

# Democracy and the Opioid Epidemic

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January 28, 2024

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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 compositional changes.

JEL No. D72, I12, I18, J13.

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Comments are welcomed. We thank Michael Baker, Ceren Baysan, Arthur Blouin, Shari Eli, Alex Hoagland, Mitchell Hoffman, Kory Kroft, Catherine Maclean, Kelli Marquardt, Eduardo Souza, Clémentine Van Effenterre, Tianyi Wang, Emily Weisburst, and seminar participants at Dalla Lana School of Public Health, EHEC, Notre Dame, and University of Toronto for their feedback. Gabriela Ramirez and Yanzun Yang provided excellent research assistance.

## 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 socio-economic 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 experience increases in out-group animosity. For example, worsening mortality rates in Germany in the early 1930s are associated with increasing votes for the far-right (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 asks if 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 socio-economic 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 right (Bickle, 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 leverages 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 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. As in [Arteaga and Barone \(2023\)](#), we use cancer mortality in 1996—i.e., before the unfolding of the epidemic—as a measure of exposure. Our identification assumption is that areas with higher cancer mortality in 1996 would have exhibited the same trends in political outcomes as areas with lower cancer mortality absent the pharmaceutical marketing. Our prior work and the work that followed, show that mid-nineties cancer mortality is a strong indicator of the exogenous exposure to the opioid epidemic.<sup>1</sup>

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.<sup>2</sup> 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 opioid mortality from the National Vital Statistics System (NVSS).

We find that exposure to the opioid epidemic 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 4.6 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. However, this shift did not stem from the election of candidates at the extreme of the political spectrum, but rather from the change in the composition of the House. We also observe a positive wedge in favor of the Republican party in terms of

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<sup>1</sup>See [Buckles et al. \(2022\)](#); [Cohle and Ortega \(2023\)](#); [Olvera et al. \(2023\)](#); [Siegal \(2023\)](#), among others.

<sup>2</sup>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 ([Tolbert and Sizer, 1996](#)).

the number of individual House campaign donations. This difference is the result of the decline in donations to Democrat candidates, with no effects observed for Republicans. When we look at Presidential elections the results follow the pattern of the congressional elections. Finally, we do not find any effects on turnout rates.

Next, we investigate what are the mechanisms behind these changes in voting patterns. First, we explore changes in the composition of the electorate pool. 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 a rise in conservative views across the board, measured as views on immigration, abortion, gun control, and self-declared ideology.

We assess alternative explanations for these changes in views and provide suggestive evidence to support three forces at play. First, the perceived effectiveness of the Republican approach to curb the opioid epidemic, as compared to that of the Democrats, might have swayed voters in their direction. Republicans favor increased law enforcement to curb drug trafficking and crime, while Democrats prefer harm reduction policies and increasing funding for opioid abuse treatment and recovery. We find that higher cancer mortality rates in the mid-1990s predict greater support for police presence and an increased sense of safety around police. On the other hand, the effectiveness of some harm reduction policies has been questioned, given recent evidence showing they may increase drug use (Doleac and Mukherjee, 2019; Packham, 2022; Spencer, 2023). Second, 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.<sup>3</sup> The opioid epidemic serves as an example of shared hardship. We provide direct evidence of this mechanism: exposure to the opioid epidemic rises affective polarization. Our results are consistent with studies by Mian et al. (2014) and De Bromhead et al. (2013) that connect adverse economic shocks and the rise of polarization and right-wing support. Third, we find that exposure to the opioid epidemic increases viewership of Fox News, which in itself can also increase support for the Republican party (DellaVigna and Kaplan, 2007; Clinton and Enamorado, 2014; Martin and Yurukoglu, 2017).

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<sup>3</sup>See Struch and Schwartz (1989); Brewer (2001); Bastian et al. (2014); and Nugent (2020). Affective polarization refers to the extent to which citizens feel more negatively toward other political parties than toward their own (Iyengar et al., 2019).

We provide several tests that support our empirical design and the robustness of our results. The validity of the identification strategy requires that in the absence of prescription opioids 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 measure of exposure to the epidemic 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 apart in terms of Republican vote share as a function of their exposure to the opioid epidemic.

Additionally, 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. We also 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 but are a measure of underlying population health. Finally, we control for geographic measures of exposure to economic and political shocks that have been documented to affect political outcomes in this period, such as Chinese import competition, economic recessions, unionization rates, the adoption of robots, and the introduction of Fox News. Our estimates remain robust when these variables are included as controls.

This paper bridges the political economy and the health economics literature. It connects two of the most salient social developments in the United States over the past three decades: the opioid epidemic and the rise in polarization and its changes in the political landscape. 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 out-group 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 community-level polarization and ideology. This paper shows how the disparate community effects of a major public health crisis 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 origins of the opioid epidemic and its community-level impacts, and explains the rationale behind our empirical strategy. It also presents the main trends in political support and partisanship in the United States that occurred 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.<sup>4</sup> 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 paperwork 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)<sup>5</sup>.*

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.<sup>6</sup> 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,

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<sup>4</sup>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).

<sup>5</sup>The Opioid Industry Documents Archive from the University of California, San Francisco UCSF (2018)

<sup>6</sup>See Maclean et al. (2020), Alpert et al. (2022), and Arteaga and Barone (2023) for detailed discussions of the marketing of prescription opioids.

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.<sup>7</sup> Indeed, fentanyl-related deaths account for almost 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.<sup>8</sup>

## 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 help rationalize why the opioid epidemic has disrupted health and economic opportunities, affecting individuals and their communities.

Notably, the epidemic has increased disability rates and Supplemental Nutrition Assistance Program (SNAP) utilization (Powell et al., 2020; Savych et al., 2019; Arteaga and Barone, 2023) and affected labor force participation and employment rates (Krueger, 2017; Ouimet et al., 2020). Further, exposure to lax regulations surrounding opioid prescriptions contributed to homelessness and a rise in violent crime (Olvera et al., 2023, Dave et al., 2021, and Sim, 2023). The added economic distress translated into broader economic impacts through their detrimental 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), sales and employment growth (Ouimet et al., 2020).

Additionally, through its impacts on increased fertility rates, 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). These individual and community-level economic

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<sup>7</sup>Heroin is approximately three times as potent as morphine, and fentanyl is 100 to 200 times more potent than morphine, depending on the batch.

<sup>8</sup>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.

distress triggered by the opioid epidemic may contribute to shifts in political attitudes and preferences.

### II.c. Trends in Political Expression and Partisanship

Contemporaneous to these 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).<sup>9</sup>

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.

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<sup>9</sup>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. 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 (a) of Figure 1 shows the distribution of the Republican vote share in congressional elections in 1996. This figure suggests a widespread variation in the level of support for the Republican party in the mid-1990s. Panel (b) 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%.<sup>10</sup>

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.<sup>11</sup> 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.<sup>12</sup> 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

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<sup>10</sup>We refrain from using the CCES to study turnout, as studies have raised issues with using these data to measure turnout ([Agadjanian, 2018](#)).

<sup>11</sup>We have excluded data for 2018 and 2020 from our analysis because donation patterns underwent significant changes during these election cycles, rendering the data incomparable.

<sup>12</sup>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.

over of taxation, spending, and redistribution.<sup>13</sup>

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.<sup>14</sup> 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 (c) 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.<sup>15</sup> Panel (d) of Figure 1 shows the geographic distribution of prescription opioid mortality from 1999 to 2018.

*Geographic harmonization.* Electoral outcomes and mortality 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.<sup>16</sup> 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 two purposes: i) the pure harmonization in a common geographic unit; and ii) accounts for redistricting of congressional districts since Ferrara

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<sup>13</sup>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 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).

<sup>14</sup>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.

<sup>15</sup>See Arteaga and Barone (2023) for the ICD10 and ICD9 codes used in constructing each variable.

<sup>16</sup>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.

et al. (2021) provide year-specific crosswalks.<sup>17</sup>

In sum, our final dataset consists of a panel of 625 commuting zones from 1982 to 2020.<sup>18</sup> 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, i.e., 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 the 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. Drawing on the insights from the internal documents of Purdue Pharma and other pharmaceutical companies, we proxy for 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:

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

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  $\Delta$  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

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<sup>17</sup>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.

<sup>18</sup>The ARCOS data are available for years from 1997, so the analyses using this measure are restricted to a later period.

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  $\tau$ . This reduced-form specification allow us to test for pre-trends and estimate time varying effects on outcomes of interest. That is, the coefficients for the pre-opioid epidemic period, i.e.,  $\phi_{1982}$ ,  $\phi_{1984}$ , to  $\phi_{1994}$ , 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, i.e.,  $\phi_{1998}$ ,  $\phi_{2000}$ , to  $\phi_{2020}$ , 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  $\gamma_{st}$  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<sup>19</sup>—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-epidemic period would have exhibited the same *trends* as areas with lower cancer mortality in the outcomes of interest (Goldsmith-Pinkham et al., 2020).<sup>20</sup> We provide supporting evidence next.

#### 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 estimates of the relationship between mid-1990s cancer mortality and prescription opioids per capita taking equation (1) to the data.<sup>21</sup> We find that there is a positive and statistically significant relationship between mid-1990s cancer mortality and shipments of prescription opioids per capita. Furthermore, Arteaga and Barone (2023) show that mid-

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<sup>19</sup>See, for example, Buchmueller and Carey (2018) and Doleac and Mukherjee (2019).

<sup>20</sup>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 instrumental-variables model.

<sup>21</sup>Since ARCos data are available from 1997 we can only estimate coefficients from this date.

90s cancer mortality predicts future opioid marketing efforts, measured as the number of targets—either physicians or pharmacists—per capita, and the share of visits and payments dedicated to promoting opioids relative to all other drugs.

We next study the relationship between 1996 cancer mortality and opioid-related mortality. When inspecting 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. In contrast, for the years after 1996, strong patterns emerge, and mid-1990s cancer mortality starts to predict opioid-related mortality. Panel (d) of Figure 2 presents reduced-form estimates of this relationship.

## 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. By 2020, we estimate that a unit increase in cancer mortality rate translates into an increase of 7.9 percentage points in Republican vote share relative to the 1996 baseline. Put another way, a one standard deviation higher cancer mortality rate (0.58) increases the vote share in 4.6 percentage points (see Panel (b) of Figure 3). These estimates, though sizable, are comparable in magnitude to the decline in democratic vote share resulting from a 5% increase in the employment-to-population ratio. In particular, Brunner et al. (2011) found that such an increase would lead to a 8-percentage-point decrease in voting for a Democratic governor and a 6-percentage-point decrease in support for party-endorsed ballot propositions.

*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.<sup>22</sup> 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

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<sup>22</sup>When using these data we can only estimate coefficients on the interaction between 1996 cancer mortality rates and year dummies for the period 2006—the first year the CCES is available—to 2020. The outcome of interest is defined in levels due to the lack of baseline data to compute long changes.

(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 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, vote share in communities with an initial median level also began to increase, contributing to the raise in the likelihood of flipping 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. Specifically, an increase of one standard deviation in cancer mortality, increases this gap by 0.32 of a standard deviation. This difference is the result of the decline in donations to Democrat candidates, with no effects observed for Republicans. In terms of the amount of the donation, we do not estimate any effects for either party (See Figure A1). These results speak to the behavior of a small share of the population who are on the margin of donating to House campaigns, on average 0.23% of the voting-age population donate in a given electoral cycle.

*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 panel a of Figure A2, we document that exposure to the opioid epidemic leads to an increase in conservative views in the House, particularly in districts with lower baseline Republican support (Panel b). Nevertheless, this shift does not originate from a change in the probability of electing candidates at the extremes of the political spectrum at each given election year (Panels c and d of Figure A2), but rather from the change in the composition of the House.

*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 A3). 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 4.9 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 A4.<sup>23</sup>

### V.b. Mechanisms Driving Changes in Voting and 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 Tax Stats (SOI) 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 any changes that 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 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 4.6 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 (1) to (4) of Table 3, we find that exposure to the epidemic predicts more conservative views in terms of abortion, gun control, immigration, 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.<sup>24</sup>

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<sup>23</sup>We do not report turnout pre-trends or effects for congress as data is not available for mid-term elections from 1990 to 1998.

<sup>24</sup>Unfortunately, the questions we use to measure ideology are not consistently included in the ANES across time, so we exploit the 2020 CCES for that analysis.

### 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 gives to addressing the crisis could explain the movement toward or away from one party. According to a YouGov survey among adult Americans in 2022, both Democrats (66%) and Republicans (74%) 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 second people addicted to opioids and pharmaceutical companies. Neither party sees the government as the primary culprit in the epidemic; however, most Republicans and Democrats agree that the government should be doing more to address the crisis (ANES, 2021).

Turning to the role of differential party-level responsiveness, legislation to tackle the opioid epidemic has had clear bipartisan support. The primary congressional response to the crisis was the Comprehensive Addiction and Recovery Act (CARA) passed in 2016 with 400 (93%) yeas. Stokes et al. (2021) analyze more than 40,000 state legislators' opioid-related social media posts from 2014 to 2019 to track partisan attention to the crisis. Using natural language processing models they find that the volume of Democrats' and Republicans' opioid-related posts was equally correlated with state overdose death rates. These findings suggest there was no differential political engagement surrounding the opioid epidemic, which might have indicated movements in one direction or the other. However, it does not rule out differential perceptions of the effectiveness of each party's approach.

With the opioid epidemic contributing to illegal drug trafficking and increased crime rates (Alpert et al., 2018; Evans et al., 2019; Sim, 2023), individuals may gravitate towards the Republican Party, which is perceived as advocating for a larger police force and stricter law enforcement measures. Along these lines, when examining data from the CCES, we observe that in 2020, mid-90s cancer mortality is positively correlated with a preference to increase the number of police officers on the street and a sense of safety around law enforcement (see columns (6) and (7) of Table 3). This policy response to the epidemic may also be perceived as more effective in addressing the consequences of the crisis among the electoral body, and it could explain the increased vote share of the Republican party. Furthermore, harm reduction policies promoted mainly by Democratic politicians, such as the legalization of drugs, syringe exchange programs, and Naloxone access laws, have been shown to increase drug use (Doleac and Mukherjee, 2019; Packham, 2022; Spencer, 2023).

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.<sup>25</sup> The results of this analysis are noisy, particularly in the later years of our analysis, owing to the decreasing proportion of commuting zones with Democrat incumbents. However, there 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-wing 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 results from relative deprivation, anger is triggered, which 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, the erosion of economic opportunities, and the deterioration of one's own and surrounding health that followed can trigger these cognitive processes.

We bring this hypothesis to data using the ANES from 1982 to 2020 to construct a measure of affective polarization following Boxell et al. (2022). Affective polarization captures the distance between *warm* feelings to one's 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—i.e., post 1996. In column (8) of Table 3, we show this result and find that exposure increases affective polarization, although the effect is small.<sup>26</sup>

Finally, with the introduction and rise of Fox News, the period of the opioid epidemic has been marked by an increase in 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, fuelled and supported by Fox News, sought to rebrand conservative principles as representative of the working class and fostered anti-elitist and anti-establishment sentiments (Peck, 2019). This narrative speaks to a segment of society that has witnessed a decline in its 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 (5) of Table 3, we find that exposure to the opioid epidemic predicts Fox

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<sup>25</sup>In case a commuting zone covers more than one congressional district, we split by the party that has the majority of house members.

<sup>26</sup>As an additional measure of in-group identity we look at church attending behavior, both in the ANES and the CCES data, see columns (9) and (10) of Table 3. We do not find any evidence of changes in church-attending behavior.

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).

## 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, but still capture community-level health trends. 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 measure 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.<sup>27</sup> 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.<sup>28</sup>

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<sup>27</sup>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.

<sup>28</sup>We take this measure directly from the replication package in [Acemoglu and Restrepo \(2020\)](#)—see

Finally, 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 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 impacted 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 one of the largest and most debated partisan shifts in a modern democracy—the exodus of white Southerners from the Democratic Party—took place (Kuziemko and Washington, 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  $\Delta X_{ct}$ , i.e., only adding states times year fixed effects. Additionally, 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).

In Figure A9 we expand the vector of controls to include interactions between the share of population over 65 years old in 1996 and year dummies. This share is correlated with a community having higher cancer mortality rates. Nonetheless, when find that

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Figure 4 and equation 18—the authors exploit variation in industry-level adoption of robots weighted by employment shares.

our conclusions remain if we flexibly add this share as a control. Since the Republican party has a significant advantage in leaned party identification among white men and this edge has widened in recent years, we considered if our results are driven by communities with larger shares of this demographic group. To asses this hypothesis, we add as an additional control the share of white male in 1996 interacted with year dummies to our main specification. We find no evidence supporting this explanation as the estimated effects are quantitatively very similar to the baseline specification.

## 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 reach 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 and seen by the same doctors. A later marketing practice that targeted high-prescribers, created a path dependency from this initial exposure. We use mid-90's 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, homelessness, 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 4.6 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 determinants 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. Particularly, in a landscape where vaccination is increasingly divided along party lines, and as result disease exposure and mortality become politicized.

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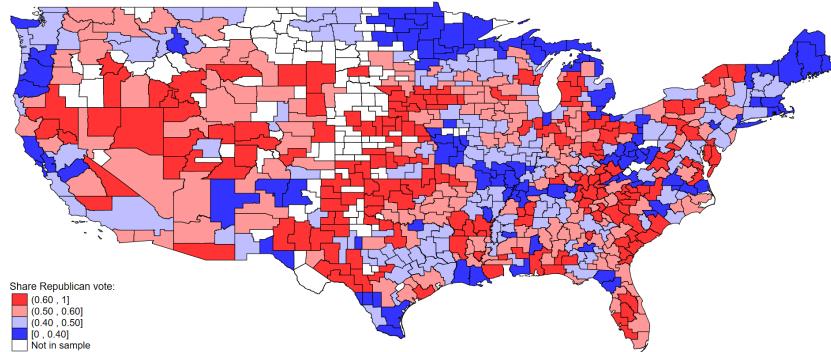
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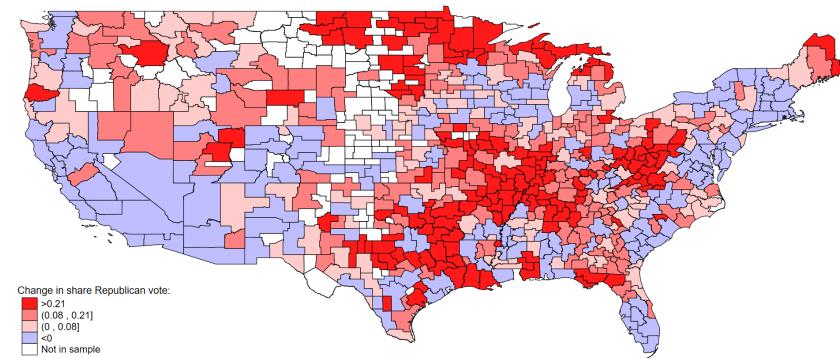
## VIII. Figures

Figure 1: Geographical Variation

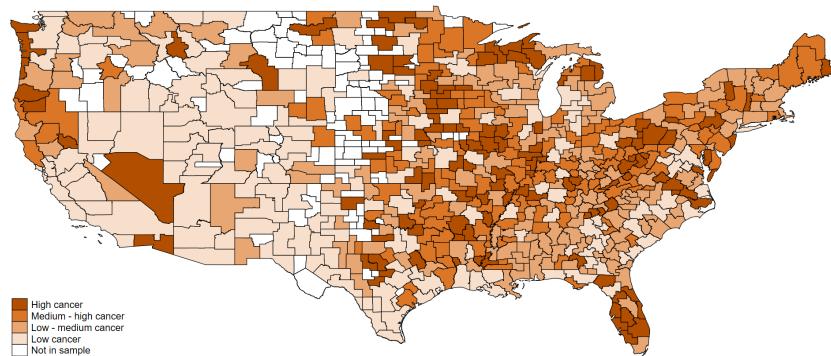
(a) Republican Vote Share - Congressional Elections, 1996



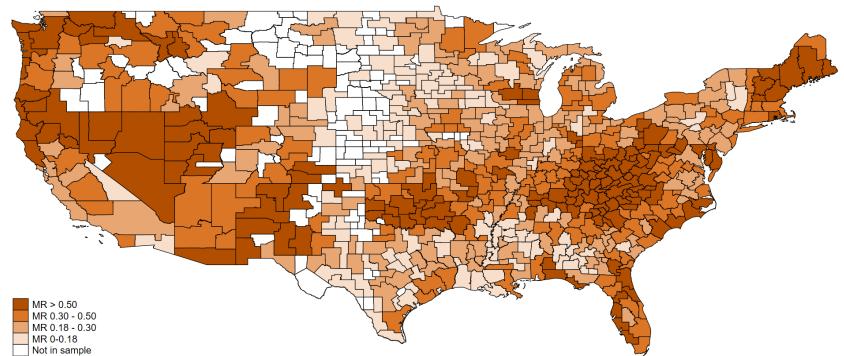
(b) Change in Republican Vote Sh. - Congressional Elections, 2020 – 1996



(c) Cancer Mortality Rates, 1996



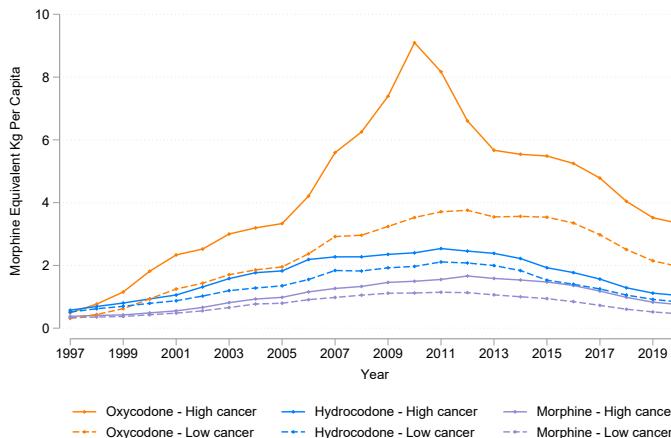
(d) Prescription Opioid Mortality Rate, 1999–2020



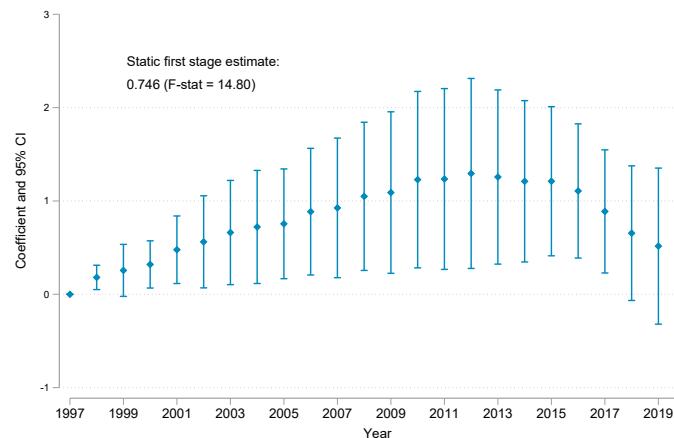
Notes: This figure shows the geographic distribution of the Republican vote share in congressional elections in panel (a), and its evolution between 1996 and 2020 in panel (b). Panel (c) shows the geographic distribution of our measure of exposure to the opioid epidemic—cancer mortality in 1996—and panel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

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

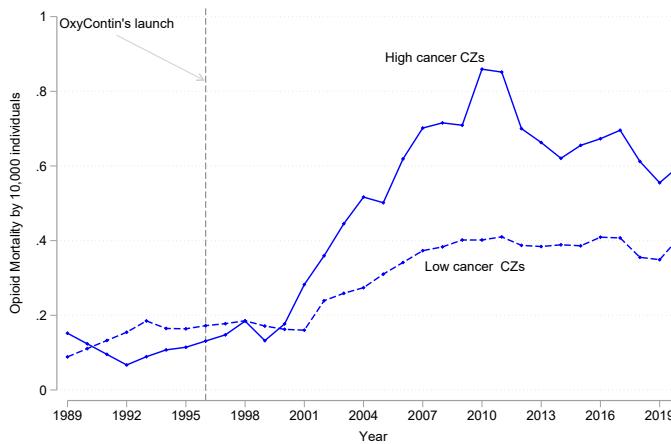
(a) Trends in High- versus Low-Cancer-Mortality CZs



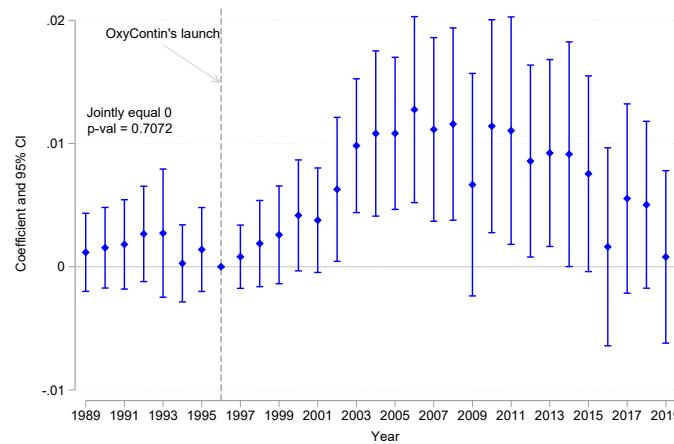
(b) Effects on Prescription Opioid Supply



(c) Trends in Prescription Opioid Mortality

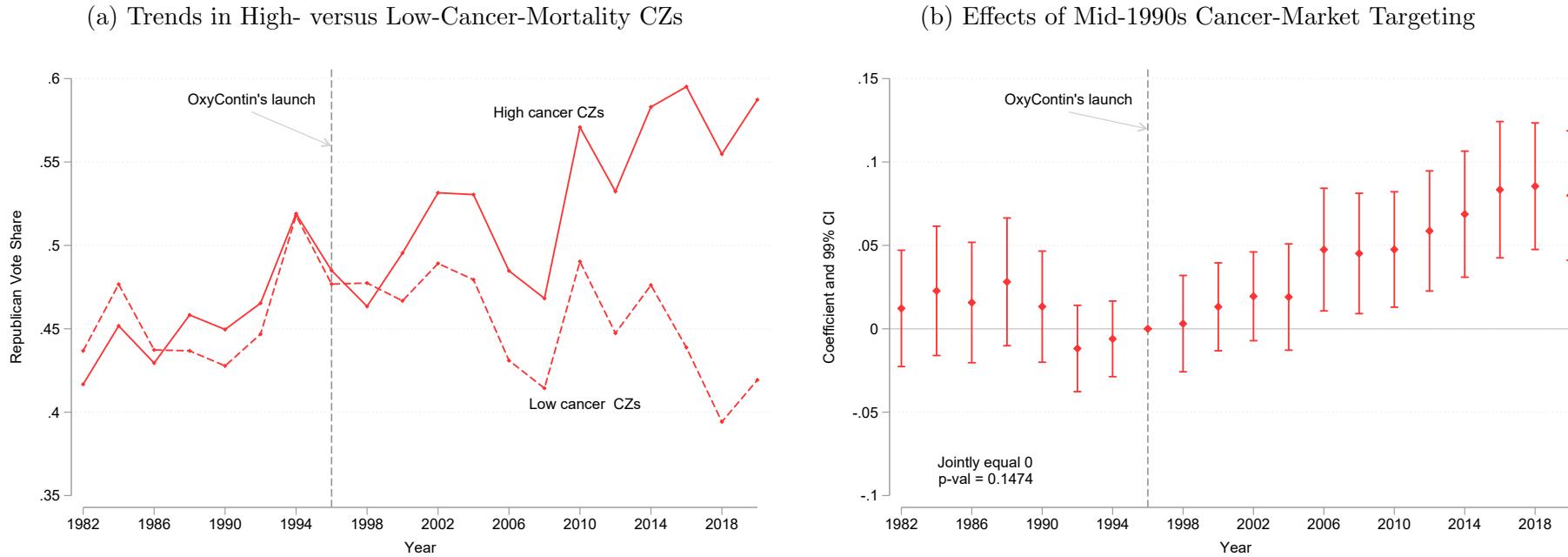


(d) Effects on Prescription Opioid Mortality



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. We run the following regression, analogous to equation (1), over a panel of CZs:  $\Delta y_{ct} = \alpha_1 + \sum_{\tau=1989}^{2020} \phi_\tau CancerMR_{ct_0} \mathbf{1}(Year = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + v_{ct}$ . Where  $y_{ct}$  is opioid prescriptions in panel (b) and prescription opioid mortality in panel (d) and the remaining variables are defined as in IV.a. Since ARCOS data are available from 1997 we can only estimate coefficients from this date. In panel d, we do not reject the null hypothesis that the estimated coefficients before 1996 ( $\phi_{1989}, \phi_{1990}, \dots, \phi_{1995}$ ) are jointly equal to zero. The  $p$  value of this test is presented in the figure. This figure is referenced in Section IV.b.

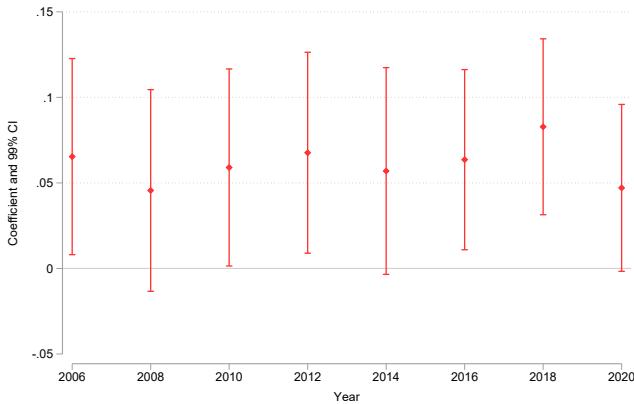
Figure 3: Republican Vote Share: Congressional Elections



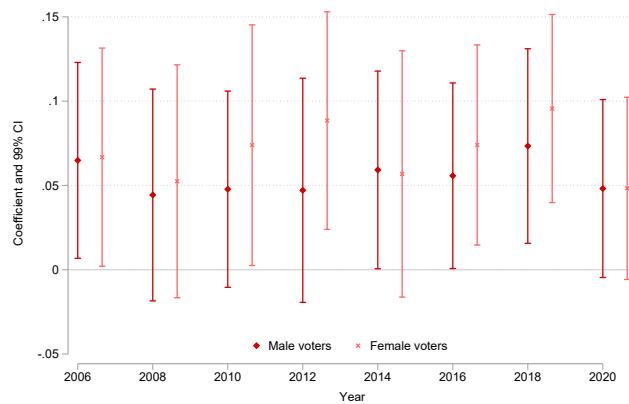
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in congressional elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between 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 ( $\phi_{1982}, \phi_{1984}, \dots, \phi_{1994}$ ) 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

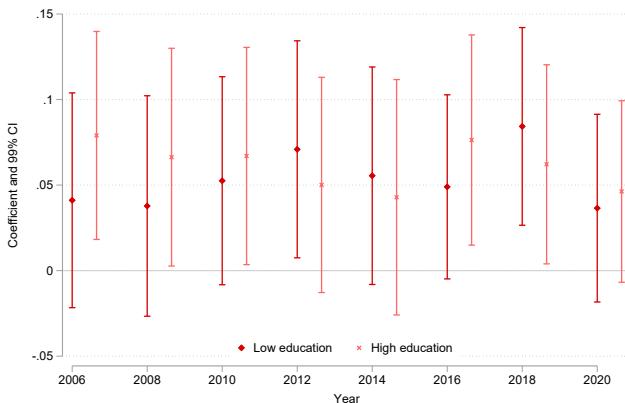
(a) Baseline estimation



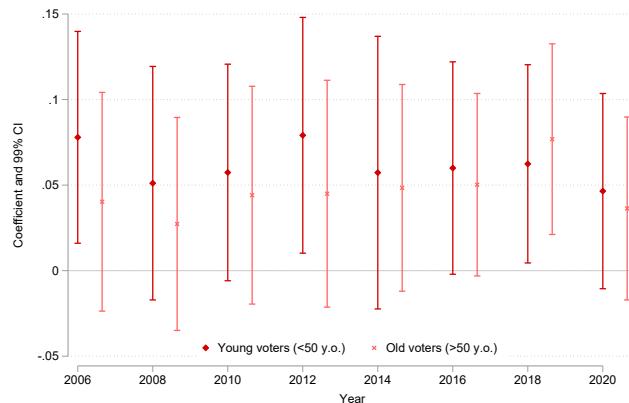
(b) By gender



(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:  $y_{ict} = \alpha_1 + \sum_{\tau=2006}^{2020} \phi_\tau \text{CancerMR}_{ct_0} \mathbf{1}(\text{Year} = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + \varepsilon_{ict}$ . This figure is referenced in Section V.a.

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

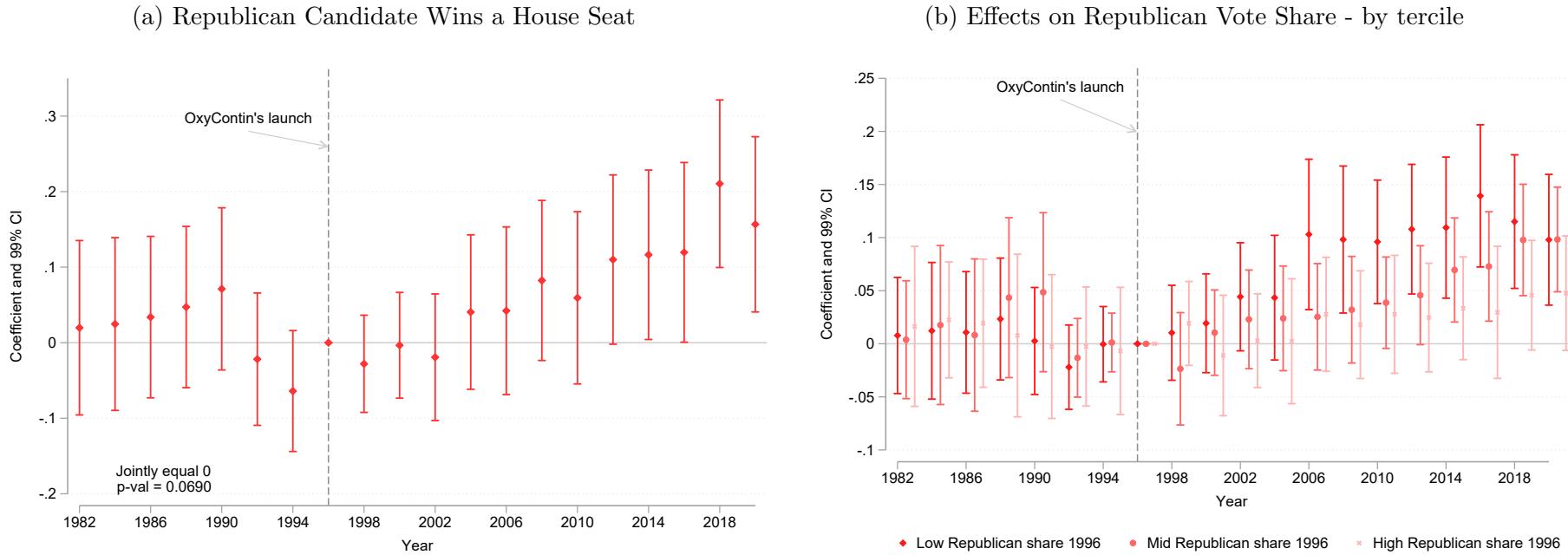
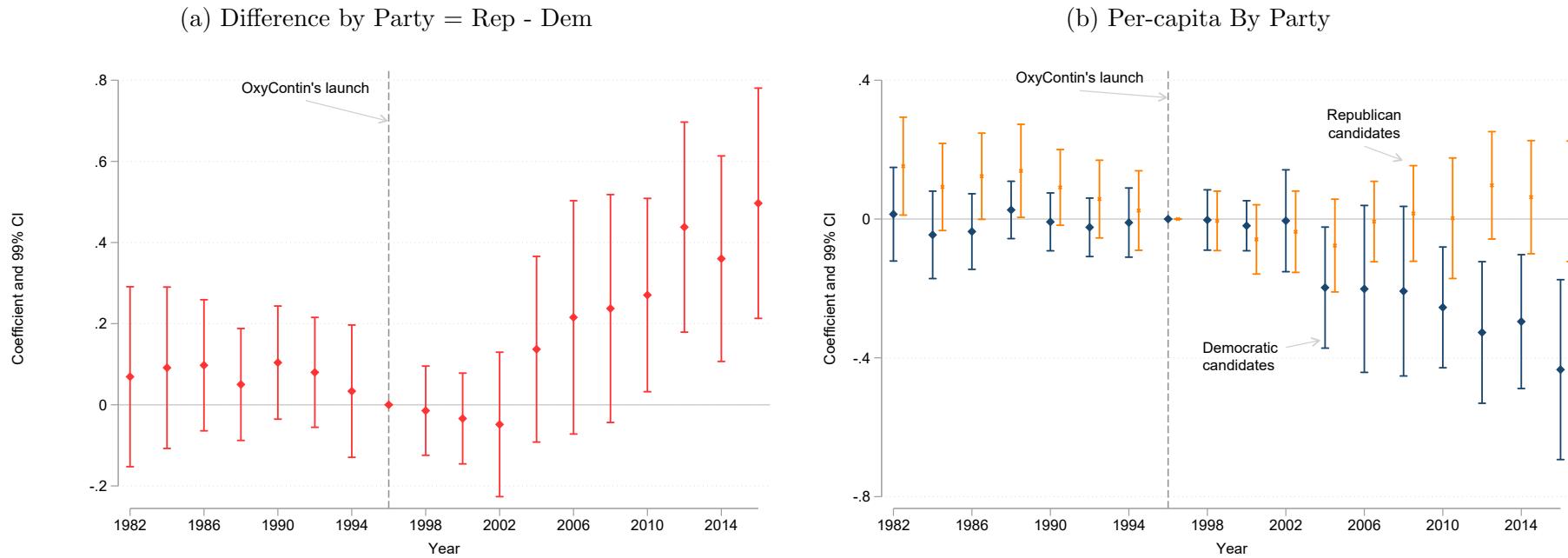
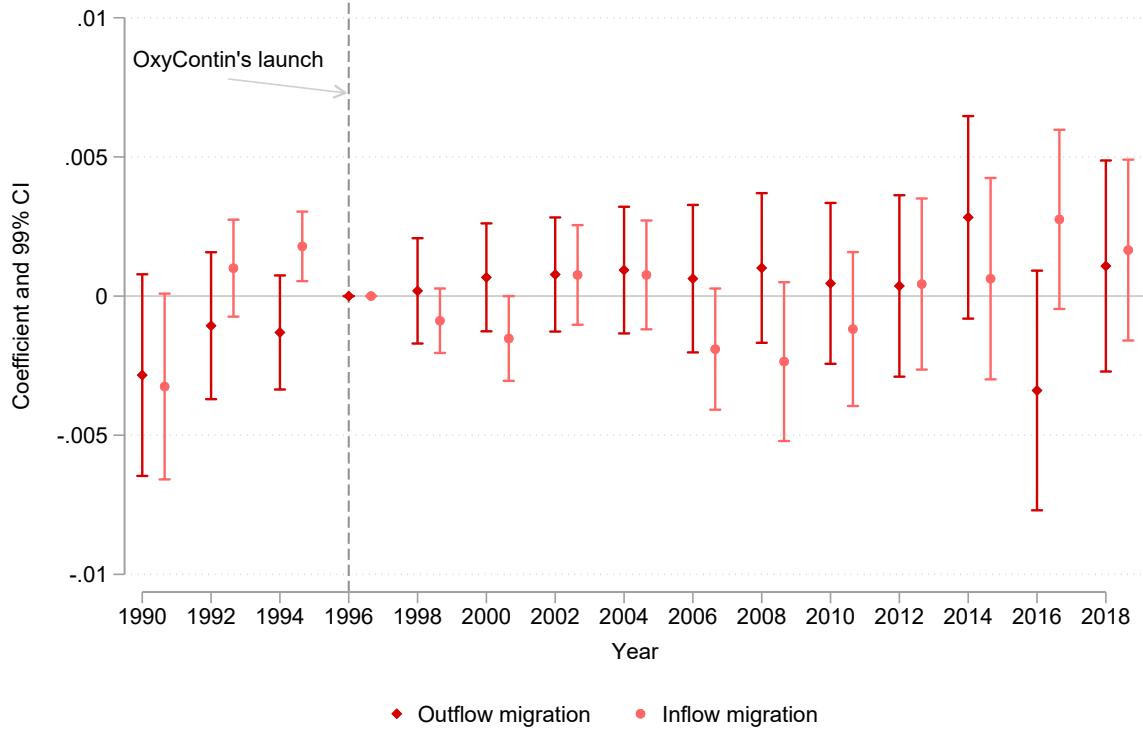


Figure 6: Effects of Exposure to the Opioid Epidemic on Per-capita Donors to Candidates for the House



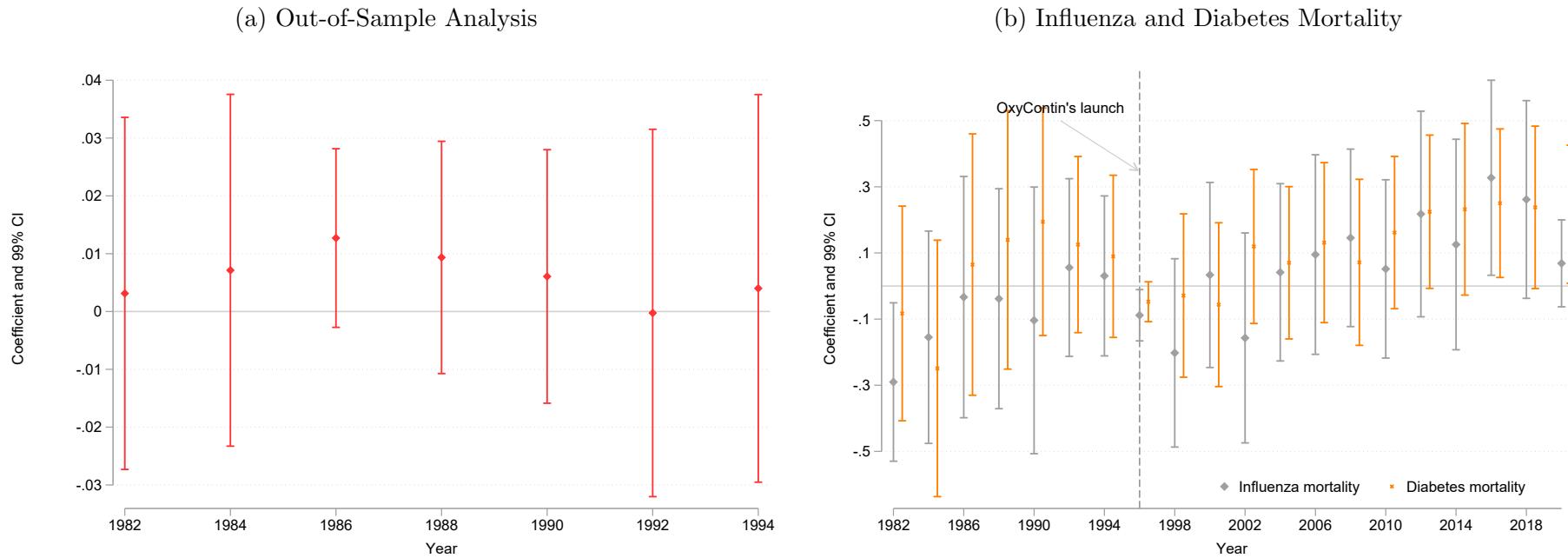
Notes: Panel (a) presents estimates of the dynamic relationship between the difference in the number of donors to Republican candidates and to Democratic candidates for House elections, and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of this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

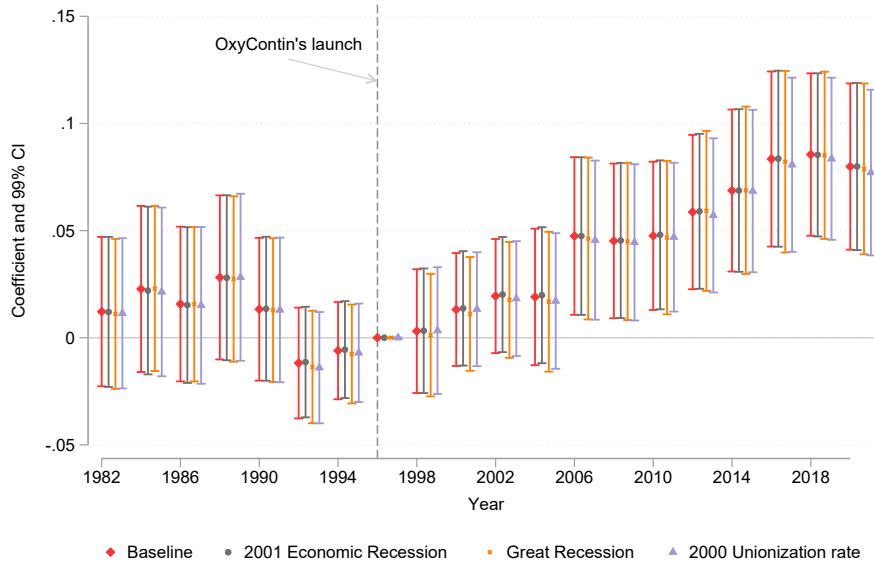
Figure 8: Placebo Checks: Out-of-Sample and Placebo Mortality Rates



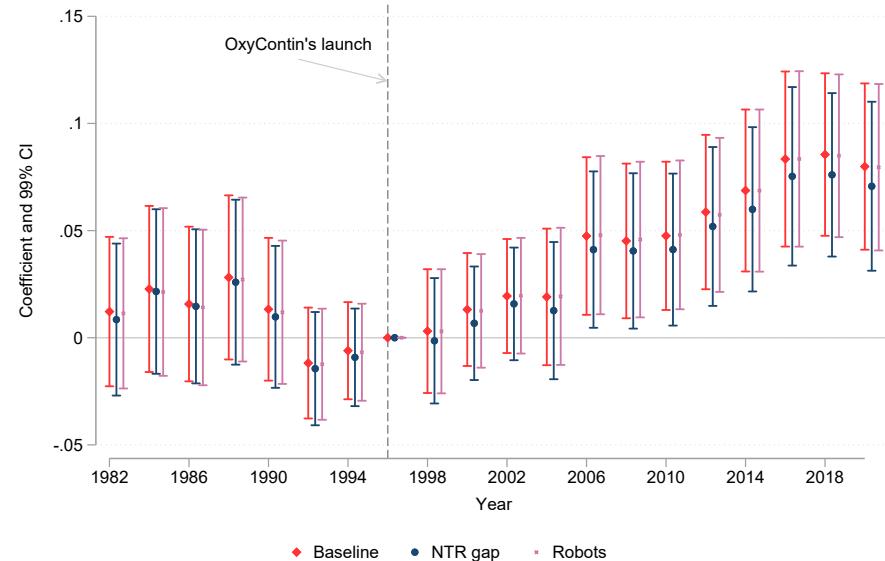
Notes: This figure presents two placebo checks. Panel (a) presents estimates of an out-of-sample dynamic reduced-form analysis for our pre-period. It provides evidence that lagged cancer mortality is not a predictor of future Republican vote share. Panel (b) presents estimates of the dynamic relationship 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 Economic Recessions & Unionization

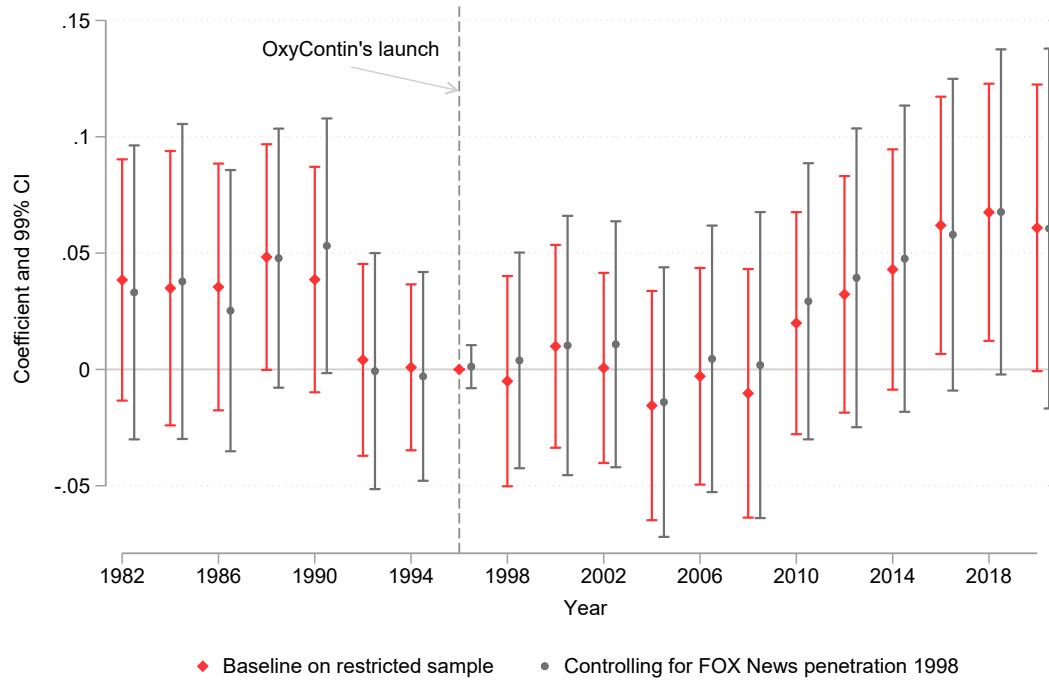


(b) Exposure to “China Shock” & Robots Adoption



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)
<b>Exposure to the opioid epidemic and mortality measures</b>						
Doses of prescription opioids per capita <sup>(a)</sup>				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 <sup>(b)</sup>	0.0652	0.0000	0.1320	0.3537	0.2410	0.4424
<b>Voting outcomes and political views</b>						
<i>Sh. Republican votes</i>						
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 <sup>(c)</sup>	0.6587	0.6853	0.1169	0.6397	0.6405	0.0987
<i>Donations to House candidates per 1,000 voting-age population<sup>(d)</sup></i>						
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	40.0955** [19.1413]	4.4302*** [1.7067]	-0.4144 [0.3496]
Sh. of population over 66	-27.8581*** [6.9707]	9.6753*** [1.1645]	0.2746 [0.2271]
Sh. White	4.7402*** [0.9862]	-0.3687* [0.2189]	0.1724*** [0.0409]
Sh. Hispanic	-4.1636*** [0.9622]	-1.0906*** [0.1895]	-0.2202*** [0.0463]
Sh. Female	7.7912 [10.2894]	0.9267 [1.7778]	-0.1382 [0.3463]
Opioid mortality	-2.7889 [8.9821]	3.7359* [2.012]	-0.0766 [0.2108]
Adult non-cancer mortality	130.8359** [59.5218]	38.9886** [17.0479]	-6.4988*** [2.3841]
Sh. HS diploma or less	-3.4405 [2.3073]	0.3442 [0.392]	0.1876** [0.0773]
Sh. empl in manufacture	-3.2681*** [1.0527]	0.0289 [0.1599]	-0.0534 [0.0416]
Ln. income	1.1094 [0.7636]	0.0332 [0.2094]	-0.0103 [0.0341]
Employment rate	-7.5561 [5.0572]	-1.9402 [1.3366]	0.7453*** [0.236]
Labor force participation	-5.7464* [3.4559]	-0.6452 [0.5179]	0.2803*** [0.0965]
Cancer mortality rate	0.2422 [0.2967]		-0.0067 [0.0083]
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.

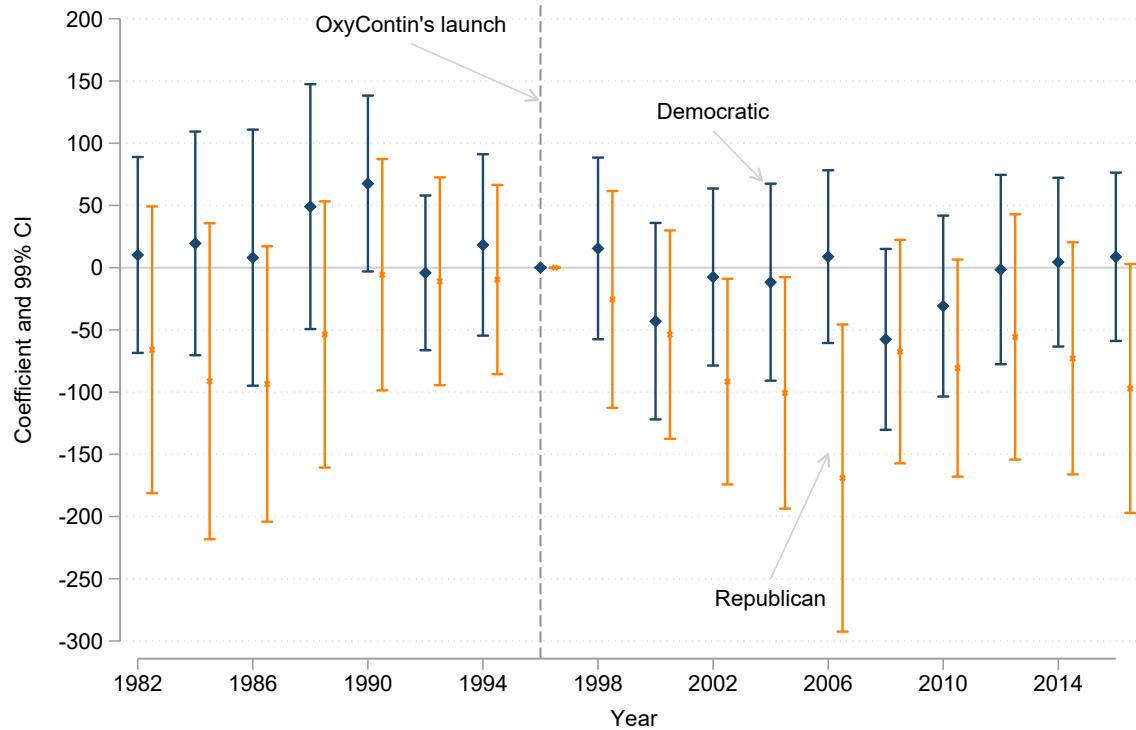
Table 3: Mid-1990s Cancer Mortality and Preferences

Panel A. Voter's views on:	Abortion (1)	Gun Control (2)	Immigration (3)	Own Ideology (4)	Fox News (5)
Cancer 1996	-0.0475*** [0.0169]	-0.0529*** [0.0154]	-0.0619*** [0.0137]	-0.175*** [0.0515]	0.0509*** [0.0194]
Observations	59,420	59,424	59,390	54,777	25,142
Dep. var. mean	0.610	0.644	0.421	5.00	0.405
Dep. var. SD	0.488	0.479	0.490	1.206	0.491
C-zones	610	610	610	607	587
Period	2020	2020	2020	2020	2020
Source	CCES	CCES	CCES	CCES	CCES
Panel B. Voter's views on:	Increase police officers (6)	Feel safe around police (7)	Affective Polarization (8)	Church Attendance (9)	Church Attendance (10)
Cancer 1996*Post			0.981** [0.412]	0.0319 [0.0284]	
Cancer 1996	0.0313*** [0.0117]	0.0778*** [0.0287]			0.0322 [0.0519]
Observations	59,419	59,354	42,462	42,462	58,155
Dep. var. mean	0.446	3.141	36.230	3.120	4.310
Dep. var. SD	0.497	0.941	32.280	1.600	0.422
C-zones	610	610	560	560	610
Period	2020	2020	1982-2020	1982-2020	2020
Source	CCES	CCES	ANES	ANES	CCES

Notes: Abortion: 1=“Always allow a woman to obtain an abortion as a matter of choice” and 0 otherwise. Gun Control corresponds to the item “Ban assault rifles,” where 1=“Support” and 0=“Against.” Immigration: “Increase the number of border patrols on the US–Mexican Border,” where 1=“Against” and 0=“Support.” 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. Police questions: “Increase police officers on the street by 10 percent.” Support=1, oppose=0. “The police makes me feel safe”: Mostly safe=4, somewhat safe=3, somewhat unsafe=2, mostly unsafe=1. Higher level of affective polarization translate to higher polarization measured as the distance between my feelings about my own party versus the opposition party. Fox News is a dummy variable equal to 1 when respondents say yes to watching Fox News. *Post* takes the value one for electoral years after the onset of the opioids epidemic. 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.c.

## A Additional Figures

Figure A1: House Campaigns Median Donations Amount



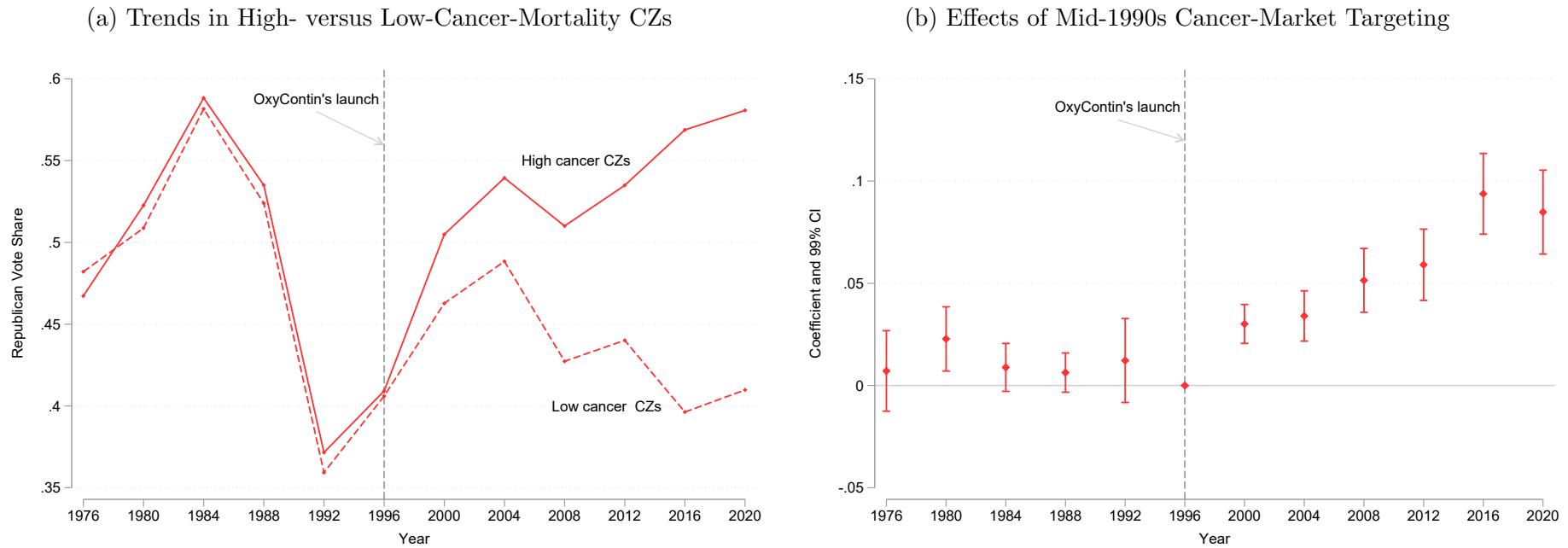
Notes: This figure presents estimates of the effect between exposure to the opioid epidemic and median donation amounts by party. This figure is referenced in Section V.a.

Figure A2: Conservative-Liberal Ideology Roll-call Voting of Members of the House



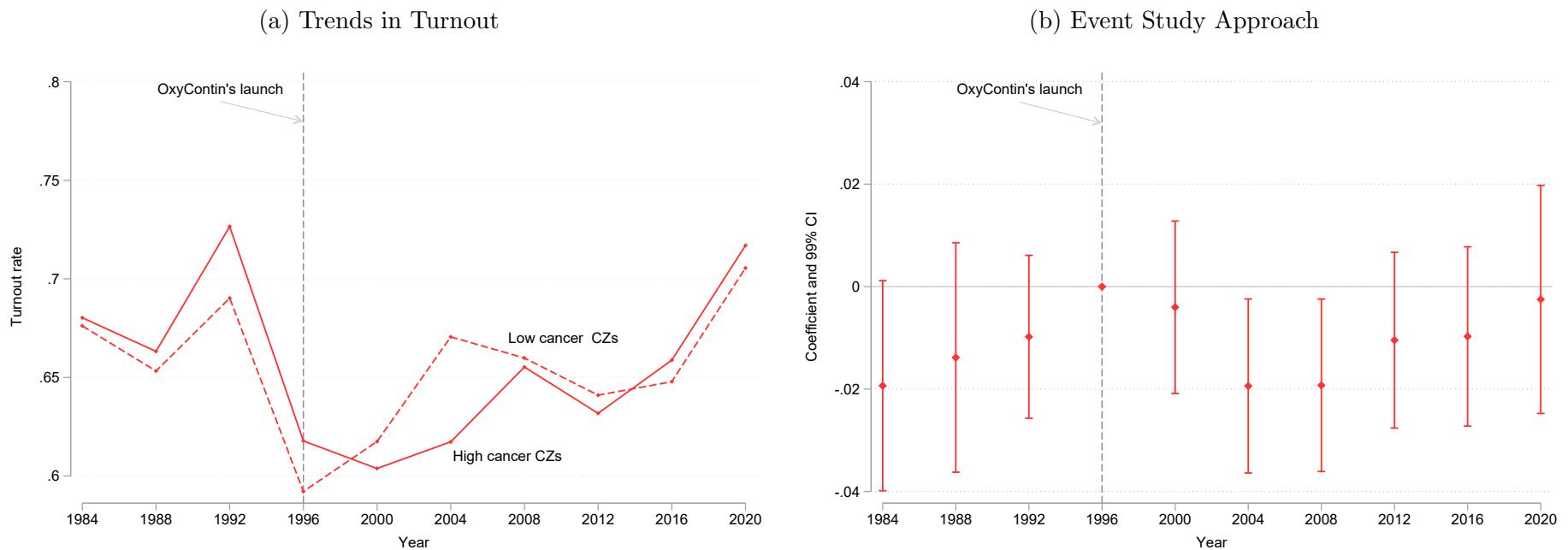
Notes: This figure presents estimates of the dynamic relationship between the candidates ideology in roll-call voting and mid-1990s cancer mortality, panel (a) shows the main effects and panel (b) splits the sample based on the initial share of Republican votes in congressional elections. Panels (c) and (d) show the probability that candidates would be in the top (bottom) percentile of the Nokken-Poole measure. This figure is referenced in Section V.a.

Figure A3: Republican Vote Share: Presidential Elections



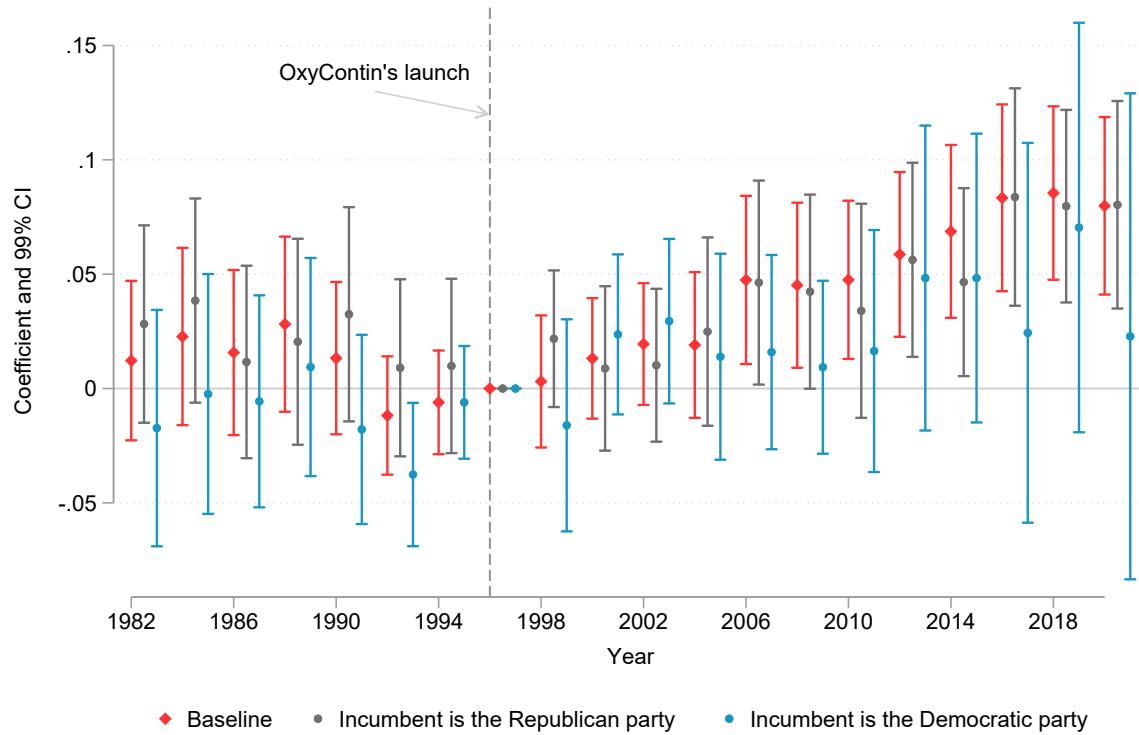
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections in the bottom (dashed line) and top (solid lines) quartiles of the cancer mortality distribution before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship 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 A4: Turnout Rates



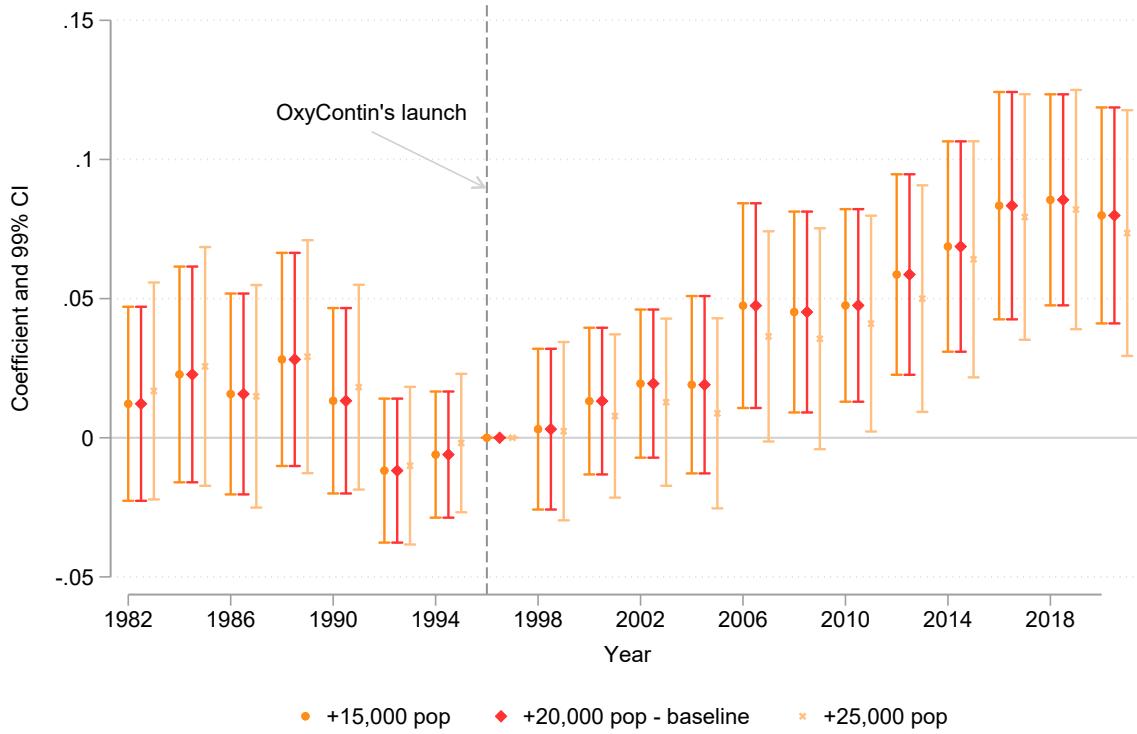
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turnout rates and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.a.

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



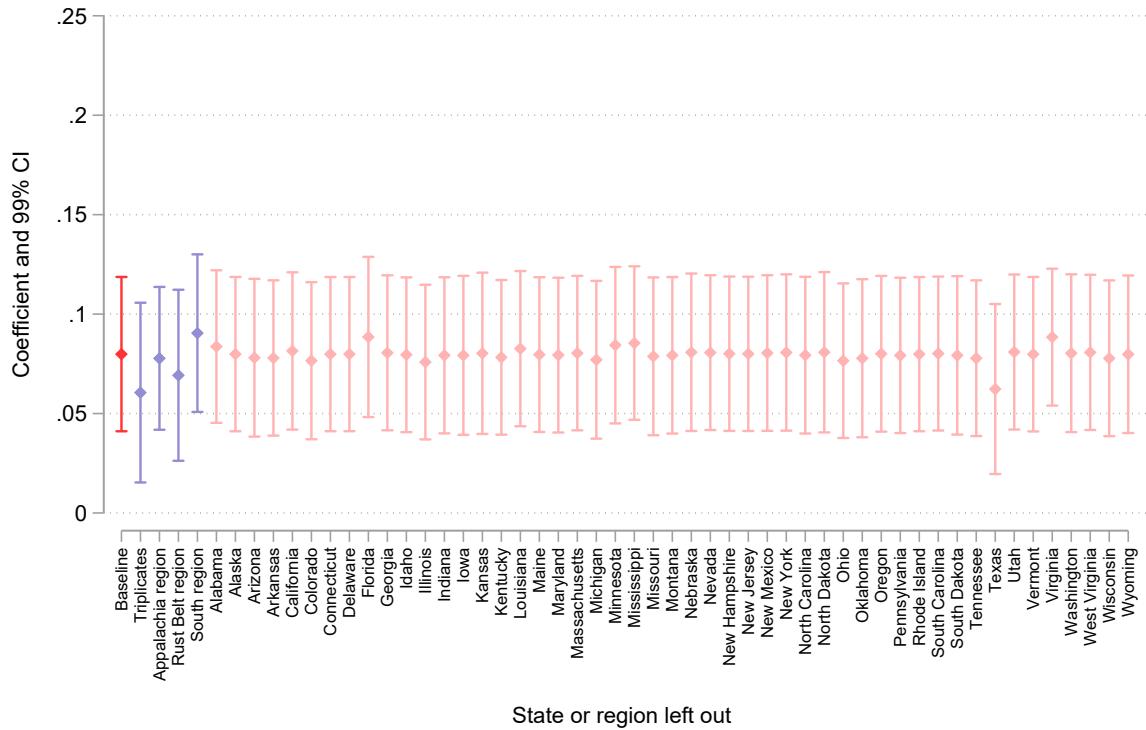
Notes: This figure presents estimates of the effects of opioid epidemic exposure on vote share splitting the sample into commuting zones with either a Republican or Democrat incumbent at the time of the election. This figure is referenced in Section V.c.

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 constraints 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.

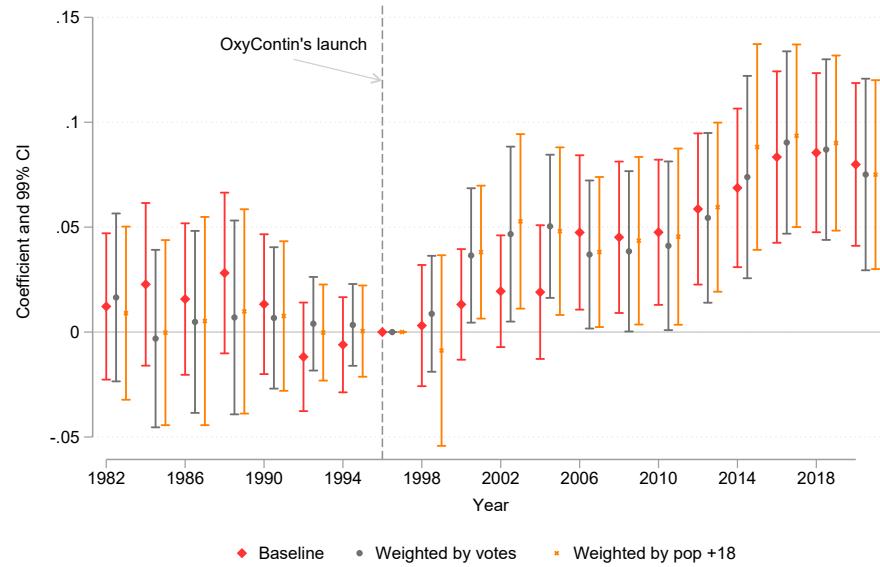
Figure A7: 2020 Coefficients – Leaving One State Out



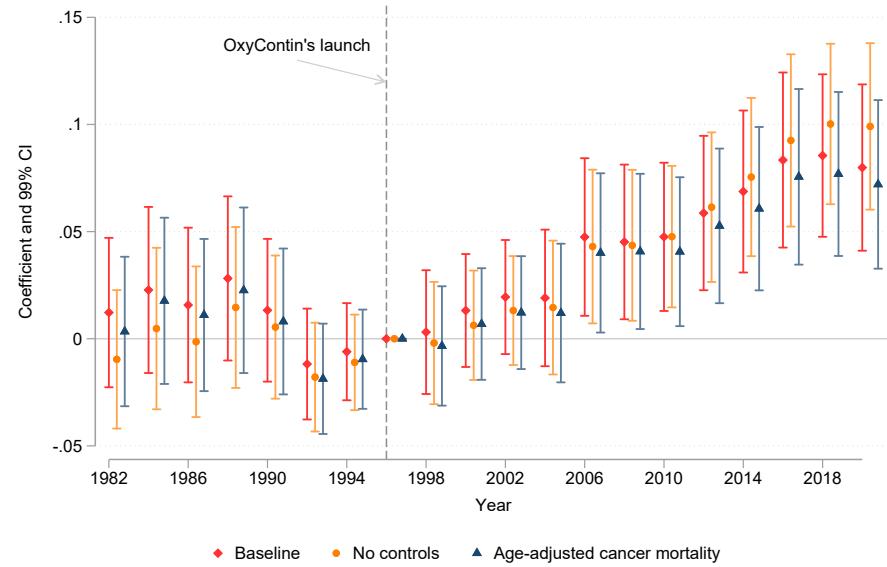
Notes: This figure presents estimates of the 2020 coefficients from an event study similar to that in equation 1 run on a sample that excludes all commuting zones in the state indicated on the horizontal axis. That is, the x-axis label indicates the state left out of the estimation. This figure is referenced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

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

(a) Population Weighted Estimations

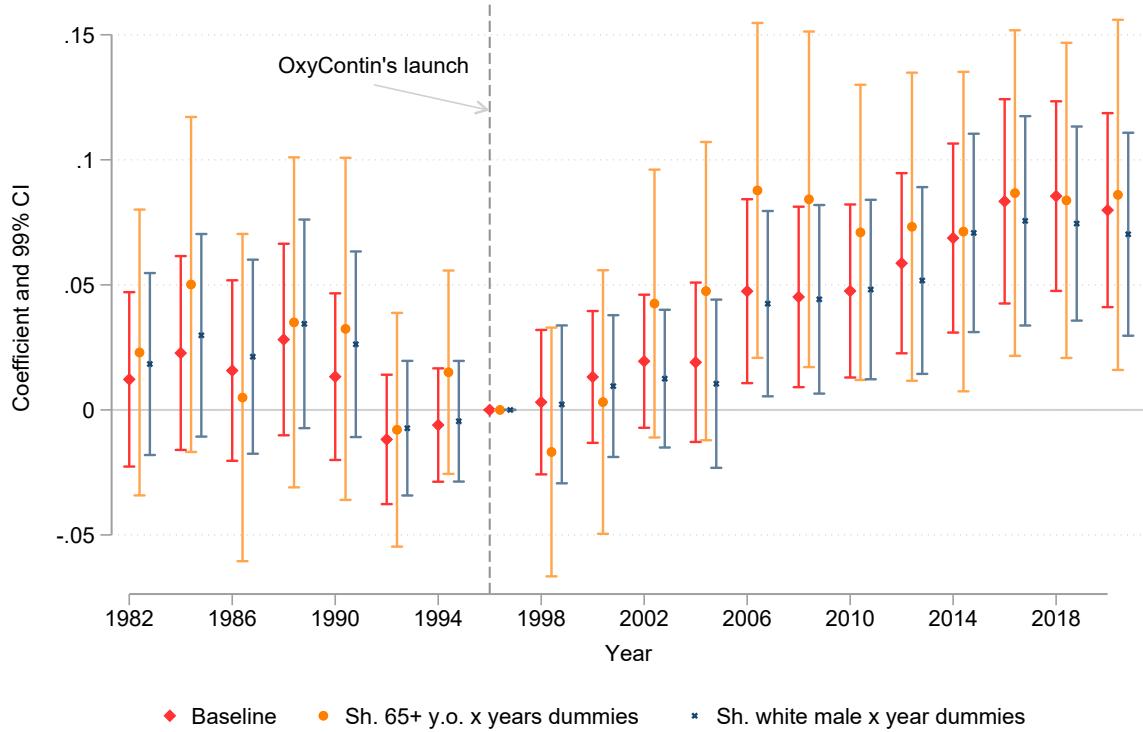


(b) Alternative controls and 1996 Age-adjusted Cancer Mortality



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.

Figure A9: Robustness Check: Additional Demographic Controls



Notes: This figure replicates our estimates of Figure 3 and adds versions with additional controls. We interact the share of the 65 years and older population in 1996 with year dummies and, analogously, we add interactions with the share of the white male population in 1996. This figure is referenced in Section VI.c.