critical role in the origins of the crisis (Eichmeyer and Zhang, 2020; Miloucheva, 2021; Alpert et al., 2022; Arteaga and Barone, 2023). In particular, the aggressive and deceptive marketing of potent opioids with high potential for addiction directed toward physicians, in a setting with financial incentives for doctors to increase prescriptions and with weak monitoring, created the perfect platform for the crisis to unfold.

The beginning of the opioid epidemic is traced to the introduction of OxyContin to the market in 1996 (Quinones, 2015). OxyContin is a prescription opioid manufactured by Purdue Pharma that changed the standard of practice for the treatment of noncancer and nonterminal pain. Prior to the mid-1990s, pain management had 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 the MS Contin market and gain ground in the noncancer pain treatment market, in which opioids were almost absent (OxyContin Launch Plan, September 1995). However, efforts at establishing the use of OxyContin for moderate and chronic pain faced clear challenges. First, considerable fear and stigma remained in relation to the use of opioids for nonterminal or noncancer pain. Second, physicians and pharmacies had to overcome administrative barriers to prescribe and sell Schedule II drugs.[6] As a result, pharmaceutical marketing efforts focused on the physicians and pharmacists who faced less stigma around opioids and who knew how to navigate the pa-

[6]Schedule II drugs are drugs with a high potential for abuse and that 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).

perwork related to the distribution of Schedule II drugs: those in the cancer pain market. Purdue stated this strategy clearly on repeated occasions, announcing, for example, 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 approach, however, was intended only as Purdue's entry path to the larger noncancer 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 prescribing opioids. Prescribing highly addictive opioids became the standard practice in treating moderate and chronic pain.[7] At their peak, opioid prescriptions 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).

In response to the widespread misuse of prescription opioids and OxyContin, prescription restrictions were tightened, and in 2010 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 toward 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 in the combined heroin and opioid death rate (Evans et al., 2019).

From 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.[8] Indeed, fentanyl-related deaths account for almost

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

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

the entire increase in drug overdose mortality between 2014 and 2021. According to law enforcement nearly all illicit fentanyl is produced abroad and smuggled into the country (O'Connor, 2017). Hansen et al. (2023) document a significant positive relationship between imports and opioid overdose deaths within a state showing that international trade is contributing to the opioid crisis by facilitating the smuggling of fentanyl. In 2020, the majority (69%) of Americans declared the federal government should be doing more about the opioid drug addiction.[9]

II.b. Economic Impacts of the Opioid Epidemic

Mortality from opioids is only one of the many social costs associated with the opioid epidemic. An estimated 10.1 million people in the U.S., aged 12 or older, misused opioids in the past year (SAMHSA, 2020). These numbers are orders of magnitude larger than the number of deaths and suggest potential community-level effects. Krueger (2017) shows that for prime-age men, taking pain medication correlates strongly with being out of the labor force. Exploiting variations in physicians' opioid prescribing tendencies, Ouimet et al. (2020) find that receiving an opioid prescription is associated with a subsequent decline in employment rates.

Over the past 27 years, the opioid epidemic caused widespread disruption to health and economic opportunities, affecting both individuals and communities. Notably, the epidemic has induced increases in disability rates and Supplemental Nutrition Assistance Program (SNAP) utilization (Powell et al., 2020; Savych et al., 2019; Arteaga and Barone, 2023). Ouimet et al. (2020) show that establishments in areas experiencing high opioid growth are subsequently characterized by lower sales and employment growth. Olvera et al. (2023), Dave et al. (2021) and Sim (2023) show that exposure to lax regulations surrounding opioid prescriptions contribute to homelessness and a rise in violent crime. These added economic distress translated into broader economic impacts through their effects on municipalities' access to capital (Cornaggia et al., 2022), house prices (D'Lima and Thibodeau, 2022; Custodio et al., 2023), mortgage credit access (Law, 2023) and innovation (Cohle and Ortega, 2023). Finally, through its impacts on increased fertility rates, a higher rates of child protective services investigations and a larger number of children living without their parents, the epidemic will also affect future generations (Buckles et al., 2022; Arteaga and Barone, 2023; Pac et al., 2022). Such community-level economic distress may contribute to shifts in political attitudes and preferences.

[9] The question in the 2020 ANES was: Do you think the federal government should be doing more about the opioid drug addiction issue, should be doing less, or is it currently doing the right amount? This was the first time this question was included.

II.c. Trends in Political Expression and Partisanship

Contemporaneous to this developments, 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 US exhibits the larger increase in affective polarization since the 1980s compare to other developed democracies. According to Boxell et al. (2022), in 1978 the average partisan rated in-party members 27.4 points higher than out-party members on a "feeling thermometer" ranging from 0 to 100; this difference was 56.3 by 2020. While cultural distance has been broadly constant over time across various demographic divisions, liberals and conservatives are more different today in their social attitudes than they have ever been in the last 40 years (Bertrand and Kamenica, 2023).[10]

Support for partisan leaders is increasingly divided along party lines. The differences in presidential approval ratings across parties—i.e., the approval rate of Democrats in regards to a Republican president and vice versa—were 81 and 70 points for presidents Donald Trump and Barack Obama, respectively. This figure is almost twice as high as the 38 points for president George H.W. Bush in the early 1990s (Jones, 2021). The political parties have sorted, meaning, liberal Republicans and conservative Democrats have largely disappeared (Fiorina, 2016). At the same time, the partisanship of language used by members of the Congress has sharply increased (Gentzkow et al., 2019; Card et al., 2022).

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), and the introduction of widely available decentralized propaganda or "fake news" (Azzimonti and Fernandes, 2018). They are also the result to increased exposure to conservative and pro-Republican Party media, as a consequence of the introduction and expansion of Fox News (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Clinton and Enamorado, 2014). Changes to the economic structure such as the decline in manufacturing and increased import competition from China have also played a role (Autor et al., 2020; Che et al., 2022). Globalization shocks, often working through culture and identity, have also contributed to this shift (Rodrik, 2021). This paper explores an additional channel: the drifting trends in the health and socio-economic outlooks of communities brought by differential exposure to the opioid epidemic.

[10] In this context, social attitudes refer to views related to the role of government in society, e.g., government spending, or views related to civil liberties, such as abortion.

III. Data and Descriptive Statistics

Our goal is to estimate the effects of exposure to the opioid epidemic on political preferences and polarization. To achieve this, we construct a panel of commuting zones from 1982 to 2020, pooling together data on House and Presidential election results, donations to candidates, political views, our measure of exposure to the epidemic—1996 cancer mortality—and direct measures of the opioid epidemic, such as opioid mortality and prescription rates.

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 the ICPSR. Combining these datasets, we construct three main outcomes: the Republican vote share for congressional 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 for the Republican party in the mid-1990s. Panel (d) shows changes in the Republican vote share in 2020 relative to that in 1996. Table 1 shows summary statistics in the pre and post periods for Republican vote shares, seats in the House and turnout. Throughout this period, Republicans increased their representation, particularly in the House, where the average vote share went from 45% to 56%. Turnout remained generally stable, experiencing a modest decline from 66% to 64%.

We use the Database on Ideology, Money in Politics, and Elections (DIME) by Bonica (2023) to construct per capita rates of individual campaign donations to House races by party, spanning the years 1982 to 2016. These data provides unique individual identifiers, with geo-located addresses and details on the contribution amount, campaign, and candidate it supports. We aggregate the count of individual campaign contributions directed toward Republican or Democrat candidates in House races, and divide this by the number of voting age population.

To measure the ideology of House members we leverage data from Lewis et al. (2023). This repository includes information on all individual votes cast by members of the Congress on rollcalls along with an estimation of the member's ideology.[11] We use the Nokken-Poole estimate, these estimates are based on the NOMINATE model, which places each member along a primary liberal–conservative axis that describes preferences over of taxation, spending and redistribution.[12]

[11] As of January 22, 2018, the Voteview.com database includes information on all 24,174,546 individual votes cast by 12,297 members on 105,721 rollcalls over the Congress's 229-year history.

[12] For further discussion of the NOMINATE model see Poole and Rosenthal (1985) and Poole (2005). In particular, the Nokken-Poole estimate is well suited to measure of how members of Congress may

We construct measures of political views and preferences of the public using survey data from the American National Election Study (ANES), and the Cooperative Congressional Election Study (CCES). These are nationally representative election surveys. In particular, ANES includes a measure of partisan thermometers and CCES provides measures of individual views regarding highly political issues, such as, support for gun control, support of access to abortion, and immigration policy, among others issues.

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.[13] From these data, we construct a commuting zone–level per capita measure of grams of prescription opioids, including oxycodone, codeine, morphine, fentanyl, hydrocodone, hydromorphone, and meperidine. Figure 1 and Table 1 show geographic variation in 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.[14] Panel (b) of Figure 1 shows the geographic distribution of prescription opioid mortality from 1999 to 2018.

Geographic harmonization. Electoral outcomes and mortaliy data are accessed at the county level, we use the crosswalks developed by Autor and Dorn (2013) to aggregate the data at the commuting zone level.[15] Survey data from the ANES and the CCES, and data on house ideology are collected at the electoral district level. We use the crosswalks developed by Ferrara et al. (2021) to compute the outcomes of interest at the commuting zone level. This second step serves to purposes, i) the pure harmonization in a common geographic unit; and ii) accounts for redistricting of congressional districts since Ferrara et al. (2021) provide year-specific crosswalks.[16]

have changed their ideological positions over time since the scores are generated allowing members to hold different positions in each Congress, see Nokken and Poole (2004).

[13]The 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.

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

[15]Some commuting zones cross state borders. When this happens, the commuting zone is assigned to the state where the higher share of the zone's population is located. This criterion helps to preserve the strong within-cluster and weak between-cluster commuting ties.

[16]Congressional district boundaries are established by states after the apportionment of congressional seats. Each congressional district is to be as equal in population to all other congressional districts in a state as practicable.

In sum, our final dataset consists of a panel of 625 commuting zones from 1982 to 2020.[17] We restrict our sample to areas with more than 20,000 residents, which account for more than 99% of all opioid deaths and 99% of the total population.

Cross-sectional correlations at baseline. In Table 2, we present regression equations that summarize the correlates of the geographic distribution of these variables at baseline, in 1996. First, the level of prescription opioids per capita is related to the demographic composition of the commuting zone. A greater white population share at the commuting zone level has a positive correlation with prescription opioids per capita; the Hispanic population share and the manufacturing share of employment have a negative correlation with the opioid supply. In terms of cancer mortality, we find that it is strongly related to share of the population over 65, negatively associated with the Hispanic population share, and positively associated with mortality from other causes of death. It does not, however, show a cross-sectional correlation with opioid mortality. Finally, the Republican vote share in 1996 is positively correlated with the white population share 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 variation in opioid epidemic exposure driven by the marketing practices of prescription opioid manufacturers. Following, the insights drawn from the disclosure of internal documents of Purdue Pharma and other pharmaceutical companies, we proxy the exposure to the epidemic using cancer mortality in the mid-1990s. For each outcome variable, we consider the following specification, which is run over our sample of commuting zones:

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

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, the white and female population shares, the shares of the population aged 18–29, 30–49, 50–64, and above 65 years, and the share of the population aged under 1 year; all of these measured at the commuting zone level.

$CancerMR_{ct_0}$ 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

[17] The ARCOS data are available for years from 1997, so the analyses using this measure are restricted to a later period.

coefficients for the pre-OxyContin period, i.e., ϕ_{1982}, ϕ_{1983}, to ϕ_{1994}, test whether the outcome of interest y_{ct} followed similar trends in areas with higher and lower cancer mortality before the launch of OxyContin. The main coefficients of interest are ϕ_{1998}, ϕ_{2000} , to ϕ_{2020}, which measure the effect of a higher cancer mortality rate in 1996—i.e., higher exposure to the opioid epidemic—on the outcome of interest by time t.

The term γ_{st} represents state-by-year fixed effects. These fixed effects control for state-specific trends and the state-level policy changes that were common during this period that directly affected the supply of opioids—e.g., the implementation of prescription drug monitoring programs (PDMPs), the regulation of "pill mill" clinics, and policies on the availability of naloxone[18]—as well as the evolution of our outcome variables.

The validity of our research design relies on two assumptions: (i) that cancer mortality in the mid-1990s is a good predictor of the growth in opioid supply and tracks opioid mortality and (ii) that, in the absence of OxyContin marketing, areas with higher cancer mortality in the pre-OxyContin period would have exhibited the same *trends* as areas with lower cancer mortality in the outcomes of interest (Goldsmith-Pinkham et al., 2020).[19]

IV.b. Is Mid-1990s Cancer Mortality a Good Proxy for Exposure to the Opioid Epidemic?

We start by showing the evolution of prescription opioids per capita by cancer mortality in 1996 in Figure 2. Commuting zones in the top quartile of cancer mortality in 1996 saw an increase of 2,900% in oxycodone gm per capita, while areas in the lowest quartile experienced growth that was one-third of that magnitude, 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-1990s cancer mortality and shipments of prescription opioids per capita.

The connection between cancer mortality and opioid shipments tracks opioid-related mortality. When we inspect the raw data, Panel (c) of Figure 2 shows that areas in the top and bottom quartiles of cancer mortality experienced a similar evolution in terms of prescription opioid mortality before the launch of OxyContin. We observe for the early 2000s, however, a wedge between these areas starting to appear. Additionally, we find that areas with higher cancer mortality in the mid-1990s were not on a differential trend in opioid-related mortality: the estimates for the pre-OxyContin period are indistinguishable from zero. In contrast, for the years after 1996, strong patterns appear, and mid-1990s cancer mortality starts to predict opioid-related mortality.

[18] See, for example, Buchmueller and Carey (2018) and Doleac and Mukherjee (2019).

[19] The identification assumptions of our research design are close to those of shift-share instruments. As Goldsmith-Pinkham et al. (2020) discuss, in these models identification is based on the exogeneity of the shares that measure differential exposure to common shocks. Using a Bartik instrument is "equivalent" to exploiting the shares as an instrument. We present the dynamic reduced-form estimates of such IV model.

V. Results

V.a. Exposure to the Opioid Epidemic and Voting

House elections. The opioid epidemic caused an increase in the share of votes for the Republican party in congressional elections. We start by presenting evidence using raw data. We split commuting zones into quartiles based on cancer incidence in 1996. Panel (a) of Figure 3 shows no difference in the pre-1996 Republican vote share between areas with high and low cancer mortality. However, soon after the introduction of OxyContin, there is an increase in the share of Republican votes in high-cancer areas. The pattern illustrated in the raw data translates into a statistically significant increase in the GOP vote share starting in 2006. Our results suggest that higher exposure to the epidemic—i.e., a one standard deviation higher cancer mortality rate—translates to a 13.8 percentage point increase in the share of votes for the Republican party (see Panel (b) of Figure 3).

Demographic Heterogeneity. We use survey data from 2006 to 2020 from the CCES to examine the heterogeneity of our effects along voters' socio-demographic characteristics.[20] We start by replicating our baseline result on voting Republican in the CCES data. Panel (a) in Figure 4 shows that we find very similar results using this alternative data source. Next, we divide the sample across gender, age, and educational attainment level. Panels (b) to (d) in Figure 4 show that along all of these characteristics, we estimate similar-sized effects and higher Republican vote share.

Election wins and geographic heterogeneity. Whether increases in the Republican vote share translate into election wins depends on how contested districts are and how much the vote increases. We show that even though the Republican vote share started to increase in 2006, it is only for years from 2012 that we start to observe evidence of an increase in the probability of a Republican win (Panel (a) of Figure 5). The main reason behind this pattern is that the initial increases in vote share were concentrated in communities with a low baseline Republican vote share (Panel (b) of Figure 5). Starting in 2014, there began to be vote share increases in communities with a median level of initial vote share, and these increases are more likely to flip election results.

Campaign Donations. As an additional measure of effects on partisanship, we construct the number of donors per capita to House campaigns for Republican and Democrat candidates at the commuting zone level. In Figure 6, we replicate Equation 1 and find that the opioid epidemic created a positive wedge in favor of the Republican party in terms of the number of donations per capita. This difference is the result of the decline in donations to Democrat candidates, with no effects observed for Republicans. In terms

[20] When using these data we can only estimate coefficients on the interaction between 1996 cancer mortality rates and year dummies for the post-period 2006 to 2020. The outcome of interest is defined in levels due to the lack of baseline data to compute long changes.

of the amount of the donation, we do not estimate any effects for either party (See Figure **??**).

House members views. The changes in vote share and additional seats won by the Republican Party translated into an elected group of House members with more conservative views. We use data from Lewis et al. (2023) to asses the evolution of elected candidates ideology, measured from roll-call votes along the liberal–conservative dimension. An increase in this measure means more conservative views. In Figure A1, we document that exposure to the opioid epidemic increases conservative views in the House, and that this increase is concentrated in districts with lower baseline Republican support.

Presidential elections and turnout. The epidemic's effects on House elections are also present in presidential election results. From the raw data, the Republican party vote share in communities in the top and bottom quartiles of the 1996 cancer incidence distribution trended similarly until the mid-1990s (Figure A2). By the 2000 election, there is a wedge in Republican support that widens as time goes on, and by 2020, the gap in GOP vote shares in areas with high relative to low cancer mortality is greater than 0.15 points. We estimate that an increase of one standard deviation in cancer mortality in the baseline period increased the share of votes for a Republican candidate in presidential elections by 12 percentage points.These increases in vote share are not driven by differential changes in the extensive margins measured by turnout. We document no notable changes along this margin in Figure A3.[21]

V.b. Mechanims Driving Changes in Voting & Candidate Support

Do these changes primarily result from shifts in the composition of the electorate pool or from changes in voter views? To investigate the first hypothesis, we examine the role of migration. We collect data on county-to-county migration flows from the IRS Statistics of Income (SOI) Tax Stats and calculate total out-migration and in-migration flows at the commuting-zone level. Figure 7 estimates equation 1 and shows that opioid epidemic exposure is not related to differential in or out-migration patterns. That is, high vs low cancer commuting zones did not experience differential migration flows either before or as a result of the opioid epidemic. However, we cannot rule out whether there are changes operate differentially by party ideology; i.e., we can not account for the party-alignment composition of these flows.

Second, we consider a back of the envelope calculation to test if our results are mechanically driven by the direct mortality effect of the epidemic. We estimate what would be the change in the Republican vote share if the missing votes due to opioid related deaths would have voted (i) for the Democrat party or independent candidates and (ii) for the Republican party. Thus, we accumulate all opioid related deaths since 1996—the

[21] We do not report turnout pre-trends or effects for congress as data is not available for mid-term elections from 1990 to 1998.

year OxyContin is introduced to the market—and compute the counterfactual Republican vote share under each assumption. This would at most have changed in 0.22 percentage points relative to the observed vote share in 2020. In contrast, our point estimates suggest that the opioid epidemic increased the Republican vote share in 13.8 percentage points by 2020 when cancer increases in one standard deviation.

To investigate the hypothesis of changes in views we use survey data from the CCES in 2020. For this cross-sectional exercise we report the coefficients on 1996 cancer mortality. In columns (3) to (7) of Table 3, we find that exposure to the epidemic predicts more conservative views in terms of immigration, abortion, and gun control, and more conservative self-reported ideology. This suggests that the wedge between communities that we document in terms of Republican vote share was also accompanied by a broader polarization and change in political views.[22]

V.c. What Explains These Changes in Views?

First, we consider whether differences in attributions of responsibility for the opioid epidemic, or in the importance each party gave to address the crisis, could explain the movement towards or away of one party. According to a YouGov survey, in 2022, both Democrats (74%) and Republicans (66%) predominantly held drug dealers who illegally sell opioids responsible for the opioid epidemic (YouGov, 2022). For Democrats this is followed by pharmaceutical companies and physicians. In contrast, Republicans blame next the people addicted to opioids and pharmaceutical companies. Neither party sees the government as the primary culprit in the epidemic. Turning to the role of differential party-level responsiveness, Stokes et al. (2021) analyze more than 40,000 state legislators' opioid-related social media posts from 2014 to 2019 using natural language processing models. They find that the volume of Democrats' and Republicans' opioid-related posts were equally correlated with state overdose death rates.[23] This suggests that neither of these channels is responsible for the shift towards Republican support we find.

Second, we also consider whether our results are driven by anti-incumbent sentiment, as voters may hold elected officials accountable for the impact of the epidemic on their communities. In Figure A5, we split the sample by party, according to who is in power at the time of each election, and replicate our baseline estimation.[24] The results of this analysis are noisy, particularly in the later years of our period of analysis, owing to the decreasing proportion of commuting zones with Democrat incumbents. However, there

[22] As an additional measure of in-group identity we look at church attending behavior, both in the ANES and the CCES data. We do not find any evidence of changes in church attending behavior.

[23] There are differences in each party's policy response to the crisis. Democrats advocate for imposing financial penalties on pharmaceutical companies, along with increased funding for opioid use disorder (OUD) treatment and recovery. In contrast, Republicans focus on addressing the illegal drug trade, particularly across international borders.

[24] In case a commuting zone covers more than one congressional district, we split by the party that has the majority of house members.

is limited evidence supporting the hypothesis that increases in Republican vote share are a response to anti-incumbent sentiment when Democrats are in power.

Next, we turn to insights from work in psychology that have been brought to economics when explaining the connection between economic hardship and right wind support and polarization (De Bromhead et al., 2013; Mian et al., 2014; Autor et al., 2020). Specifically, the social identity and intergroup threat theory, suggest that shared experiences of hardship strengthen in-group identity, change the perceived distance between groups, and increase affective polarization (Struch and Schwartz, 1989; Brewer, 2001; Bastian et al., 2014; Nugent, 2020). Furthermore, when such hardship is the result of relative deprivation, anger is triggered, and this has been shown to decrease cognitive processing and increase reliance on heuristics and stereotypes (Carver and Harmon-Jones, 2009). Anger also involves attributions of blame, which could be directed at political groups or institutions (Allred, 1999; Keltner and Lerner, 2010). We hypothesize that the opioid epidemic and the erosion of economic opportunities and deterioration of own and surrounding health that followed, can trigger this cognitive processes.

We bring this mechanisms to data using the ANES from 1982 to 2020, to construct a measure of affective polarization following Boxell et al. (2022). This measure is constructed as the distance between *warm* feelings to ones own party versus the opposition party. To estimate the effect of exposure to the opioid epidemic on affective polarization, we interact cancer mortality in 1996 with a dummy that takes value one after the onset of the opioid epidemic—post 1996. In column 1 of Table 3, we show the results and find that exposure increases affective polarization.[25]

Finally, with the introduction and rise of Fox News, the period of the opioid epidemic has been marked by an increase in the exposure to conservative and pro-Republican Party media. At the same time, a transformation in the narrative and platform of a faction within the Republican Party took place. This transformation, which was fuelled and supported by Fox News, sought to rebrand conservative principles as representative of the working class, and fostered anti-elite and anti-establishment sentiments (Peck, 2019). This narrative speaks to a segment of society that has witnessed a decline in their relative socio-economic standing, partly due to external factors. For communities that have experienced higher exposure to the opioid epidemic, this message may resonate particularly well. Indeed, in Column 8 of Table 3, we find that exposure to the opioid epidemic predicts Fox News viewership. This is an additional channel that can further reinforce out-group antagonism and Republican support as shown by DellaVigna and Kaplan (2007); Clinton and Enamorado (2014); and Martin and Yurukoglu (2017).

[25] Throughout 1982 to 2020 there are no changes in the questions that are used to construct the measure of affective polarization, and these questions were always included the survey. This is not the case for other measures of ideology, so we move to the CCES for that analysis.

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 the future Republican vote share in the absence of the opioid epidemic. To do so, we perform an out-of-sample dynamic reduced-form analysis for the years in our pre-period. That is, we run equation 1 over a sample of commuting zones for the years 1982 to 1994 and estimate whether lagged cancer mortality—namely, cancer mortality rate in 1980—predicts our outcome variables for the years of interest. We present the results of this analysis in Panel (a) of Figure 8. These results demonstrate that before the onset of the opioid epidemic, there was no relationship between the Republican vote share and lagged cancer mortality: the estimated coefficients are statistically indistinguishable from zero.

Our identification strategy connects mid-1990s cancer mortality to future exposure to the opioid epidemic. Thus, we can test the validity of our design by estimating event study regressions with 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 that of 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, especially among elderly age groups. With this caveat, in Panel (b) of Figure 8, we show placebo instrument regressions for under-65 influenza and diabetes mortality rates, which are less likely to be affected by the previous concern. We find no relationship between these placebo mortality rates and the post-1996 Republican vote share.

VI.b. Economic Shocks and the Introduction of Fox News

At the same time as the opioid epidemic was unfolding, the United States economy faced increased import competition from China, unionization rates were declining, Fox News was introduced, two economic recessions occurred, and the adoption of robotic technology advanced significantly. Previous work has documented the effects of these events on political preferences and polarization, as well as the heterogeneity in their geographic exposure. Potentially, some of our results could reflect the exposure to these shocks instead of the effects of the opioid epidemic. This sub-section addresses this concern by estimating our baseline specification with additional controls capturing geographic exposure to those events. In each exercise, we add a measure of exposure to a particular economic change interacted with year-dummies to flexibly control for this shock.

First, we assess whether the 2001 economic recession mediates 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 in the commuting zone. In this same vein, we follow Yagan (2019) to construct a measure of the severity of the Great Recession. This measure is a function of the percentage point change in the commuting zone unemployment rate between 2007 and 2009.[26] We find that our estimates do not change when controlling for exposure to these economic shocks (see Figure 9).

We use commuting zone level union rates in 2000 constructed by Connolly et al. (2019) to assess whether some of the effects we estimate could be attributed to a correlation between our measure of exposure to the opioid epidemic and broader dynamics related to the political effects of the decline in unionization rates. Figure 9 also incorporates a specification where union membership rates are added as an additional control, and we find that our results remain unaffected.

In October 2000, the US Congress passed a bill granting permanent normal trade relations (PNTR) with China. This trade liberalization's 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 more significant declines in employment, 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 policy change. A higher NTR gap indicates larger trade liberalization after the passage of PNTR. Our findings are unaffected by the inclusion of this variable in our specification (see Panel (b) of Figure 9).

Additionally, robotics technology advanced significantly in the 1990s and 2000s, leading to a fourfold rise in the stock of (industrial) robots in the United States. We exploit exposure measures to robotic technology adoption constructed by Acemoglu and Restrepo (2020) to assess whether its adoption mediates our effects. Panel (b) of Figure 9 shows that our main estimates remain unaffected when we control for this exposure.[27]

Finally, as we mentioned, 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 higher initial exposure to Fox News increases the Republican vote share in the 2000 presidential elections. If Fox News's initial coverage

[26]We take this measure directly from the replication package in Yagan (2019). In its construction, the author computes the annual commuting-zone unemployment rate, calculated by averaging monthly unemployment rates. These are constructed by summing monthly county-level counts of the unemployed and the number of people in the labor force across counties within a commuting zone.

[27]We take this measure directly from the replication package in Acemoglu and Restrepo (2020)—see Figure 4 and equation 18—the authors exploit variation in industry-level adoption of robots weighted by employment shares.

is correlated with cancer incidence, it is possible that some of the effects that 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 estimates. The data in DellaVigna and Kaplan (2007) cover only 60% of commuting zones, so there is a substantial loss of sample size, making the results noisy. However, the point estimates are very similar to those from our baseline specification ran over a sample that includes only commuting zones for which data on Fox News coverage is available (see Figure 10).

VI.c. Alternative Samples and Specifications

In our main specification, we restrict our sample to areas with more than 20,000 residents, which represent 99.5% of the total population. We reproduce our analysis using alternative restrictions on the size of commuting zones. We arrive at conclusions analogous to the main analysis: a strong and positive relation exists between mid-1990s cancer mortality and the post-1996 Republican vote share (see Figure A6).

We also examine whether the relationship we observe is contingent on any particular state. In Figure A7, we present coefficient estimates corresponding to 2020 and demonstrate that our findings remain robust when excluding any individual state. Furthermore, we exclude commuting zones in i) the Appalachian region, given its disproportionate impact by the epidemic (Shiels et al., 2020), ii) the Rust Belt, characterized by significant de-industrialization (Alder et al., 2014), and iii) the South, where a shift towards the Republican party occurred during the analysis period (Hill and Tausanovitch, 2018). Our analysis does not reveal evidence of our results being driven by any specific region.

We replicate our main specification using either population weights or votes weights, and we find that both pre-trends and our effects estimations are unaffected (see panel (a) of Figure A8). We also present estimates of the main effects without the inclusion of vector the vector ΔX_{ct}, i.e., only adding states times year fixed effects. We also estimate our main specification expanding the vector of controls to include interactions with the share of population over 65 years old in 1996 interacted with year dummies. Both of these exercises provide the same conclusions as the baseline specification. Finally, we provide estimates using age-adjusted cancer mortality rates as a measure of exposure to the epidemic and arrive at similar conclusions (see panel (b) of Figure A8).

VII. Discussion

The opioid epidemic stands as one of the most tragic events in recent U.S. history. Its effects extend beyond the direct loss of life and extend to the economic and political life of the communities most affected. We exploit rich quasi-exogenous geographic variation in the exposure to the opioid epidemic, uncovered from unsealed internal documents from the pharmaceutical industry. Specifically, we demonstrate that the industry exploited the lower stigma surrounding opioid use in cancer patients to increase opioid prescriptions for non-cancer patients in the same communities, seen by the same doctors. A later marketing practice that targeted high-prescribers, created a path dependency from this initial exposure. We use mid-'90s cancer mortality at the commuting-zone level as a measure of this initial exposure. Past research has shown that this exposure predicts opioid prescriptions, opioid deaths, SNAP, disability claims, crime, homelesness, employment, and household structure changes. Here, we document that the opioid epidemic set communities on different trajectories in terms of their political support. Places that looked very similar in the mid-90's, by 2020 saw a substantial gap in their Republican-Democrat preferences, as a function of their exposure to the epidemic. Specifically, we find that the opioid epidemic increased Republican vote shares and started to flip elections by 2012. A one standard deviation higher level of 1996 cancer mortality increased Republican vote share by 13.8 percentage points in the 2020 congressional elections. This gap was accompanied by an increase in polarization on 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 indicates how it will continue to shape these communities through its effects on their elected officials and inter-group perceptions. This adds to a rich literature on the economic determinates of political preferences, where factors such us inequality, trade, unemployment and income level have been studied, but where health has received less attention. We hope this work inspire further research into the political and long-term consequences of health disparities and health shocks. This becomes particularly crucial in a landscape where vaccination is increasingly divided along party lines, and as result disease exposure and mortality becomes politicized.

References

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and jobs: Evidence from US labor markets." *Journal of Political Economy*, 128(6): 2188–2244.

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

Alder, Simeon, David Lagakos, and Lee Ohanian. 2014. "Competitive pressure and the decline of the Rust Belt: A macroeconomic analysis." National Bureau of Economic Research.

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

Allred, Keith G. 1999. "Anger and retaliation: Toward an understanding of impassioned conflict in organizations."

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.

Bastian, Brock, Jolanda Jetten, and Laura J Ferris. 2014. "Pain as social glue: Shared pain increases cooperation." *Psychological science*, 25(11): 2079–2085.

Bertrand, Marianne, and Emir Kamenica. 2023. "Coming apart? Cultural Distances in the United States Over Time." *American Economic Journal: Applied Economics*, 15(4): 100–141.

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).

Bonica, Adam. 2023. "Database on Ideology, Money in Politics, and Elections: Public version 3.0 [computer file]." *Stanford, CA: Stanford University Libraries. Retrieved October*, 1: 2023.

Bor, Jacob. 2017. "Diverging life expectancies and voting patterns in the 2016 US presidential election." *American journal of public health*, 107(10): 1560–1562.

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

Boxell, Levi, Matthew Gentzkow, and Jesse M Shapiro. 2022. "Cross-country trends in affective polarization." *Review of Economics and Statistics*, 1–60.

Brewer, Marilynn B. 2001. "Ingroup identification and intergroup conflict." *Social identity, intergroup conflict, and conflict reduction*, 3: 17–41.

Brunner, Eric, Stephen L Ross, and Ebonya Washington. 2011. "Economics and policy preferences: causal evidence of the impact of economic conditions on support for redistribution and other ballot proposals." *Review of Economics and Statistics*, 93(3): 888–906.

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.

Carver, Charles S, and Eddie Harmon-Jones. 2009. "Anger is an approach-related affect: evidence and implications." *Psychological bulletin*, 135(2): 183.

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

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

Che, Yi, Yi Lu, Justin R Pierce, Peter K Schott, and Zhigang Tao. 2022. "Did Trade Liberalization With China Influence Us Elections?" *Journal of International Economics*, 139: 103652.

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

Clinton, Joshua D, and Ted Enamorado. 2014. "The national news media's effect on Congress: How Fox News affected elites in Congress." *The Journal of Politics*, 76(4): 928–943.

Cohle, Zachary, and Alberto Ortega. 2023. "The effect of the opioid crisis on patenting." *Journal of Economic Behavior & Organization*, 214: 493–521.

Connolly, Marie, Miles Corak, and Catherine Haeck. 2019. "Intergenerational Mobility between and within Canada and the United States." *Journal of Labor Economics*, 37(S2): S595–S641.

Cornaggia, Kimberly, John Hund, Giang Nguyen, and Zihan Ye. 2022. "Opioid crisis effects on municipal finance." *The Review of Financial Studies*, 35(4): 2019–2066.

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.

Custodio, Claudia, Dragana Cvijanovic, and Moritz Wiedemann. 2023. "Opioid crisis and real estate prices." *Available at SSRN 3712600.*

Cutler, David M, and Edward L Glaeser. 2021. "When innovation goes wrong: Technological regress and the opioid epidemic." *Journal of Economic Perspectives*, 35(4): 171–196.

Dave, Dhaval, Monica Deza, and Brady Horn. 2021. "Prescription drug monitoring programs, opioid abuse, and crime." *Southern Economic Journal*, 87(3): 808–848.

De Bromhead, Alan, Barry Eichengreen, and Kevin H O'Rourke. 2013. "Political extremism in the 1920s and 1930s: Do German lessons generalize?" *The Journal of Economic History*, 73(2): 371–406.

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.

D'Lima, Walter, and Mark Thibodeau. 2022. "Health crisis and housing market effects-evidence from the US opioid epidemic." *The Journal of Real Estate Finance and Economics*, 1–18.

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.

Ferrara, Andreas, Patrick A Testa, Liyang Zhou, et al. 2021. "New area-and population-based geographic crosswalks for US counties and congressional districts, 1790-2020." Competitive Advantage in the Global Economy (CAGE).

Fiorina, Morris P. 2016. "The Political Parties Have Sorted." *A Hoover Institution Essay on Contemporary American Politics*, 1–20.

Galofré-Vilà, G, M McKee, J Bor, CM Meissner, and D Stuckler. 2021. "A lesson from history? Worsening mortality and the rise of the Nazi Party in 1930s Germany." *Public health*, 195: 18–21.

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.

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

Goodwin, James S, Yong-Fang Kuo, David Brown, David Juurlink, and Mukaila Raji. 2018. "Association of chronic opioid use with presidential voting patterns in US counties in 2016." *JAMA Network Open*, 1(2): e180450–e180450.

Guriev, Sergei, and Elias Papaioannou. 2022. "The political economy of populism." *Journal of Economic Literature*, 60(3): 753–832.

Gurr, Ted Robert. 2015. *Why men rebel.* Routledge.

Hansen, Benjamin, Timothy Moore, and William Olney. 2023. "Importing the Opioid Crisis? International Trade and Drug Overdoses." *Working Paper.*

Hill, Seth J, and Chris Tausanovitch. 2018. "Southern realignment, party sorting, and the polarization of American primary electorates, 1958–2012." *Public Choice*, 176(1-2): 107–132.

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

Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J Westwood. 2019. "The origins and consequences of affective polarization in the United States." *Annual review of political science*, 22: 129–146.

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.*

Keltner, Dacher, and Jennifer S Lerner. 2010. "Emotion."

Krueger, Alan B. 2017. "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate." *Brookings Papers on Economic Activity*, 2017(2): 1.

Law, Kody. 2023. "The Opioid Epidemic and Mortgage Lending: Credit or Demand Shock?" *Available at SSRN 4558249.*

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.

Lewis, Jeffrey B, Keith Poole, Howard Rosenthal, Adam Boche, Aaron Rudkin, and Luke Sonnet. 2023. "Voteview: Congressional roll-call votes database." *See https://voteview.com/(accessed 27 July 2023).*

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.

Margalit, Yotam. 2019. "Political responses to economic shocks." *Annual Review of Political Science*, 22: 277–295.

Martin, Gregory J, and Ali Yurukoglu. 2017. "Bias in Cable News: Persuasion and Polarization." *American Economic Review*, 107(9): 2565–99.

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.

Mian, Atif, Amir Sufi, and Francesco Trebbi. 2014. "Resolving debt overhang: Political constraints in the aftermath of financial crises." *American Economic Journal: Macroeconomics*, 6(2): 1–28.

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.

Nokken, Timothy P, and Keith T Poole. 2004. "Congressional party defection in American history." *Legislative Studies Quarterly*, 29(4): 545–568.

Nugent, Elizabeth R. 2020. "The psychology of repression and polarization." *World Politics*, 72(2): 291–334.

O'Connor, Sean. 2017. *Fentanyl: China's deadly export to the United States.* US-China Economic and Security Review Commission.

Olvera, Johabed G, Felipe Lozano-Rojas, Julio Alberto Ramos Pastrana, and Sumedha Gupta. 2023. "Opioids Prescribing Restrictions and Homelessness: Evidence from Hydrocodone Rescheduling." *Available at SSRN 4386200.*

Ouimet, Paige, Elena Simintzi, and Kailei Ye. 2020. "The impact of the opioid crisis on firm value and investment." *Available at SSRN 3338083.*

OxyContin Launch Plan. September 1995. Purdue Pharma.

OxyContin Team Meeting. April 1994. Purdue Pharma.

OxyContin Team Meeting. March 1995. Purdue Pharma.

Pac, Jessica, Christine Durrance, Lawrence Berger, and Deborah B Ehrenthal. 2022. "The Effects of Opioid Use during Pregnancy on Infant Health and Well-Being." *The ANNALS of the American Academy of Political and Social Science*, 703(1): 106–138.

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.

Peck, Reece. 2019. *Fox populism: Branding conservatism as working class.* Cambridge University Press.

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

Poole, Keith T. 2005. *Spatial Models of Parliamentary Voting.* Cambridge University Press.

Poole, Keith T, and Howard Rosenthal. 1985. "A Spatial Model for Legislative Roll Call Analysis." *American journal of political science*, 357–384.

Powell, David, Rosalie Liccardo Pacula, and Erin Taylor. 2020. "How Increasing Medical Access to Opioids Contributes to the Opioid Epidemic: Evidence From Medicare Part D." *Journal of Health Economics*, 71: 102286.

Quinones, Sam. 2015. *Dreamland: The true tale of America's opiate epidemic.* Bloomsbury Publishing USA.

Rodrik, Dani. 2021. "Why does globalization fuel populism? Economics, culture, and the rise of right-wing populism." *Annual Review of Economics*, 13: 133–170.

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

SAMHSA. 2020. "Key Substance Use and Mental Health Indicators in the United States: Results from the 2019 National Survey on Drug Use and Health."

Savych, Bogdan, David Neumark, and Randall Lea. 2019. "Do Opioids Help Injured Workers Recover and Get Back to Work? The Impact of Opioid Prescriptions on Duration of Temporary Disability." *Industrial Relations: A Journal of Economy and Society*, 58(4): 549–590.

Shiels, Meredith S, Zaria Tatalovich, Yingxi Chen, Emily A Haozous, Patricia Hartge, Anna M Nápoles, Eliseo J Pérez-Stable, Erik J Rodriquez, Susan Spillane, David A Thomas, et al. 2020. "Trends in Mortality From Drug Poisonings, Suicide, and Alcohol-Induced Deaths in the United States From 2000 to 2017." *JAMA network open*, 3(9): e2016217–e2016217.

Siegal, Nicole. 2023. "Exposure to Deaths of Despair and US Presidential Election Outcomes."

Sim, Yongbo. 2023. "The effect of opioids on crime: Evidence from the introduction of OxyContin." *International Review of Law and Economics*, 74: 106136.

Stokes, Daniel C, Jonathan Purtle, Zachary F Meisel, and Anish K Agarwal. 2021. "State legislators' divergent social media response to the opioid epidemic from 2014 to 2019: longitudinal topic modeling analysis." *Journal of general internal medicine*, 1–10.

Struch, Naomi, and Shalom H Schwartz. 1989. "Intergroup aggression: Its predictors and distinctness from in-group bias." *Journal of personality and social psychology*, 56(3): 364.

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).*

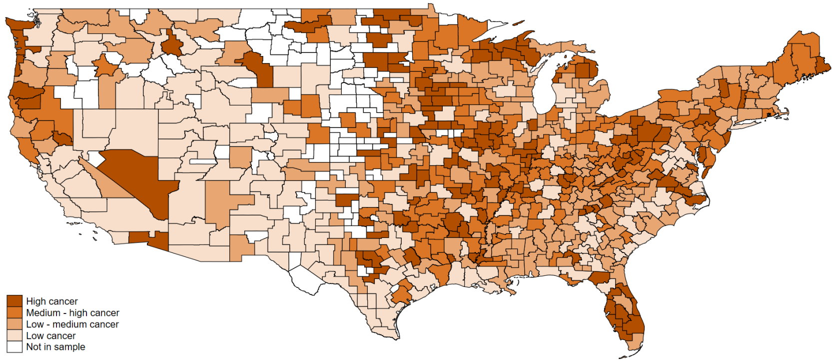
Yagan, Danny. 2019. "Employment Hysteresis from the Great Recession." *Journal of Political Economy*, 127(5): 2505–2558.

YouGov. 2022. "Americans' attitudes on opioid addiction from a May 12 - 16, 2022."

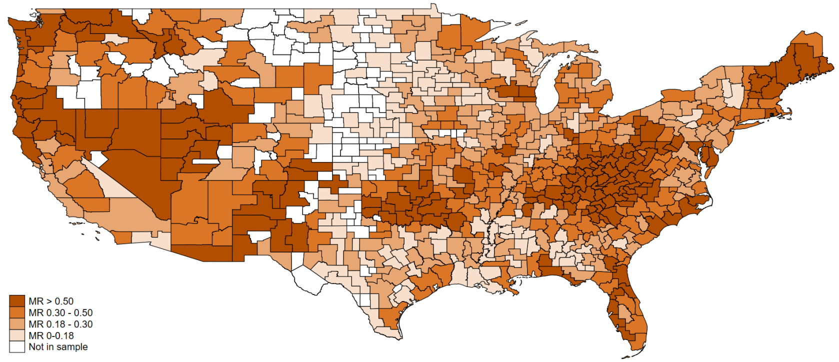
VIII. Figures

Figure 1: Geographical Variation

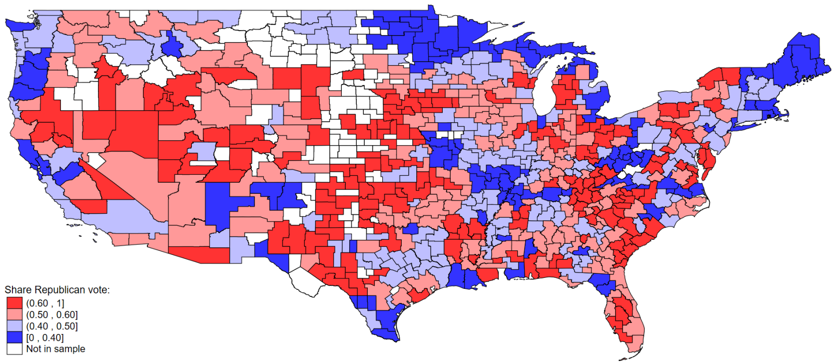
(a) Cancer Mortality Rates, 1996



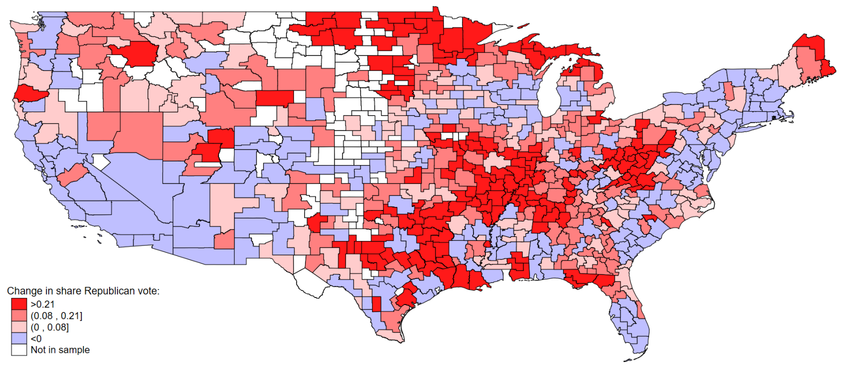
(b) Prescription Opioid Mortality Rate, 1999–2020



(c) Republican Vote Share - Congressional Elections, 1996

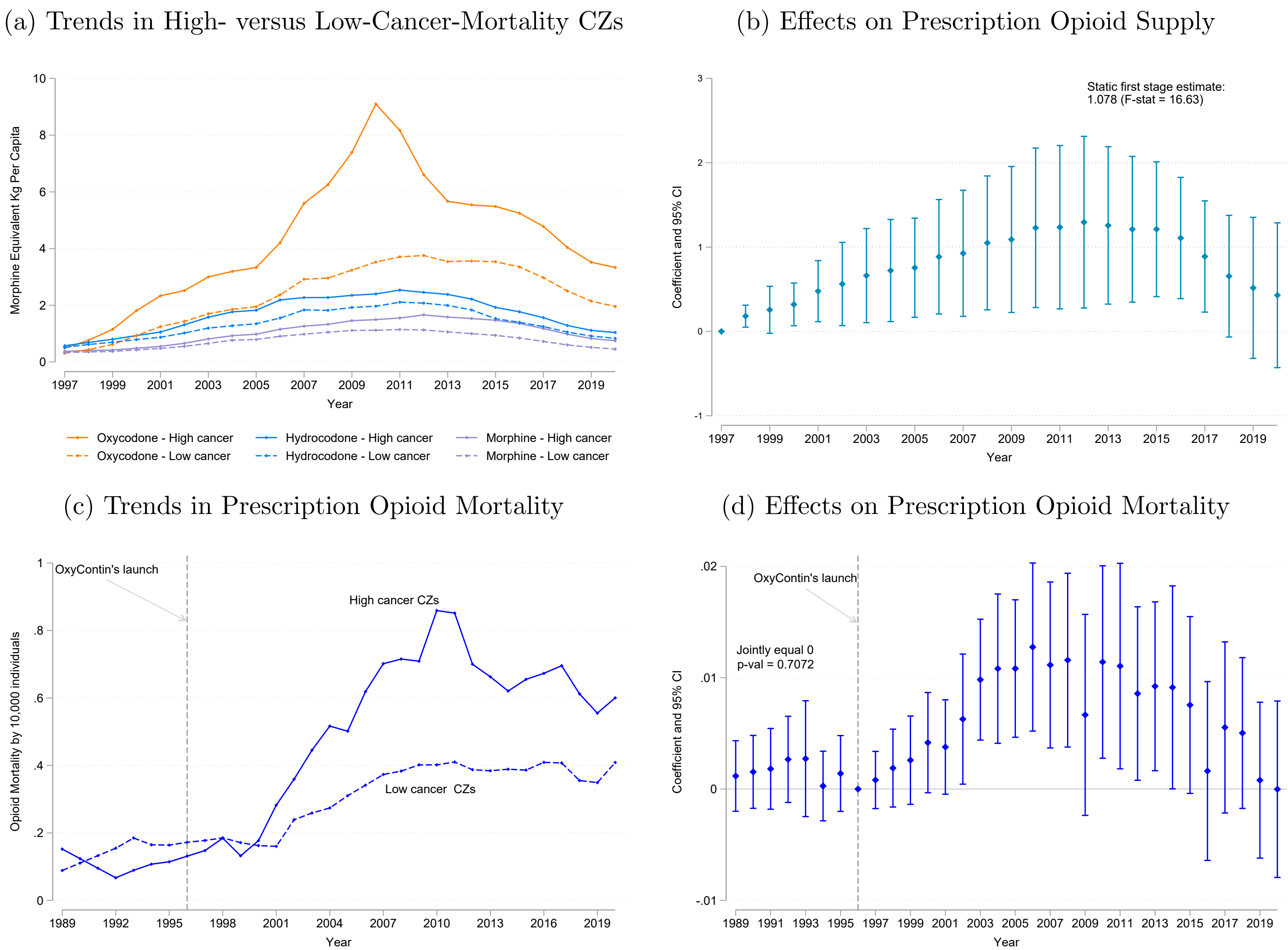


(d) Change in Republican Vote Sh. - Congressional Elections, 2020 – 1996



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). Panel (c) shows the geographic distribution of the Republican vote share in congressional elections, and Panel (d) shoes its evolution between 1996 and 2020. This figure is referenced in Section III.

Figure 2: Effects of Mid-1990s Cancer-Market Targeting on Opioid Dispensing & Mortality

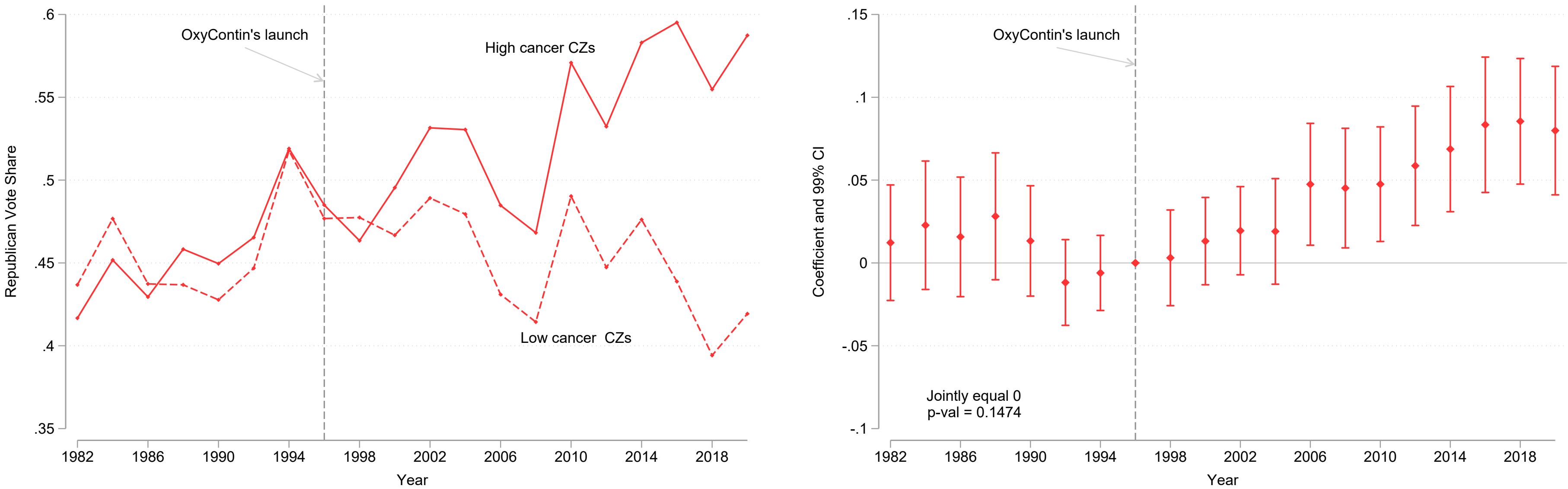


Notes: Panels (a) and (c) show the evolution of the distribution of prescription opioids and mortality in commuting zones (CZs) in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Oxycodone is OxyContin's active ingredient. Panels (b) and (d) show estimates of the effects of mid-1990s cancer-market targeting on the distribution of prescription opioids and mortality. ARCOS data are available from 1997. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1989}, \phi_{1990}, \ldots, \phi_{1995}$) are jointly equal to zero. The p value of this test is presented in the figure. This figure is referenced in Section IV.b.

Figure 3: Republican Vote Share: Congressional Elections

(a) Trends in High- versus Low-Cancer-Mortality CZs

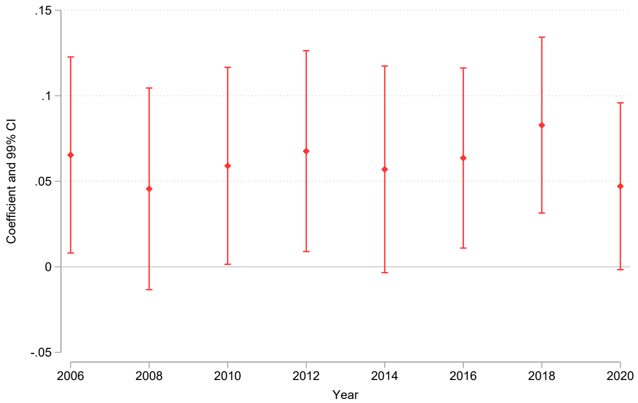
(b) Effects of Mid-1990s Cancer-Market Targeting



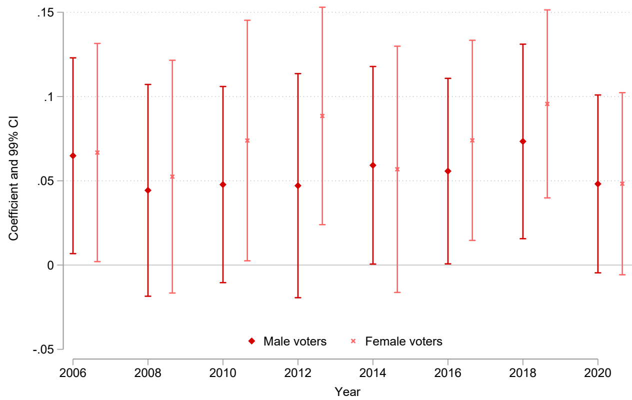
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in congressional elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. 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. The p value of this test is presented in the figure. This figure is referenced in Section V.a.

Figure 4: Demographic Heterogeneity on Effects on Republican Vote Share

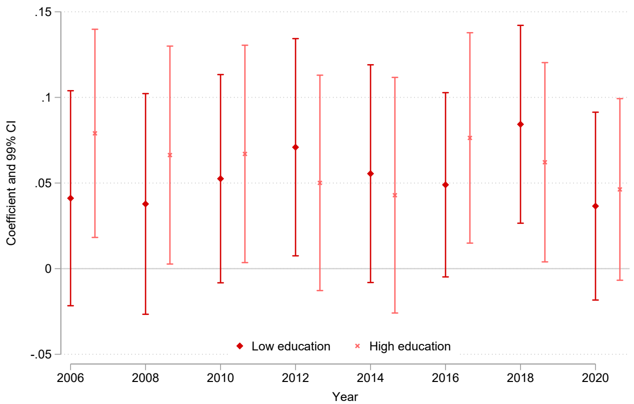
(a) Baseline estimation



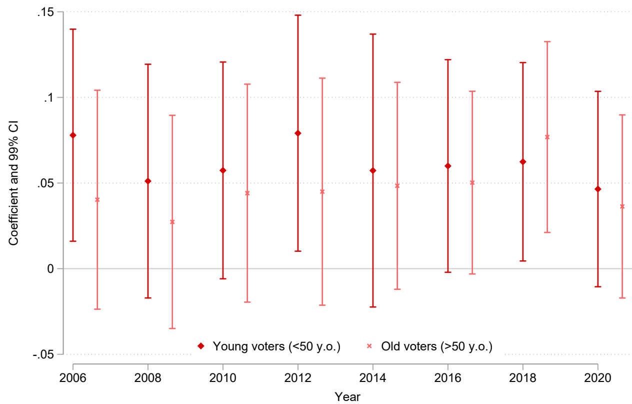
(b) By gender



(c) By education



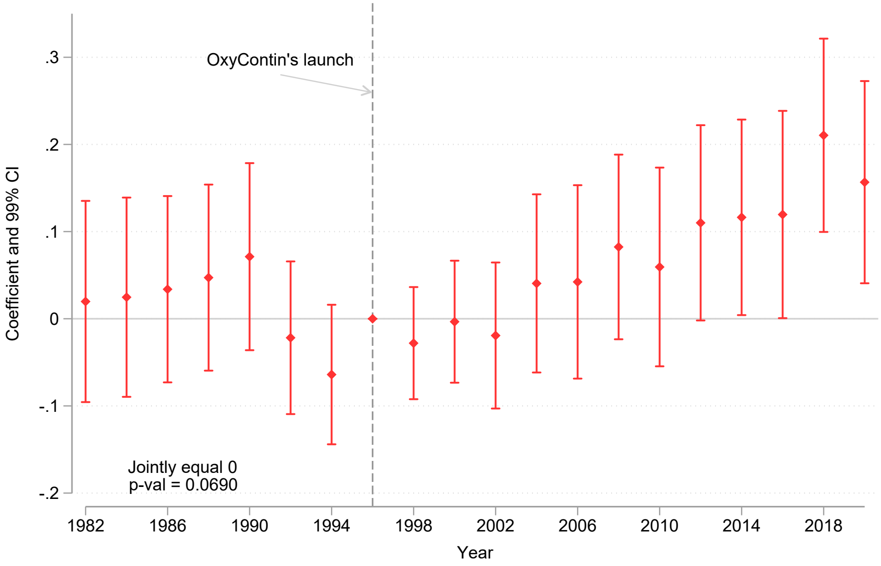
(d) By age



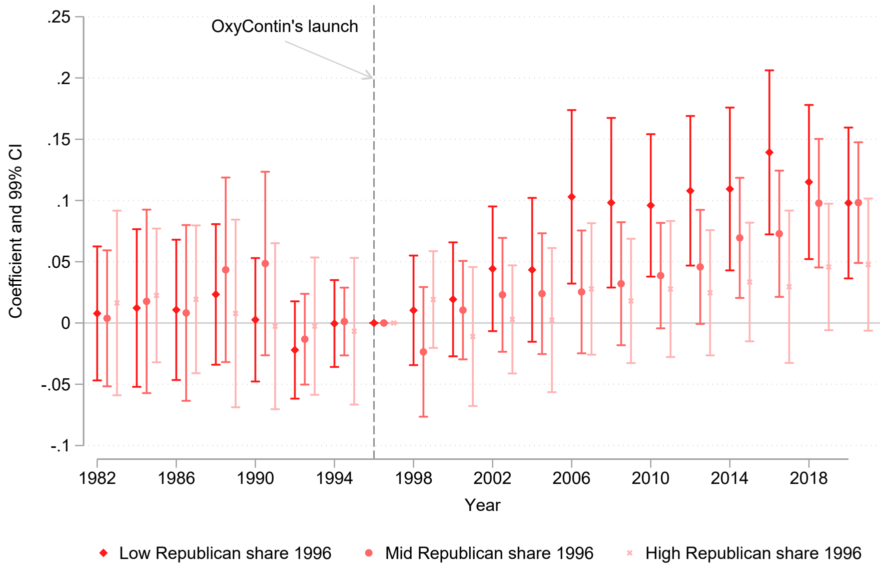
Notes: Panel (a) of this figure presents the baseline estimates of the relation between the share of votes for Republican candidates and cancer mortality using data from the CCES. Panels (b), (c), and (d) estimate these effects by demographic characteristics. High education includes the group of individuals reporting having completed a 4-year college degree or post-graduate education. We estimate the following equation on an individual-level repeated-cross section dataset: $y_{ict} = \alpha_1 + \sum_{\tau=1996}^{2020} \phi_\tau \; CancerMR_{ct_0} \mathbf{1}(Year = \tau) + \alpha \; \Delta X_{ct} + \gamma_{st} + \varepsilon_{ict}$. This figure is referenced in Section V.a.

Figure 5: Congressional Elections: House Wins and Vote Share Heterogeneity

(a) Republican Candidate Wins a House Seat



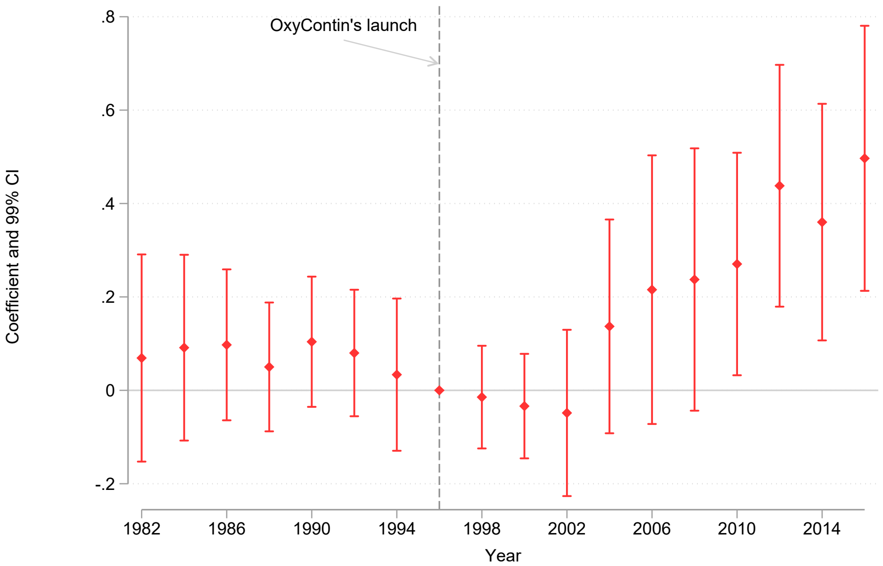
(b) Effects on Republican Vote Share - by tercile



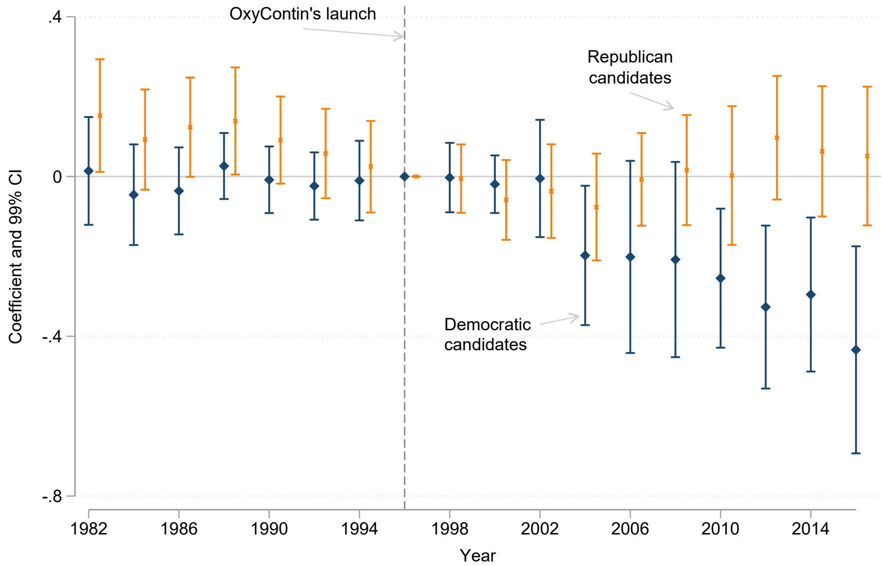
Notes: Panel (a) presents estimates of the dynamic relationship between the probability that a Republican candidate wins a seat in House elections and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality by the initial level of Republican support in the 1996 House elections. 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. The p value of this test is presented in the figure for the model presented in panel (a). For the estimates on panel (b) the p values are: 0.1823, 0.2619, 0.9316; respectively for low, mid, and high Republican support. This figure is referenced in Section V.a.

Figure 6: Effects of Exposure to the Opioid Epidemic on Per-capita Donors to Candidates for the House

(a) Difference by Party = Rep - Dem

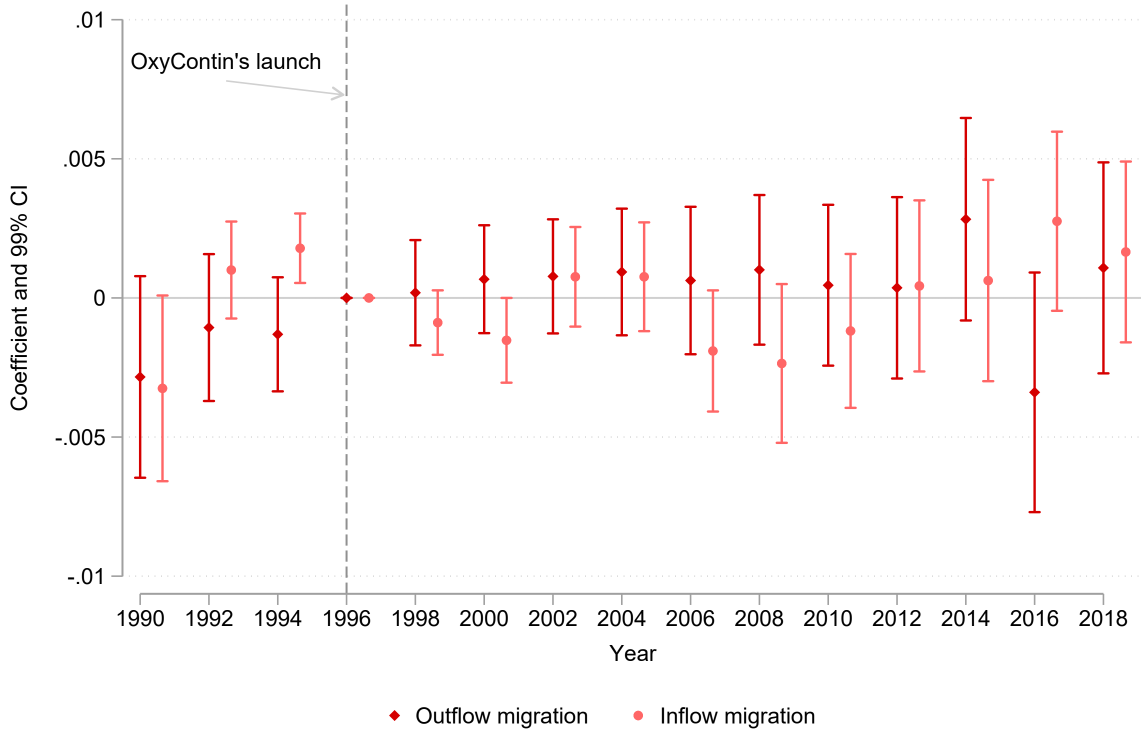


(b) Per-capita By Party



Notes: Panel (a) presents estimates of the dynamic relationship between the difference in the number of donors to Republican candidates and to Democratic candidates for House elections, and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of this relationship by party of the donation recipient. This figure is referenced in Section V.a.

Figure 7: Commuting Zone Out-Migration Flows

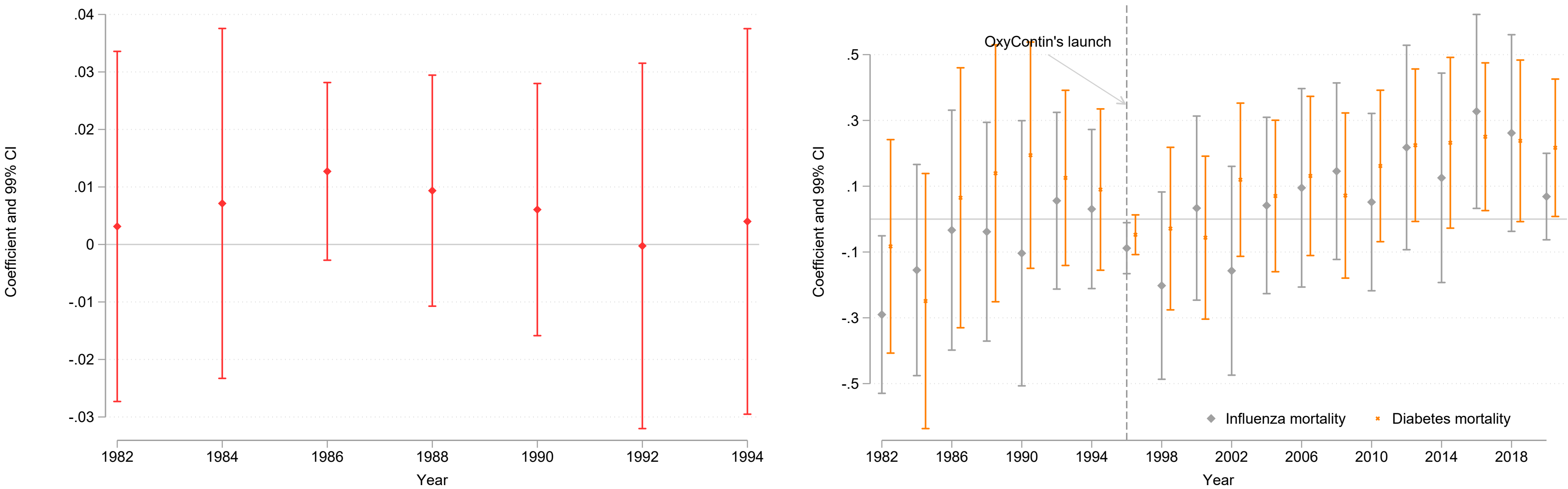


Notes: This figure presents estimates of the dynamic relationship between (i) out-migration (dark red) and (ii) in-migration (light red); and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. The IRS SOI data are available starting in 1990. This figure is referenced in Section V.b.

Figure 8: Placebo Checks: Out-of-Sample and Placebo Mortality Rates

(a) Out-of-Sample Analysis

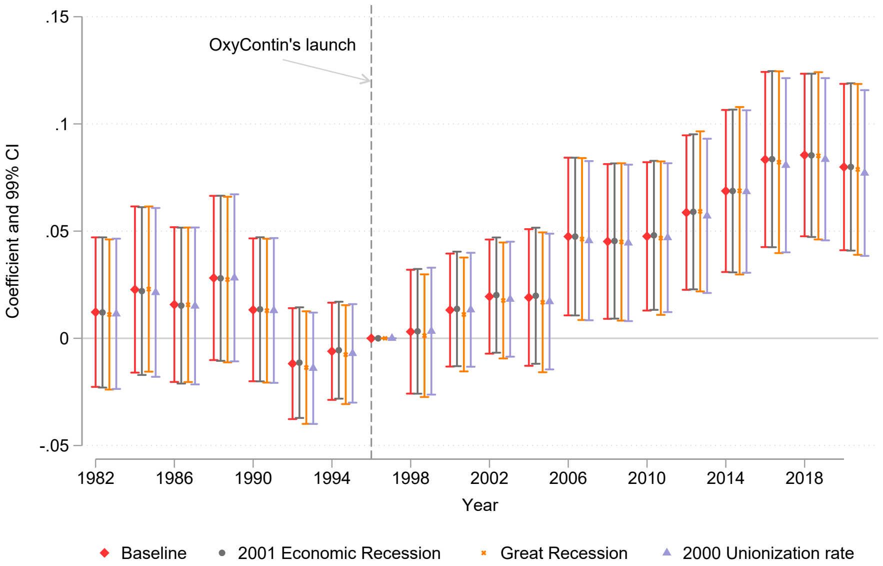
(b) Influenza and Diabetes Mortality



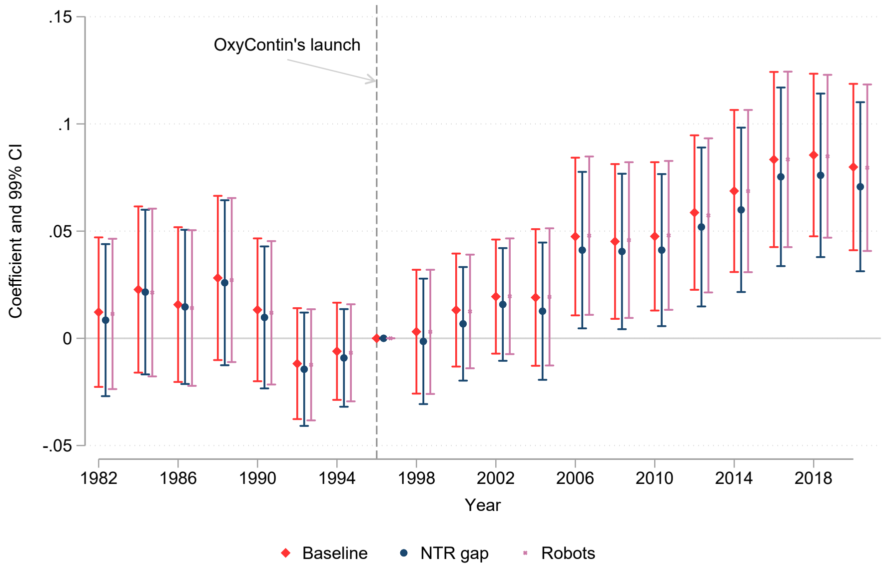
Notes: This figure presents two placebo checks. Panel (a) presents estimates of an out-of-sample dynamic reduced-form analysis for our pre-period. It provides evidence that lagged cancer mortality is not a predictor of future Republican vote share. Panel (b) presents estimates of the dynamic relationship between the Republican vote share and under-65 influenza or diabetes mortality. This figure is referenced in Section VI.a.

Figure 9: Robustness Checks – Congressional Elections and Economics Shocks

(a) Exposure to "China Shock" and Economic Recessions

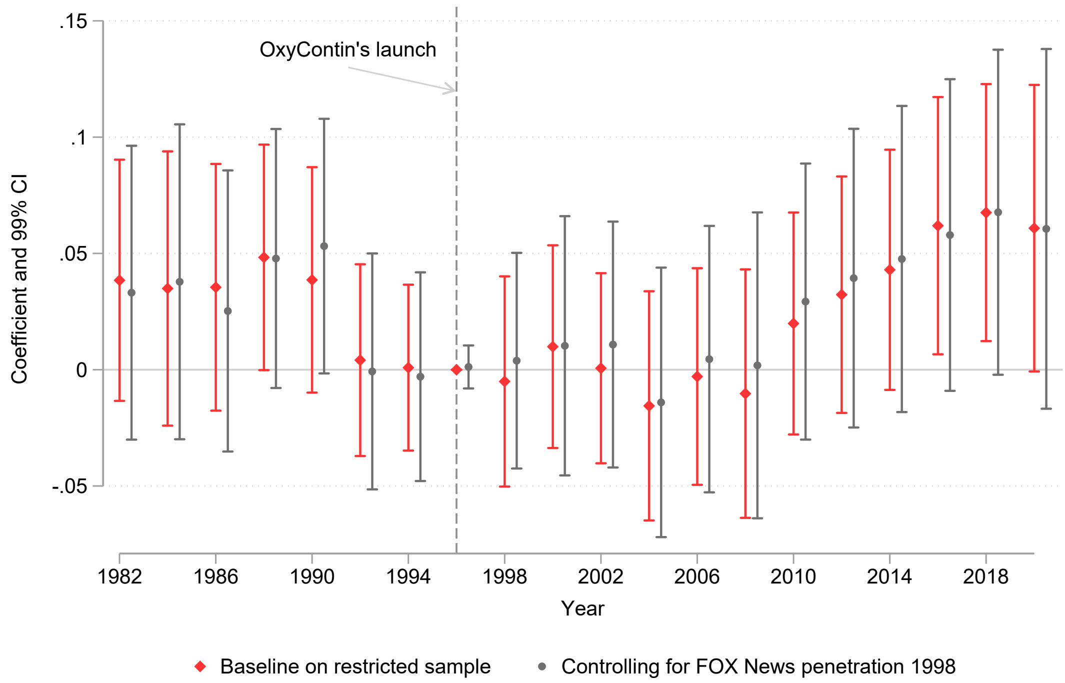


(b) Introduction of Fox News



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 in which we control for exposure to the 2001 and 2007 economic recessions. We construct a measure of exposure to the recession as the change in the unemployment rate from 2001 to 2000 in the commuting zone. Similarly, we use Yagan (2019)'s measure of severity of the Great Recession and commuting-zone level union rates in 2000 constructed by Connolly et al. (2019). Panel (b) presents the baseline estimates of the relation between the share of votes for Republican candidates and cancer mortality along with estimates in which we control for exposure to permanent normal trade relations with China—termed the "China shock" in the trade literature—and exposure to adoption of robots. 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 policy change. In each of this exercises, we add a measure to exposure to a given shock interacted with year dummies. This figure is referenced in Section VI.b.

Figure 10: Robustness Checks – Congressional Elections and the Introduction of Fox News



Notes: This figure presents the baseline estimates of the relation between the share of votes for Republican candidates and cancer mortality along with estimates in which we control for initial Fox News coverage. We use data from DellaVigna and Kaplan (2007). Unfortunately, the data cover only 60% of commuting zones, so there is a substantial loss of sample size. Thus, we present estimates of the baseline equation restricting the sample to those commuting zones included in their data, we name this "Baseline on restricted sample". 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)
Exposure to the opioid epidemic and mortality measures						
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	2.4907	2.4994	0.5840
Prescription opioids mortality per 10,000[b]	0.0652	0.0000	0.1320	0.3537	0.2410	0.4424
Voting outcomes and political views						
Sh. Republican votes						
House elections	0.4522	0.4665	0.2131	0.5659	0.5782	0.1798
Presidential elections	0.5227	0.5277	0.1201	0.5586	0.5568	0.1282
Sh. of seats held by Republicans candidates	0.4176	0.4050	0.0506	0.5118	0.5215	0.0464
Turn out rate[c]	0.6587	0.6853	0.1169	0.6397	0.6405	0.0987
Donations to House candidates per 1,000 voting-age population[d]						
All	0.3640	0.2188	0.4241	2.2560	1.3048	3.1843
to Republican candidates	0.2146	0.1156	0.2799	0.9757	0.6870	0.9768
to Democrat candidates	0.1841	0.0980	0.2379	1.2728	0.4912	2.4669
House members' ideology (positive = conservative)	0.0529	0.0375	0.2738	0.2327	0.3290	0.3216
Affective polarization	25.6481	20.0000	28.2703	41.8095	40.0000	32.8734

Notes: This table presents summary statistics for the main dependent variables and our measure of exposure to the opioid epidemic for the periods before and after the launch of OxyContin. (*a*) Data on opioids prescribed per capita are available from 1997, (*b*) We construct prescription opioid mortality from 1989. (*c*) Turn out rates are computed for Presidential elections years. House members' ideology is measured using the Nokke-Poole first dimension estimate, positive values in this category indicate more conservative views. (*d*) Statistics of donation data are from 1982 to 2016. This table is referenced in Section III.

Table 2: Baseline Determinants of Opioid Supply, Cancer Mortality & Republican Vote Share

	Prescription Opioid 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 noncancer 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-sectional 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-1990s Cancer Mortality and Preferences

	Affective Polarization	Church Attendance	Immigration	Abortion	Gun Control	Church Attendance	Own Ideology	Fox News
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cancer 1996*Post	0.981**	0.0319						
	[0.412]	[0.0284]						
Cancer 1996			-0.0619***	-0.0475***	-0.0529***	0.0322	-0.175***	0.0509***
			[0.0137]	[0.0169]	[0.0154]	[0.0519]	[0.0515]	[0.0194]
Obs	42,462	42,462	59,390	59,420	59,424	58,155	54,777	25,142
Mean	36.23	3.12	0.422	0.610	0.644	4.310	3.059	0.405
SD	32.28	1.60	0.494	0.488	0.479	1.673	1.206	0.491
CZ	560	560	610	610	610	610	607	587
Period	1982-2020	1982-2020	2020	2020	2020	2020	2020	2020
Source	ANES	ANES	CCES	CCES	CCES	CCES	CCES	CCES

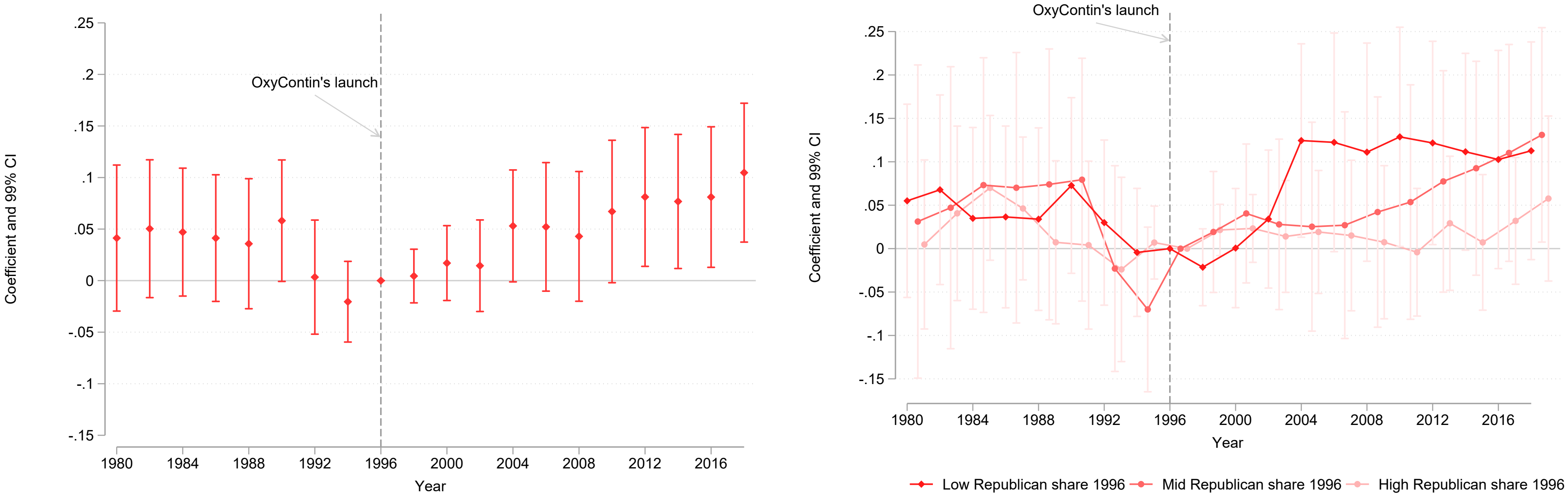
Notes: We follow Boxell et al. (2022) to construct our measure of affective polarization. Higher level translate to higher polarization measured as the distance between my feelings about my own party versus the opposition party. This variable is only defined for respondents who are Democrats or Republican. Fox News is a dummy variable equal to 1 when respondents say yes to watching Fox News. Other variables are coded such that higher values represent liberal/progressive views. ANES Immigration is the thermometer regarding illegal immigration. ANES Abortion corresponds to the item "By law, when should abortion be allowed?" and takes values 1 to 4, where 1="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." CCES Immigration corresponds to the item "Increase the number of border patrols on the US–Mexican Border," where 1="Against" and 0="Support." CCES Abortion: 1="Always allow a woman to obtain an abortion as a matter of choice" and 0 otherwise. CCES Gun Control corresponds to the item "Ban assault rifles," where 1="Support" and 0="Against." CCES Own ideology: Thinking about politics these days, how would you describe your own political viewpoint. Answer from 1-5, 1 being very conservative and 5 being very liberal. *Post* takes the value one for electoral years after the introduction of OxyContin. All regressions include a set of control variables at the commuting-zone level and at the individual level. *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Section V.b.

A Additional Figures

Figure A1: Conservative-Liberal Ideology Roll-call Voting of Members of the House

(a) Main Effect of Exposure to the Opioid Epidemic

(b) Effects by Initial Support for Republican Party

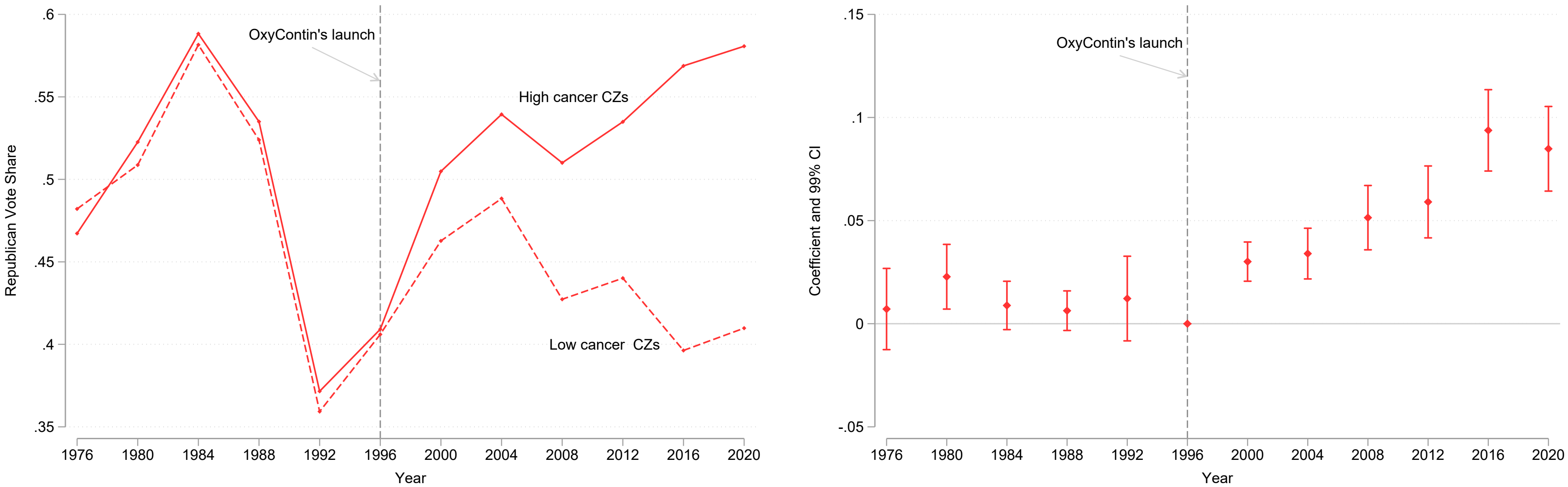


Notes: This figure presents estimates of the dynamic relationship between the candidates ideology in roll-call voting and mid-1990s cancer mortality, panel (a) shows the main effects and panel (b) splits the sample based on the initial share of Republican votes in congressional elections, darker colors indicate lower Republican support at baseline. We exploit data from Lewis et al. (2023) and measure candidates ideology using the Nokken-Poole first dimension estimate. This figure is referenced in Section V.a.

Figure A2: Republican Vote Share: Presidential Elections

(a) Trends in High- versus Low-Cancer-Mortality CZs

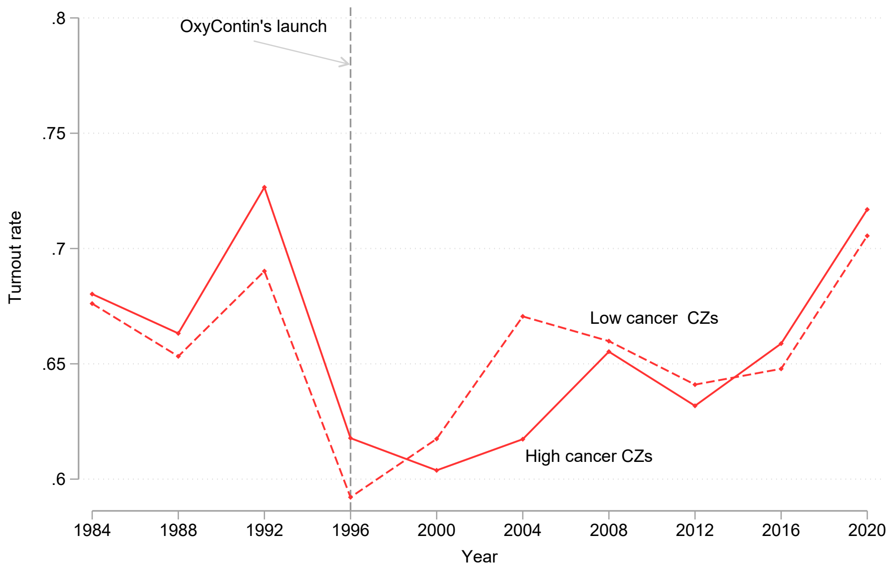
(b) Effects of Mid-1990s Cancer-Market Targeting



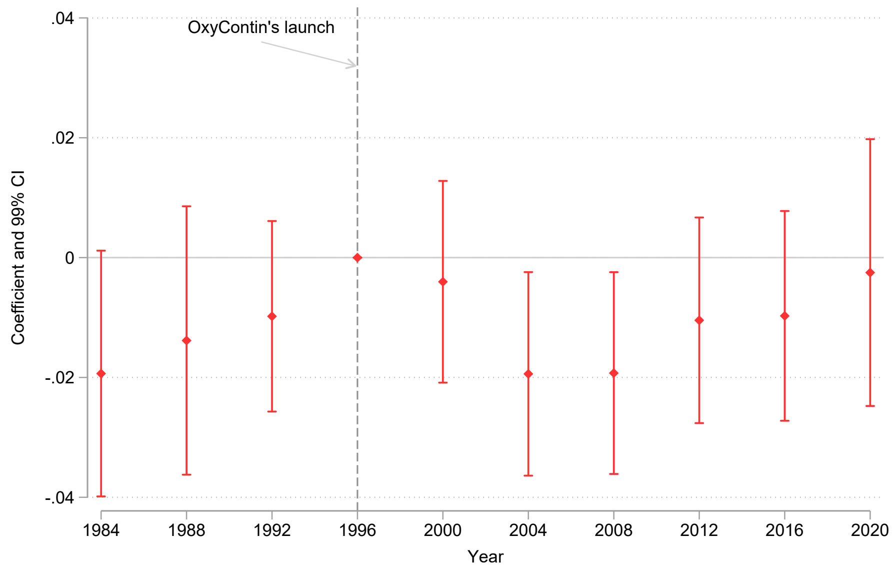
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections in the bottom (dashed line) and top (solid lines) quartiles of the cancer mortality distribution before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.a.

Figure A3: Turnout Rates

(a) Trends in Turnout

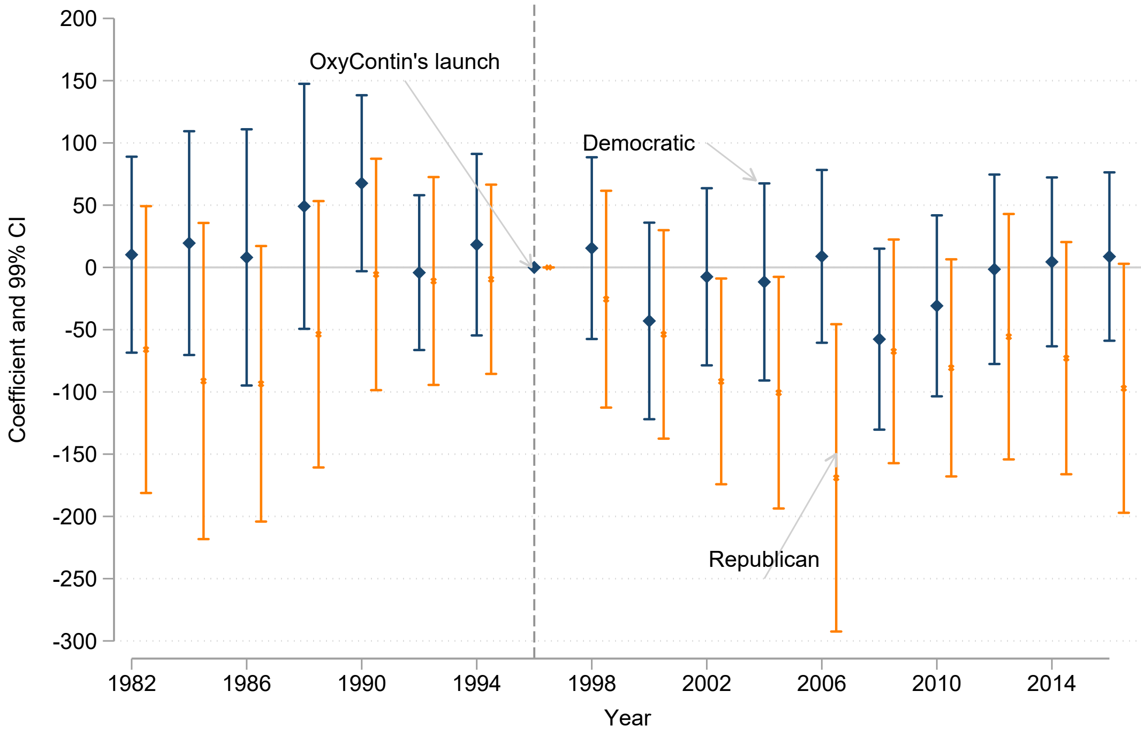


(b) Event Study Approach



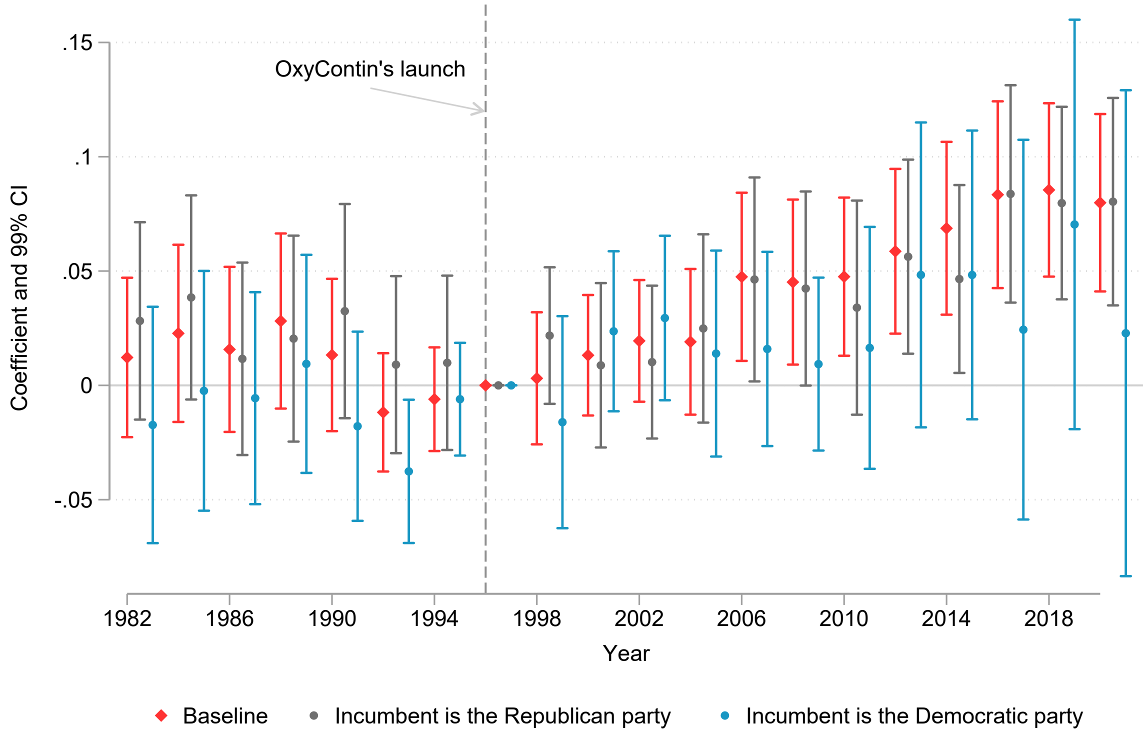
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turnout rates and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.a.

Figure A4: House Campaigns Median Donations Amount



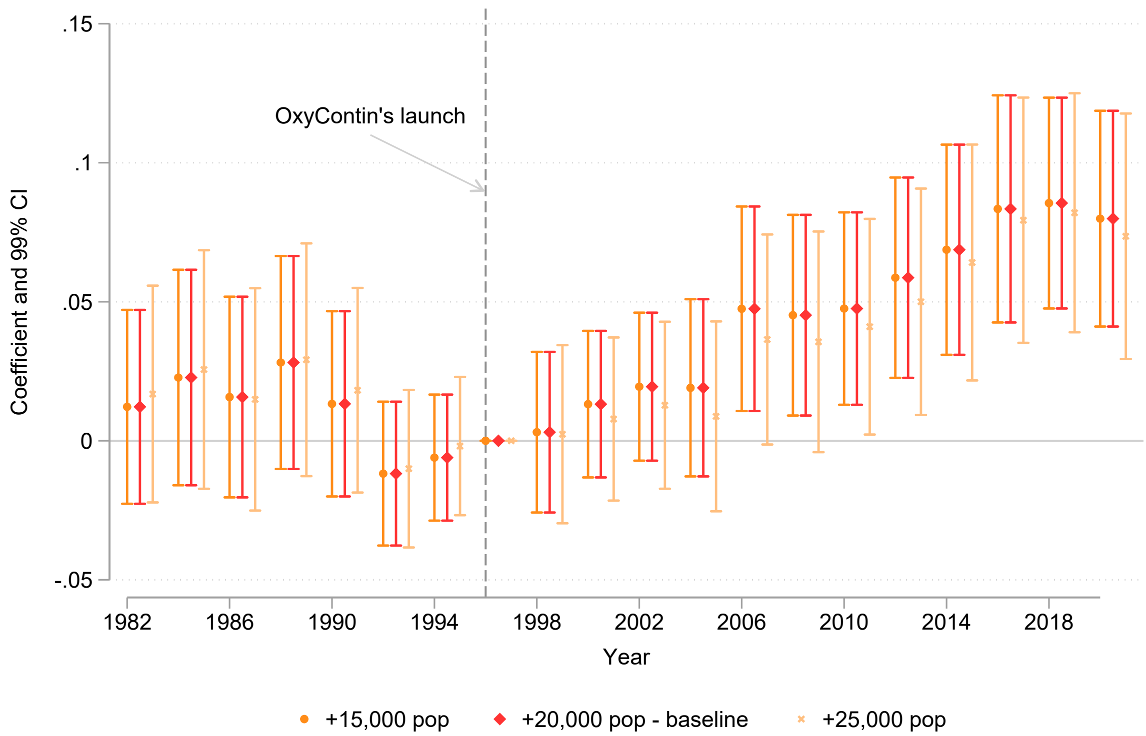
Notes: This figure presents estimates of the effect between exposure to the opioid epidemic and median donation amounts by party. This figure is referenced in Section V.a.

Figure A5: Effects on Republican Vote Share by Party of the Incumbent



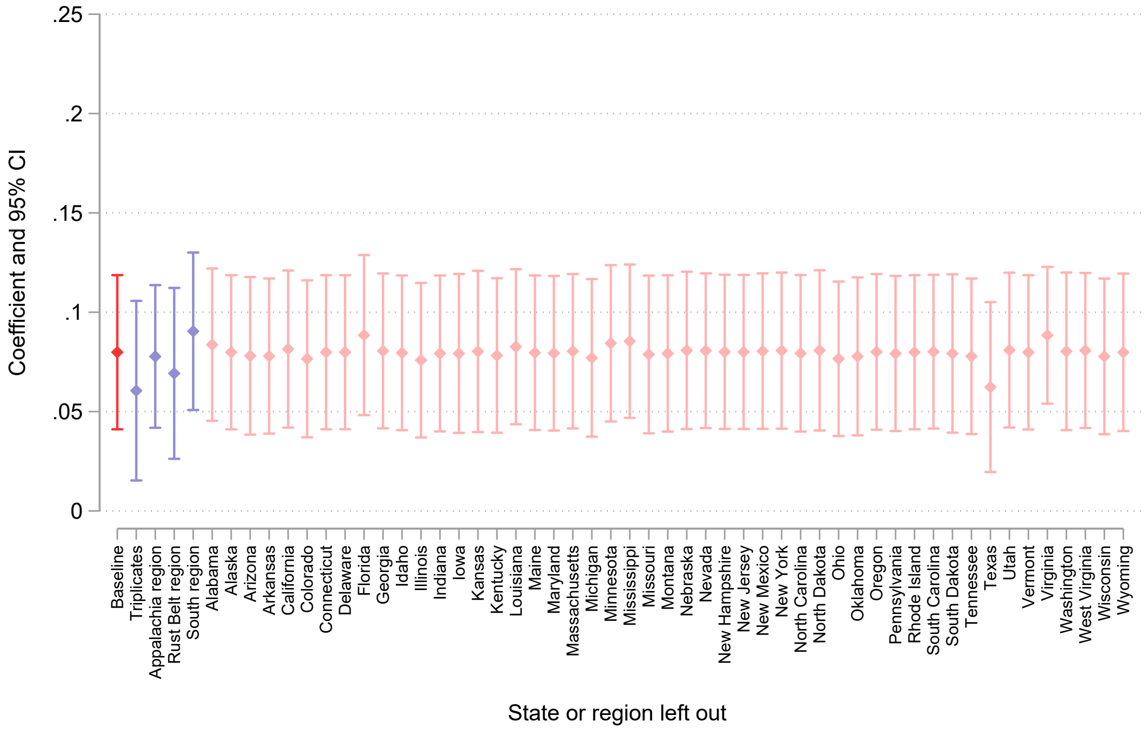
Notes: This figure presents estimates of the effects of opioid epidemic exposure on vote share splitting the sample into commuting zones with either a Republican or Democrat incumbent at the time of the election. This figure is referenced in Section V.

Figure A6: Effects of Mid-1990s Cancer-Market Targeting for Alternative Sample Restrictions



Notes: This figure presents estimates of the effects of opioid epidemic exposure on the share of votes for Republican candidate for alternative constrains on the population size of community zones included in the sample. Our baseline specification restricts the analysis to areas with more than 20,000 residents, which represents 99.5% of the total population. This figure is referenced in Section VI.c.

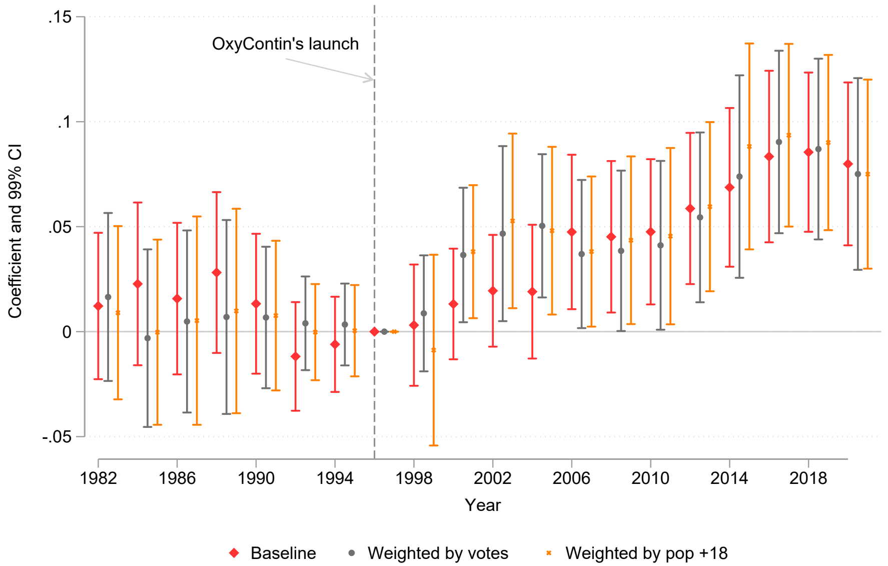
Figure A7: 2020 Coefficients – Leaving One State Out



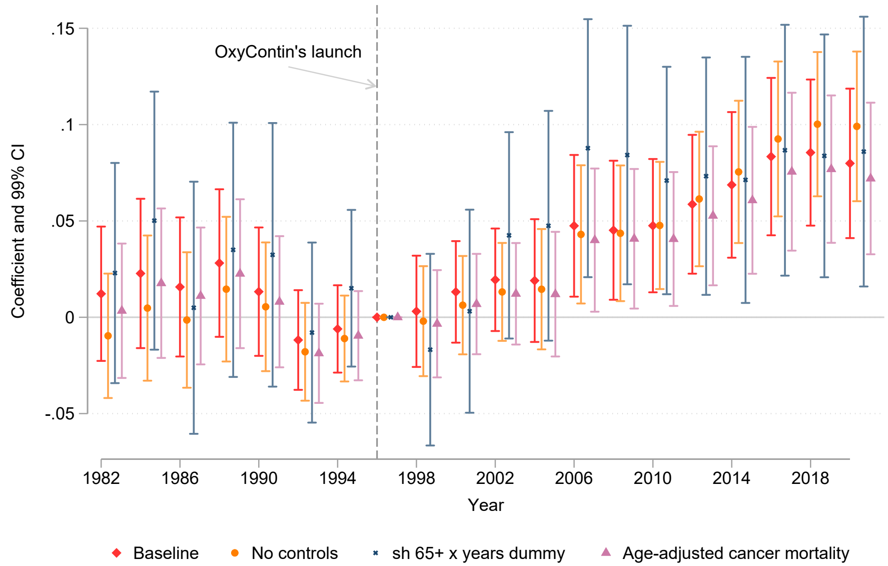
Notes: This figure presents estimates of the 2020 coefficients from an event study similar to that in equation 1 run on a sample that excludes all commuting zones in the state indicated on the horizontal axis. That is, the x-axis label indicates the state left out of the estimation. This figure is referenced in Section VI.c.

Figure A8: Robustness Check: Weighted, Alternative Specifications, and Age-adjusted Regressions

(a) Population Weighted Estimation



(b) 1996 Age-adjusted Cancer Mortality



Notes: Panel (a) of this figure replicates our estimates of Figure 3 and adds weighted versions, where weights correspond to the number of votes and total population over 18 years old. Panel (b) shows the results of our baseline specification without controls, the baseline specification adding the share of population above 65 times year dummies as controls, and a model that uses age adjusted cancer mortality as a measure of exposure to the epidemic. This figure is referenced in Section VI.c.