

Democracy and the Opioid Epidemic

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Abstract

In this paper, we estimate 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 Republicans winning additional seats in the House from 2014 until 2020 and House members holding more conservative views. These effects are explained by changes in voter views rather than in voter composition.

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I. Introduction

The opioid epidemic stands as one of the most tragic public health crises to affect the United States in the past century (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 socioeconomic paths (Arteaga and Barone, 2023). The unfolding of the epidemic coincides with a historical moment of enhanced partisanship and polarization. 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).

In this paper, we ask whether community exposure to the opioid epidemic caused political and ideological divergence along party lines. Historical and contemporaneous evidence point towards a connection between communities experiencing deteriorating health and political changes. For example, worsening mortality rates in Germany in the early 1930s are associated with increasing votes for the far right and out-group animosity (Galofré-Vilà et al., 2021). Voigtländer and Voth (2012) document persistent antisemitic 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 stagnant life expectancy and midlife mortality (Monnat, 2016; Bor, 2017; Bilal et al., 2018; Goodwin et al., 2018; Case and Deaton, 2022, and Siegal, 2023). However, establishing causality is challenging since deteriorating socioeconomic conditions can both increase demand for opioids (Ruhm, 2019; Currie and Schwandt, 2021) and fuel anti-establishment sentiment and support for the right (Blickle, 2020).

To overcome the identification challenge, we exploit rich geographic quasi-exogenous variation in 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. This work and subsequent research, show that mid-nineties cancer mortality is a strong indicator of exogenous exposure to the opioid epidemic.¹ 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.

To estimate the causal effects of opioid epidemic exposure on political outcomes, we collect data from multiple sources and construct a panel of commuting zones (CZs) covering the United States from 1982 to 2020.² We use county-level data on political outcomes from Dave Leip’s Atlas of US Elections ([Leip, 2022](#)) and the United States Historical Election Returns Series assembled by the Inter-university Consortium for Political and Social Research (ICPSR), which provides information on House and presidential election results. We combine these data with two surveys on political views: the American National Election Survey (ANES) and the Cooperative Congressional Election Study (CCES). To measure opioid prescriptions at the CZ level, we use data from the Drug Enforcement Administration (DEA) on the distribution of controlled substances. Finally, we construct cancer and opioid mortality measures from the National Vital Statistics System (NVSS).

We find that exposure to the opioid epidemic increased the Republican vote share in House 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 House elections, a one-standard-deviation higher 1996 cancer mortality rate would yield an increase in the Republican vote share of 4.6 percentage points. Using survey data, we document that this shift toward 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, as measured by legislative roll-call voting by members of Congress. However, this shift stemmed not from the election of candidates at the extreme of the political spectrum but from a change in the composition of the House. We also observe a positive wedge in favor of the Republican party in terms of the number of individual House campaign donations. This difference is the result of a decline in donations to Democrat candidates, with no effects observed for Republicans. When we look at presidential

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

²CZs are geographic areas defined to capture local economic markets. They encompass all metropolitan and nonmetropolitan areas in the US. While CZ-level data are less granular than those at the county level, they are much more granular than state-level data ([Tolbert and Sizer, 1996](#)).

elections, the results follow the pattern of the House elections. Finally, we find no effects on turnout rates.

Next, we investigate whether these changes in voting patterns result from changes in the composition of the electorate or a shift in views. To address the first hypothesis, we use 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 epidemic’s direct mortality effects. Back-of-the-envelope calculations suggest that, by 2020, the vote share for Republicans would have changed by at most 0.22 percentage points in the absence of the epidemic. Instead, we find evidence for the hypothesis that the voting patterns resulted from changes in views and political preferences. We use CCES and ANES survey data to measure this ideological realignment. Specifically, we estimate that exposure to the epidemic translated into a rise in conservative views across the board, as measured by views on immigration, abortion and gun control and by self-declared ideology.

We assess alternative explanations for these changes in views and provide evidence suggestive of three forces at play. First, the perceived greater effectiveness of the Republicans’ than of the Democrats’ approach to curbing the opioid epidemic might have swayed voters in the direction of the former. Republicans favor increased law enforcement to curb drug trafficking and crime, while Democrats prefer harm reduction policies and funding increases 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 that they may increase drug use and mortality (Doleac and Mukherjee, 2019; Packham, 2022; Spencer, 2023). Second, work in psychology—particularly the social identity and intergroup threat theories—proposes that shared experiences of hardship strengthen in-group identity, alter the perceived distance between groups, and increase affective polarization.³ The opioid epidemic serves as an example of shared hardship. We provide direct evidence of this mechanism: exposure to the opioid epidemic raises affective polarization. Our results are consistent with those from Mian et al. (2014) and De Bromhead et al. (2013) that connect adverse economic shocks with 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).

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

³See 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).

prescription opioids marketing, areas with higher cancer mortality in 1996 would have exhibited the same trends in our outcome variables as areas with lower cancer mortality. 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 epidemic exposure 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 reproduce our empirical strategy for the pre-period from 1982 to 1994. We find no evidence of a relationship between lagged cancer mortality and future Republican support. We also construct placebo 1996 mortality rates 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 documented to have affected political outcomes in this period, such as Chinese import competition, economic recessions, unionization rates, robot adoption, and the introduction of Fox News. Our estimates remain robust when these variables are included as controls.

In this paper, we establish a causal connection between two of the most salient social developments in the United States over the past decades: the opioid epidemic and the rise in polarization. We build a bridge between the political economy and health economics literatures, contributing to the understanding of the socioeconomic determinants of political preferences and ideological views. Previous studies have explored the effects of economic conditions, globalization, trade, automation, and immigration on political ideology and polarization (among others, [Brunner et al., 2011](#); [Voorheis et al., 2015](#); [McCarty et al., 2016](#); [Margalit, 2019](#); [Autor et al., 2020](#); [Rodrik, 2021](#); [Che et al., 2022](#); and [Guriev and Papaioannou, 2022](#)). Closer to our work is [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. 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 ideological distance along conservative–liberal lines between more and less exposed communities.

Finally, we extend the literature on the community-level effects of the opioid epidemic by estimating the overall political impact resulting from its complex and multidimensional consequences. Previous work has documented its effects on poverty, disability, employment, crime, municipal finances, house prices, fertility, and children’s outcomes: see,

among others, [Park and Powell \(2021\)](#); [Buckles et al. \(2022\)](#); [Arteaga and Barone \(2023\)](#); [Ouimet et al. \(2020\)](#); [Cornaggia et al. \(2022\)](#) and [Custodio et al. \(2023\)](#) as well as [Maclean et al. \(2020\)](#) for a review.

II. Background: Opioid Epidemic & Political Landscape

In this section, we discuss the origins of the opioid epidemic and its community-level impacts, and explain the rationale behind our empirical strategy. We also present 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 because of 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.⁴

⁴Schedule II drugs are drugs that have high potential for abuse and may lead to severe psychological or physical dependence. Examples of Schedule II narcotics include hydromorphone (Dilaudid),

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), and “*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 non-cancer pain market:

“The use of OxyContin in cancer patients, initiated by their oncologists and then referred back to FPs/GPs/IMs, will result in a comfort that will enable the expansion of use in chronic non-malignant pain patients also seen by the family practice specialists” (OxyContin Launch Plan, September 1995).⁵

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.⁶ 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. Evans et al. (2019) and Alpert et al. (2018) show that the reformulation unfortunately led many consumers to substitute toward a dangerous and inexpensive alternative: heroin. As a result, deaths, poisonings, emergency room visits, and enrollments in treatment programs for heroin abuse increased. In particular, between 2010 and 2013, heroin death rates increased by a factor of four with no reduction in the combined heroin and opioid death rate (Evans et al., 2019).

From 2013 to this day, 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

methadone (Dolophine), meperidine (Demerol), oxycodone (OxyContin, Percocet), and fentanyl (Sublimaze, Duragesic).

⁵Opioid Industry Documents Archive from the University of California, San Francisco UCSF (2018)

⁶See Maclean et al. (2020); Alpert et al. (2022); and Arteaga and Barone (2023) for detailed discussions of the marketing of prescription opioids.

higher risk of overdose.⁷ 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 smuggling of fentanyl. In 2020, the majority (69%) of Americans said the federal government should be doing more about opioid addiction.⁸

II.b. Economic Impacts of the Opioid Epidemic

Mortality from opioids is only one of the many social costs associated with the opioid epidemic. Some 10.1 million people aged 12 or older are estimated to have misused opioids in the past year in the US (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; 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), innovation (Cohle and Ortega, 2023), and sales and employment growth (Ouimet et al., 2020).

Additionally, through its impacts in increasing fertility rates, rates of child protective services investigations, and the 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). The individual- and community-level economic 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., 2023). Since the 1980s, the US has exhibited

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

⁸The 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.

the largest increase in affective polarization among 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; by 2020, this difference was 56.3. 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](#)).⁹

Support for partisan leaders is increasingly divided along party lines. The differences in presidential approval ratings across parties—i.e., approval among Democrats of a Republican president and vice versa—were 81 and 70 points for presidents Donald Trump and Barack Obama, respectively. These figures are almost twice as high as the 38-point difference for president George H.W. Bush in the early 1990s ([Jones, 2021](#)). The political parties have sorted along ideological lines, meaning that liberal Republicans and conservative Democrats have largely disappeared ([Fiorina, 2016](#)). At the same time, the partisanship of language used by members of 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 of 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](#)). In this paper, we explore an additional channel: the drifting trends in communities’ health and socioeconomic outlooks driven by their differential exposure to the opioid epidemic.

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 data on House and presidential election results, donations to candidates, political views, our measure of epidemic exposure—1996 cancer mortality—and direct measures of opioid epidemic severity, such as opioid mortality and prescription rates.

⁹In 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.

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 outcome variables: the Republican vote shares for House and presidential elections, and voter turnout. Panel (a) of Figure 1 shows the distribution of the Republican vote share in House elections in 1996. This figure suggests 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%.¹⁰

We use the Database on Ideology, Money in Politics, and Elections (DIME) from Bonica (2023) to construct per capita rates of individual campaign donations to House races by party, spanning the years 1982 to 2016.¹¹ These data provide unique individual identifiers, with geolocated addresses and details on the contribution amount, campaign, and candidate supported. We aggregate the count of individual campaign contributions directed toward Republican or Democrat candidates in House races and divide this by the 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 Congress on roll calls along with an estimation of the member’s ideology.¹² We use the Nokken–Poole estimate and focus on House members; these estimates are based on the NOMINATE model, which places each member along a primary liberal–conservative axis that describes preferences over taxation, spending, and redistribution.¹³

We construct measures of the public’s political views and preferences using survey data from nationally representative election surveys, the ANES and CCES. In particular, the ANES includes a partisan thermometer measure, and the CCES provides measures of individual views on highly political issues such as support for gun control, support for

¹⁰We refrain from using the CCES to study turnout, as studies have raised issues with using these data to measure turnout (Agadjanian, 2018).

¹¹We exclude data for 2018 and 2020 from our analysis because donation patterns underwent significant changes during these election cycles, rendering the data incomparable.

¹²As of January 22, 2018, the Voteview.com database included information on all 24,174,546 individual votes cast by 12,297 members on 105,721 roll calls over Congress’s 229-year history.

¹³For further discussion of the NOMINATE model, see Poole and Rosenthal (1985) and Poole (2005). In particular, the Nokken–Poole estimate is well suited for measuring how members of Congress’s ideological positions may have changed over time since the scores are generated with members allowed to hold different positions in each Congress; see Nokken and Poole (2004).

access to abortion, and immigration policy, among other issues.

Prescription opioids. We digitize historical records from the DEA’s Automation of Reports and Consolidated Orders System (ARCOS). These reports contain the distribution records of all Schedule II substances by active ingredient (e.g., oxycodone, morphine) at the 3-digit ZIP code level from 1997 to 2020.¹⁴ From these data, we construct a CZ-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 on 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.¹⁵ Panel (d) of Figure 1 shows the geographic distribution of prescription opioid mortality from 1999 to 2018.

Geographic harmonization. The electoral outcome and mortality data are available at the county level; we use the crosswalks developed by Autor and Dorn (2013) to aggregate the data to CZ level.¹⁶ The survey data from the ANES and 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 CZ level. This second step serves two purposes: i) to harmonize to a common geographic unit and ii) to account for redistricting of congressional districts since Ferrara et al. (2021) provide year-specific crosswalks.¹⁷

In sum, our final dataset consists of a panel of 625 CZs from 1982 to 2020.¹⁸ 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

¹⁴The 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 Centers for Disease Control.

¹⁵See [Arteaga and Barone \(2023\)](#) for the ICD10 and ICD9 codes used in constructing each variable.

¹⁶Some CZs cross state borders. When this happens, the CZ is assigned to the state with the larger share of the CZ population. This criterion helps to preserve the strong within-cluster and weak between-cluster commuting ties.

¹⁷Congressional district boundaries are established by states after apportionment of congressional seats. Each congressional district is to be as equal in population as practicable to all a state’s other congressional districts.

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

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 CZ’s demographic composition. A greater white population share at CZ 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 epidemic exposure using cancer mortality in the mid-1990s. For each outcome variable, we consider the following specification, which is run over our sample of CZs:

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

where c indexes the commuting zone, s the state, and t the year and t_0 corresponds to 1996, the year of OxyContin’s launch. We define Δ as the long-change operator: for any random variable W_{ct} , $\Delta W_{ct} = W_{ct} - W_{ct_0}$. The model includes a vector ΔX_{ct} that represents the long changes in the time-varying control variables. These are contemporaneous cancer mortality, the white and female population shares, the shares of the population aged 18–29, 30–49, 50–64, and above 65 years, and the share of the population aged under 1 year; all of these measured at CZ level.

$CancerMR_{ct_0}$ is the cancer mortality rate in CZ c in 1996 (t_0) and is interacted with a full set of year dummies indexed by τ . This reduced-form specification allows us to test for pre-trends and estimate time-varying effects on outcomes of interest. That is, the coefficients for the pre-epidemic period, i.e., ϕ_{1982} , ϕ_{1984} , to ϕ_{1994} , test whether the outcome of interest y_{ct} followed similar trends in areas with higher and lower cancer mortality before the launch of OxyContin. The main coefficients of interest, i.e., ϕ_{1998} , ϕ_{2000} , to ϕ_{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 γ_{st} represents state-by-year fixed effects. These fixed effects control for state-specific trends and the state-level policy changes that were common during this period that directly affected the supply of opioids—e.g., the implementation of prescription drug monitoring programs (PDMPs), the regulation of “pill mill” clinics, and policies on the availability of naloxone¹⁹—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* in the outcomes of interest as areas with lower cancer mortality (Goldsmith-Pinkham et al., 2020).²⁰ We provide supporting evidence for the first assumption in the next subsection and discuss the trends assumption in the results section.

IV.b. Validity of Mid-1990s Cancer Mortality as Proxy for Epidemic Exposure

We start by showing the evolution of prescription opioids per capita by cancer mortality in 1996 in Figure 2. CZs in the top quartile of cancer mortality in 1996 saw an increase of 2,900% in grams of oxycodone 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.²¹ We find 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-1990s 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 those for all other drugs.

We next study the relationship between 1996 cancer mortality and opioid-related mortality. When we inspect the raw data, Panel (c) of Figure 2 shows that areas in the top and bottom quartiles of cancer mortality experienced a similar evolution in prescription opioid mortality before the launch of OxyContin. In contrast, for the years after 1996,

¹⁹See, for example, Buchmueller and Carey (2018) and Doleac and Mukherjee (2019).

²⁰The identification assumptions of our research design are close to those associated with shift-share instrumental designs. 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 this instrumental variables model.

²¹Since the ARCOS data are available only from 1997, we can estimate coefficients only from this date.

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. Opioid Epidemic Exposure and Voting and Candidate Support

House elections. The opioid epidemic increased the share of votes for the Republican party in House elections. We start by presenting evidence using raw data. We split CZs 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 was 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. We estimate that, by 2020, a one-unit higher 1996 cancer mortality rate would yield an increase of 7.9 percentage points in the Republican vote share relative to the 1996 baseline. Put another way, a one-standard-deviation higher cancer mortality rate (0.58) would increase the vote share by 4.6 percentage points (see Panel (b) of Figure 3). These estimates, though sizable, are comparable in magnitude to the decline in the Democratic vote share resulting from a 5% increase in the employment-to-population ratio. In particular, Brunner et al. (2011) find that such an increase would lead to a 8-percentage-point decrease in votes for a Democratic governor and a 6-percentage-point decrease in support for party-endorsed ballot propositions.

Demographic heterogeneity. We use CCES survey data from 2006 to 2020 to examine the heterogeneity in the effects along voters' sociodemographic characteristics.²² We start by replicating our baseline result on voting Republican in the CCES data. Panel (a) in Figure 4 shows very similar results from this alternative data source. Next, we divide the sample by gender, age, and educational attainment level. Panels (b) to (d) in Figure 4 show that along all of these characteristics, we estimate similar-sized effects and a higher Republican vote share.

Election wins and geographic heterogeneity. Whether increases in the Republican vote share translate into election wins depends on how contested districts are and how much the vote increases. We show that even though the Republican vote share started to increase in 2006, it is only for years from 2012 that we start to observe evidence of an increase in the probability of a Republican win (Panel (a) of Figure 5). The main reason behind this pattern is that the initial increases in vote share were concentrated in

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

communities with a low baseline Republican vote share (Panel (b) of Figure 5). Starting in 2014, the vote share in communities with an initially median level also began to increase, contributing to the rise in the seats' likelihood of flipping in the election.

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 CZ 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 the number of donations per capita. Specifically, a one-standard-deviation increase in cancer mortality increases this gap by 0.32 standard deviations. This difference is the result of the decline in donations to Democrat candidates, with no effects observed for Republicans. In terms of the donation amount, 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 on the margin of donating to House campaigns: on average, 0.23% of the voting-age population donates 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 assess the evolution of elected candidates' ideology, measured from their 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 opioid epidemic exposure increased conservative views in the House, particularly among representatives from districts with lower baseline Republican support (Panel (b)). Nevertheless, this shift originated not from a change in the election probability of candidates at the extremes of the political spectrum in each given election year (Panels (c) and (d) of Figure A2) but rather from a change in the composition of the House.

Presidential elections and turnout. The epidemic's effects on elections are also present in the 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, a wedge had emerged in Republican support that widened as time went on, and by 2020, the gap in GOP vote shares in areas with high relative to low cancer mortality was 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 margin as measured by turnout. We document no notable changes along this margin in Figure A4.²³

²³We do not report turnout pre-trends or effects for House elections as data are not available for midterm elections from 1990 to 1998.

V.b. What Drives Changes in Voting and Candidate Support: Shifts in the Composition of the Electorate or Changes in Views?

First, to investigate changes in the composition of the electorate, we examine the role of migration. We collect data on county-to-county migration flows from the IRS Statistics of Income (SOI) Tax Stats and calculate total out-migration and in-migration flows at CZ level. Figure 7 estimates Equation (1) and shows that opioid epidemic exposure is not related to differential in- or out-migration patterns. That is, CZs with high versus low 1996 cancer mortality did not experience differential migration flows either before or as a result of the opioid epidemic. However, we cannot rule out differential changes by party ideology (i.e., we do not observe the partisan composition of these flows).

Second, we consider a back-of-the-envelope calculation to test whether our results are mechanically driven by the direct mortality effect of the epidemic. We estimate what the change in the Republican vote share would have been had the missing votes attributable to opioid-related deaths gone to (i) the Democratic party or independent candidates and (ii) the Republican party. To do so, we accumulate all opioid-related deaths since 1996—the year OxyContin was introduced to the market—and compute the counterfactual Republican vote share under each assumption. The latter counterfactual indicates at most a change in this share of only 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 by 4.6 percentage points by 2020 for an increase of one standard deviation in 1996 cancer mortality.

To investigate the hypothesis of changes in views, we use survey data from the 2020 CCES. 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 on abortion, gun control and immigration and more conservative self-reported ideology. This suggests that the wedge in Republican vote share between communities that we document was accompanied by a broader polarization and change in political views.²⁴

V.c. What Are the Mechanisms Driving These Changes in Views?

First, we consider whether differences in attributions of responsibility for the opioid epidemic or in the importance that each party places on 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 consider drug dealers who illegally sell opioids responsible for the opioid epidemic (YouGov, 2022). Among Democrats, the next most culpable parties are considered to be pharma-

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

ceutical companies and physicians. In contrast, Republicans next attribute blame to the people addicted to opioids and pharmaceutical companies. Members of neither party see the government as the primary culprit for the epidemic; however, most Republicans and Democrats agree that the government should be doing more to address the crisis (ANES, 2021).

When we turn to the role of differential party-level responsiveness, legislation to address 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 no differential political engagement surrounding the opioid epidemic, which might have indicated vote share movements in one direction or the other. However, they do not rule out differential perceptions of the effectiveness of each party's approach to addressing the crisis.

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 toward the Republican party, which is perceived as advocating for a larger police force and stricter law enforcement measures. Along these lines, when examining the 2020 CCES data, we observe that mid-1990s cancer mortality is positively correlated with expressing a preference to increase the number of police officers on the street and reporting 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 for the Republican party. Furthermore, harm reduction policies promoted mainly by Democratic politicians, such as drug legalization, syringe exchange programs, and naloxone access laws, have been shown to increase drug use (Doleac and Mukherjee, 2019; Packham, 2022; Spencer, 2023).

Second, we 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.²⁵ The results of this analysis are noisy, particularly for the later years of our analysis, owing to the decreasing proportion of CZs with Democrat incumbents. However, there is limited evidence supporting the hypothesis that the increases in Republican vote share are a response to anti-incumbent sentiment when Democrats are in power.

²⁵Where a CZ covers more than one congressional district, we split by the party with the majority of House members.

Next, we turn to insights from work in psychology that have been brought to economics to explain 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, social identity and intergroup threat theories 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 subsequent deterioration of one’s own or associates’ health can trigger these cognitive processes.

We take this hypothesis to the 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 toward one’s own party versus the opposition party. To estimate the effect of exposure to the opioid epidemic on affective polarization, we interact 1996 cancer mortality 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.²⁶

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.²⁷ This transformation, fueled and supported by Fox News, sought to rebrand conservative principles as representative of the working class and fostered anti-elite and anti-establishment sentiment (Peck, 2019). This narrative speaks to a segment of society that has witnessed a decline in its relative socioeconomic standing, partly because of 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 News viewership. This is an additional channel through which out-group antagonism and Republican support can be reinforced, as shown by DellaVigna and Kaplan (2007); Clinton and Enamorado (2014); and Martin and Yurukoglu (2017).

²⁶As an additional measure of in-group identity, we look at church attendance behavior as reported in both the ANES and the CCES data; see columns (9) and (10) of Table 3. We find no evidence of changes in this behavior.

²⁷In the robustness section VI.b., we show that early exposure to Fox News does affect our estimated treatment effects.

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 CZs 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; 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. The Introduction of Fox News and Economic Shocks

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 increased the Republican vote share in the 2000 presidential elections. If early exposure to Fox News is correlated with cancer incidence, some of the effects that we estimate might reflect the Fox News effect and not the effects of the opioid epidemic. To investigate this possibility, we control for early Fox News exposure using the data in DellaVigna and Kaplan (2007) and replicate our estimates. The data in DellaVigna and Kaplan (2007) cover only 60% of our CZs, so there is a substantial shrinkage in sample size, making the results noisy. However, the point estimates from

a sample that includes only the CZs for which data on early Fox News exposure are available are very similar to those from our baseline specification (see Figure 9).

At the same time as the opioid epidemic was unfolding, the United States economy faced increased import competition from China, unionization rates were declining, two economic recessions occurred, and the adoption of robotic technology advanced significantly. Previous work has documented the effects on political preferences and polarization of these phenomena as well as the heterogeneity in geographic exposure to them. Potentially, some of our results could reflect exposure to these shocks instead of effects of the opioid epidemic. This subsection addresses this concern by estimating our baseline specification with additional controls capturing geographic exposure to those trends. 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 recession exposure as the change in the unemployment rate from 2001 to 2000 in the CZ. In this 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 CZ unemployment rate between 2007 and 2009.²⁸ We find that our estimates do not change when we control for exposure to these economic shocks (see Figure 10).

We use the CZ-level unionization rates in 2000 constructed by [Connolly et al. \(2019\)](#) to assess whether some of the effects that we estimate can be attributed to a correlation between our measure of opioid epidemic exposure and broader dynamics related to the political effects of the decline in unionization. Figure 10 also incorporates a specification where union membership rates are added as an additional control; 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 subject 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](#); [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 10).

²⁸We take this measure directly from the replication package in [Yagan \(2019\)](#). In its construction, the author computes the annual CZ 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 CZ.

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 the measures of exposure to robotic technology adoption constructed by [Acemoglu and Restrepo \(2020\)](#) to assess whether this mediates our effects. Panel (b) of Figure 10 shows that our main estimates remain unaffected when we control for this exposure.²⁹

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 in samples with alternative restrictions on the size of CZs. We arrive at conclusions analogous to those from 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 that 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 we exclude any individual state. Furthermore, we exclude CZs in i) the Appalachian region, given that it has been disproportionately impacted by the epidemic ([Shiels et al., 2020](#)); ii) the Rust Belt, which is characterized by significant deindustrialization ([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 the pre-trends and our effect estimations are unaffected (see Panel (a) of Figure A8). We also present estimates of the main effects without the vector ΔX_{ct} , i.e., with only state \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’s having higher cancer mortality rates. Nonetheless, we find that our conclusions hold when 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 consider whether our results are driven by communities with larger shares of this demographic group. To assess this hypothesis, we add to our main specification as an additional control the share of white men in 1996 interacted with

²⁹We take this measure directly from the replication package in [Acemoglu and Restrepo \(2020\)](#) (see Figure 4 and Equation (18)); the authors exploit variation in industry-level adoption of robots weighted by employment shares.

year dummies. We find no evidence supporting this explanation: the estimated effects are quantitatively very similar to those from the baseline specification.

VII. Discussion

The opioid epidemic stands as one of the most tragic events in recent US history. Its effects extend beyond the direct loss of life to the economic and political life of the communities most affected. We exploit rich quasi-exogenous geographic variation in 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 noncancer patients in the same communities and seen by the same doctors. A later marketing practice that targeted heavy prescribers created path dependency from this initial exposure. We use mid-1990s cancer mortality at the CZ level as a measure of this initial exposure. Past research has shown that this exposure predicts opioid prescriptions, opioid deaths, SNAP use, 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. By 2020, places that had looked very similar in the mid-1990s 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 the Republican vote share by 4.6 percentage points in the 2020 House elections. This gap was accompanied by an increase in polarization on immigration, abortion, gun control, and own ideology.

In this paper we document 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 intergroup perceptions. Our findings add to a rich literature on the economic determinants of political preferences, where factors such as inequality, trade, unemployment, and income level have been studied but health has received less attention. We hope this work inspires further research into the political and long-term consequences of health disparities and health shocks—particularly in a landscape where vaccination behavior is increasingly divided along party lines and, as a result, disease exposure and mortality have become politicized.

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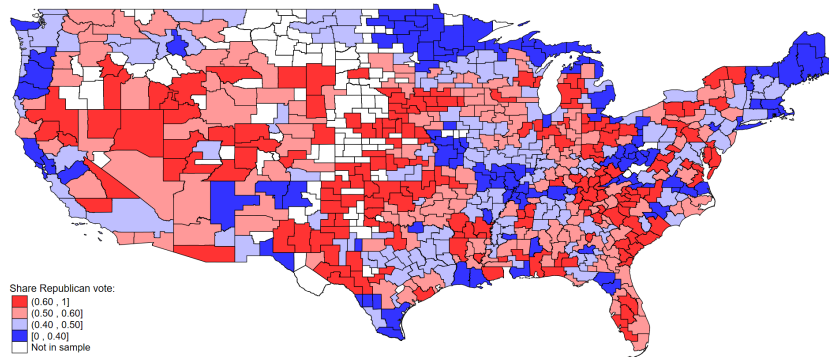
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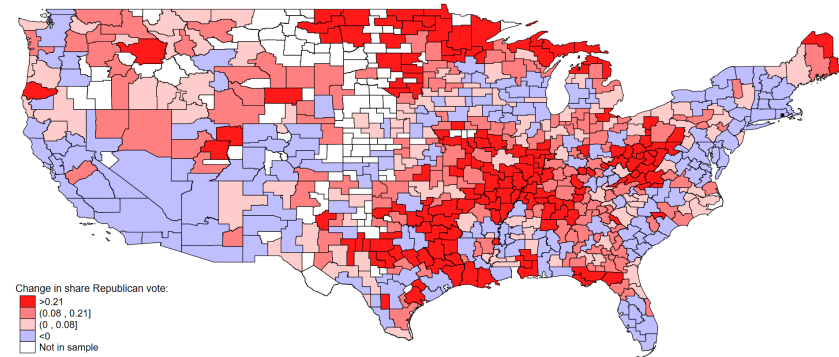
VIII. Figures

Figure 1: Geographical Variation

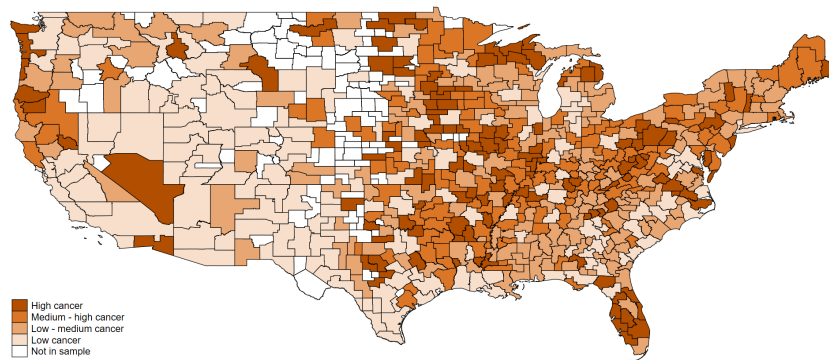
(a) Republican Vote Share – House Elections, 1996



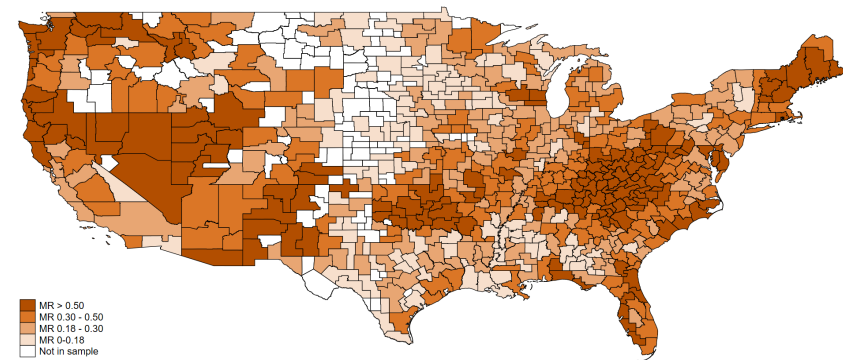
(b) Change in Republican Vote Sh. – House Elections, 2020–1996



(c) Cancer Mortality Rates, 1996



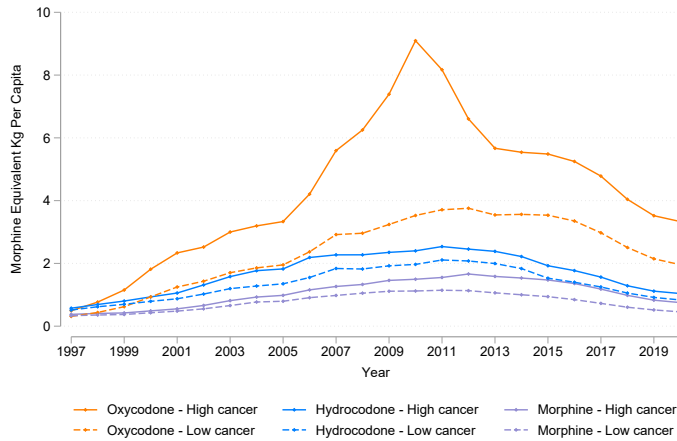
(d) Prescription Opioid Mortality Rate, 1999–2020



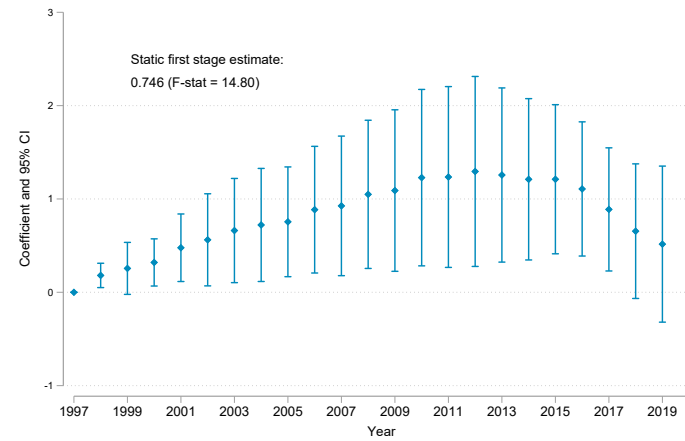
Notes: This figure shows the geographic distribution of the Republican vote share in House elections in Panel (a) and its evolution between 1996 and 2020 in Panel (b). Panel (c) shows the geographic distribution of our measure of exposure to the opioid epidemic—cancer mortality in 1996—and Panel (d)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

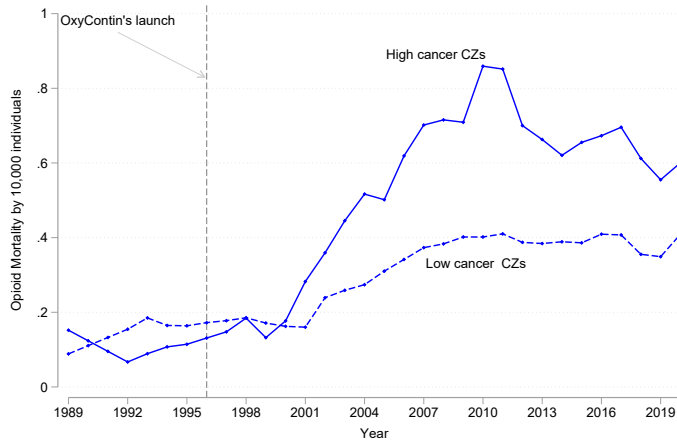
(a) Trends in High- versus Low-Cancer-Mortality CZs



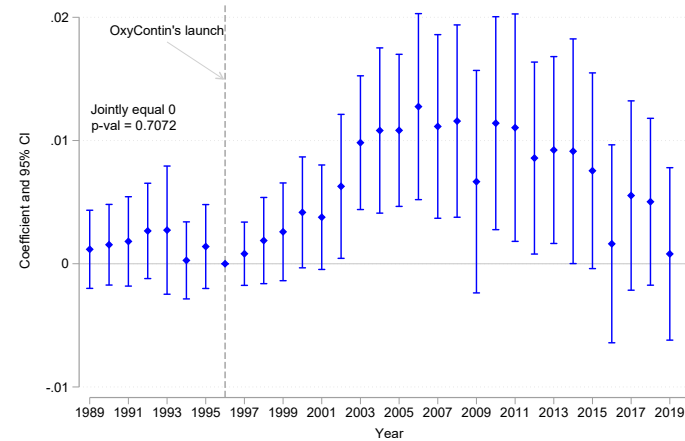
(b) Effects on Prescription Opioid Supply



(c) Trends in Prescription Opioid Mortality

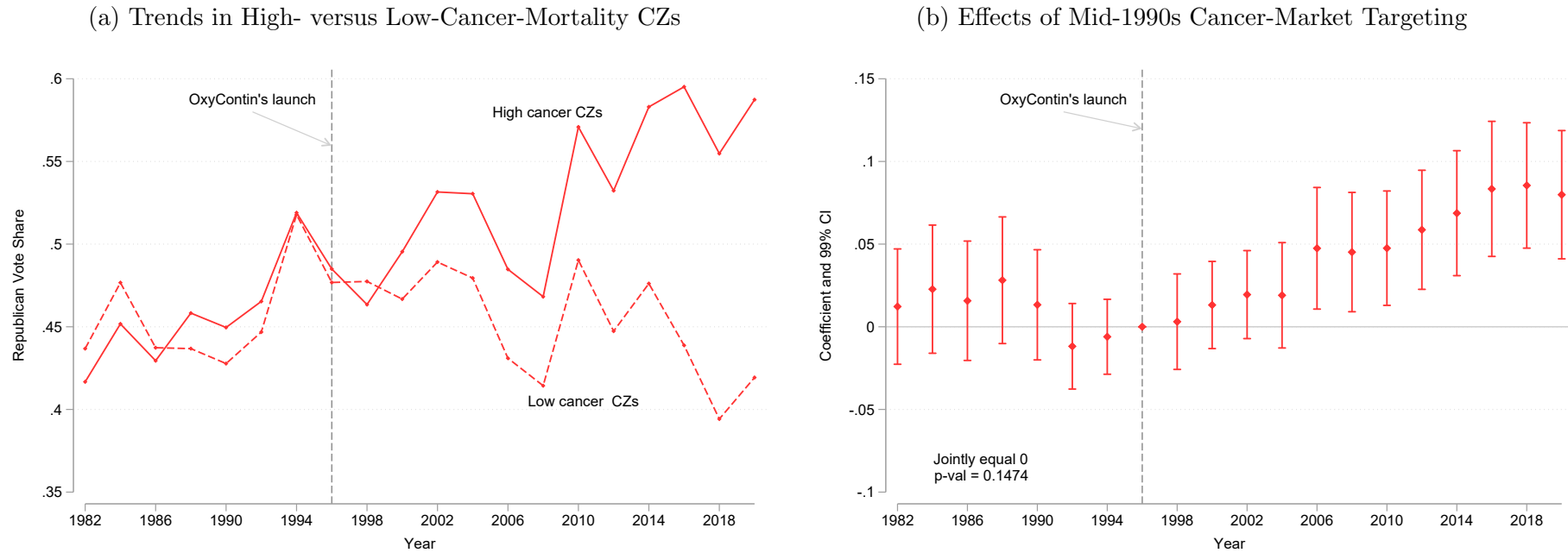


(d) Effects on Prescription Opioid Mortality



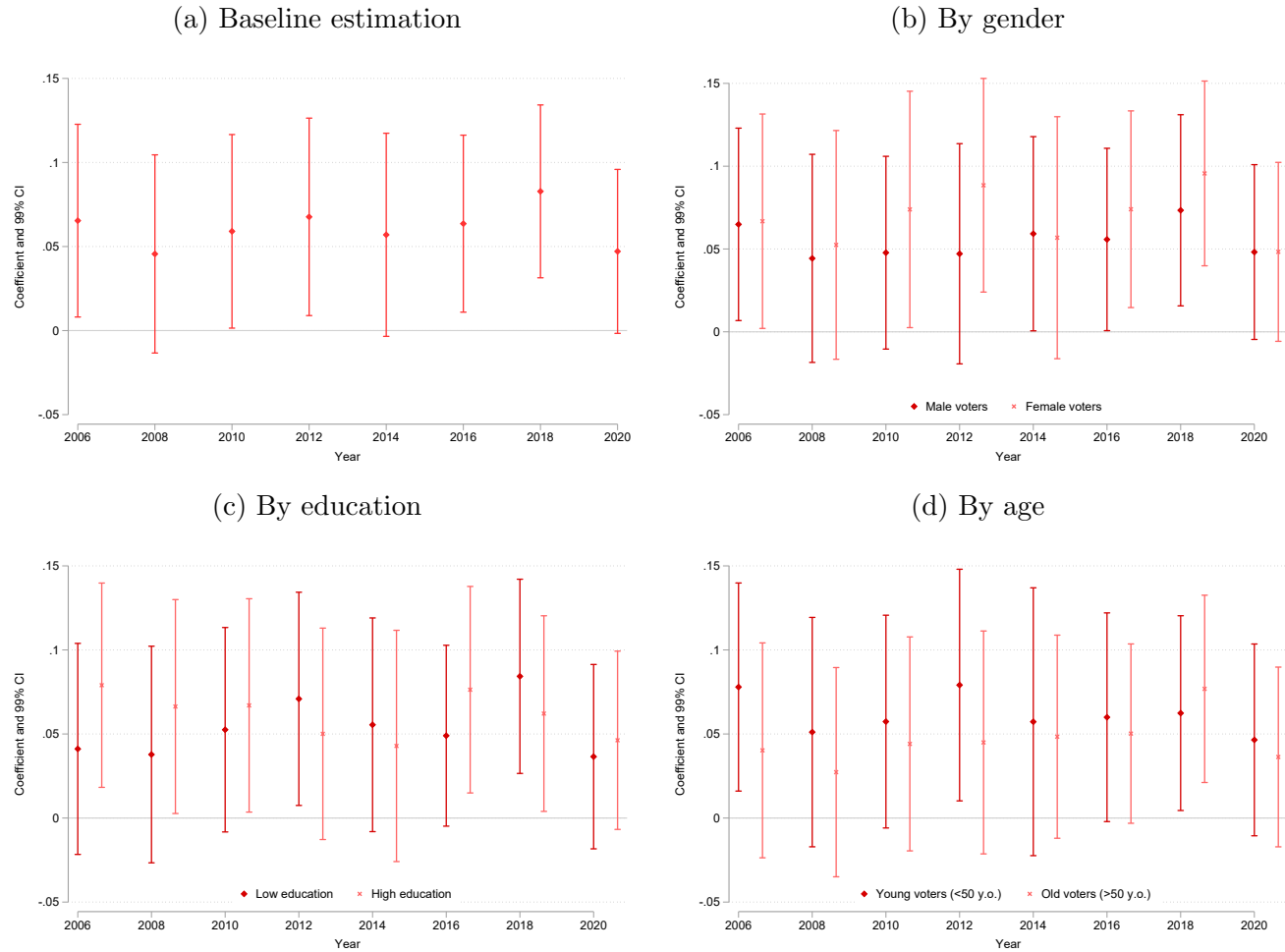
Notes: Panels (a) and (c) show the evolution of the distribution of prescription opioids and mortality in CZs in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Oxycodone is OxyContin's active ingredient. Panels (b) and (d) show estimates 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: $\Delta y_{ct} = \alpha_1 + \sum_{\tau=1989}^{2020} \phi_{\tau} CancerMR_{ct0} \mathbf{1}(Year = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + v_{ct}$, 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 the ARCOS data are available only from 1997, we can estimate coefficients only 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: House Elections



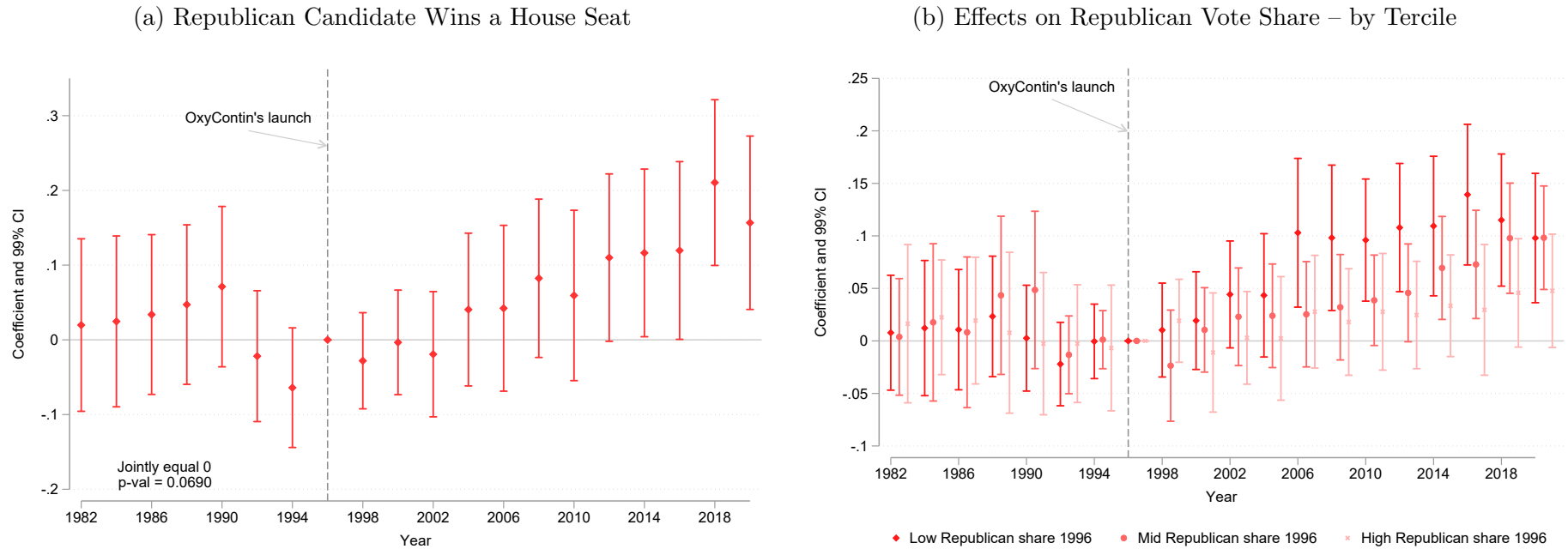
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in House elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share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



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 postgraduate education. We estimate the following equation in an individual-level repeated cross-section dataset: $y_{ict} = \alpha_1 + \sum_{\tau=2006}^{2020} \phi_{\tau} CancerMR_{ct0} \mathbf{1}(Year = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + \varepsilon_{ict}$. This figure is referenced in Section V.a.

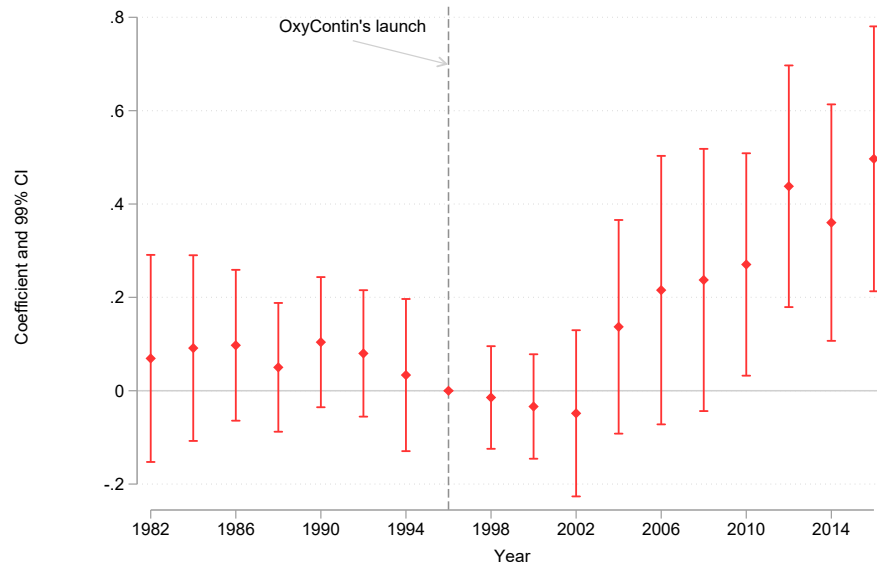
Figure 5: House Wins and Vote Share Heterogeneity



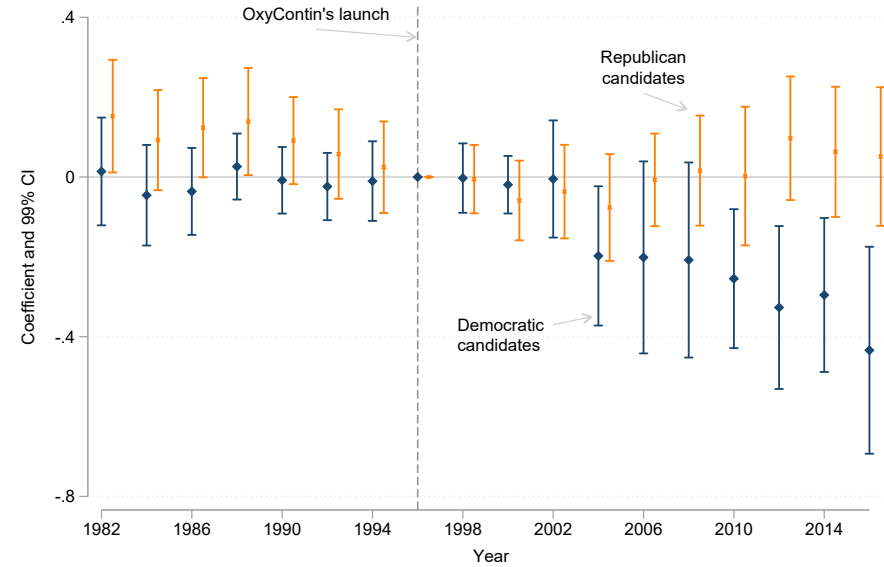
Notes: Panel (a) presents estimates of the dynamic relationship between the probability that a Republican candidate wins a seat in House elections and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality by the initial level of Republican support in the 1996 House elections. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1982}, \phi_{1984}, \dots, \phi_{1994}$) are jointly equal to zero. The p value of this test is presented in the figure for the model presented in Panel (a). For the estimates in Panel (b), the p values are 0.1823, 0.2619, and 0.9316, respectively, for low, medium, and high Republican support. This figure is referenced in Section V.a.

Figure 6: Effects of Exposure to Opioid Epidemic on Per Capita Donors to House Candidates

(a) Difference by Party = Rep – Dem

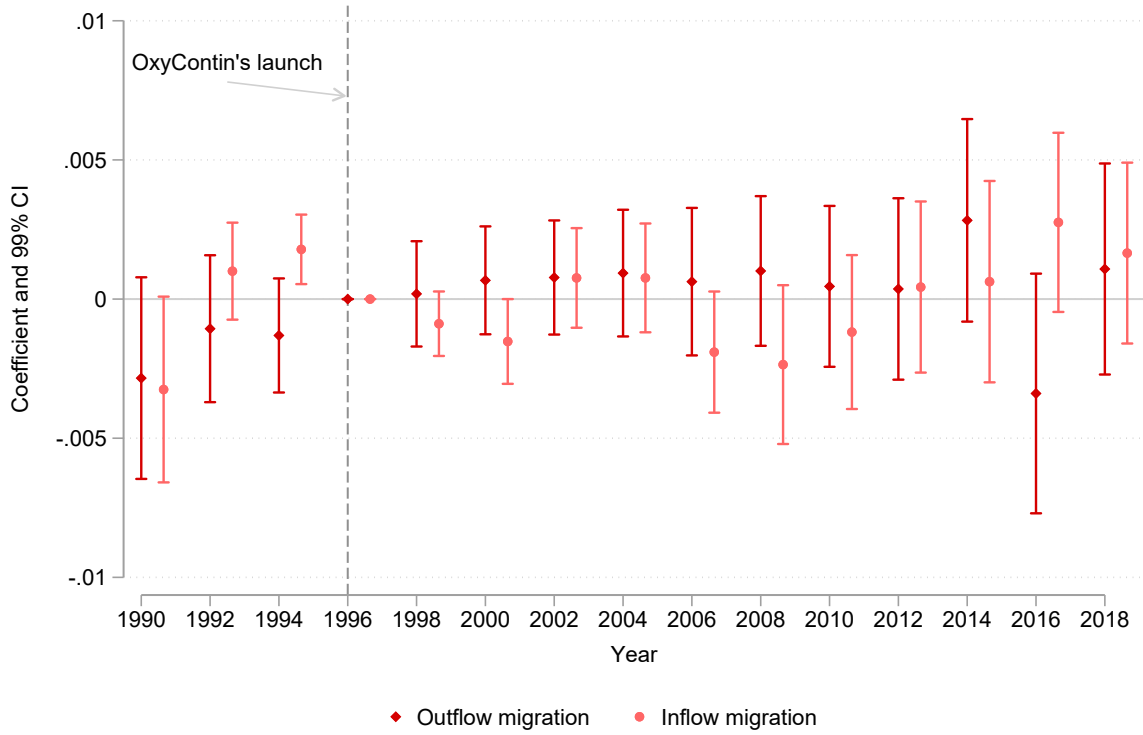


(b) Per Capita by Party



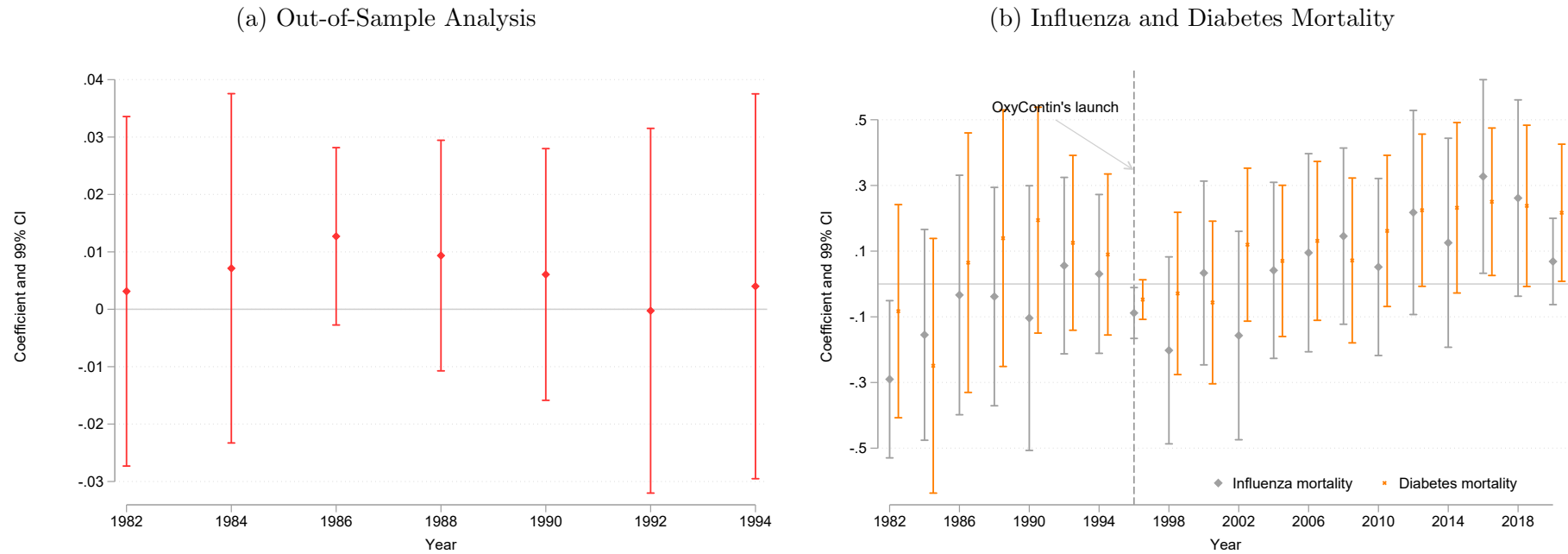
Notes: Panel (a) presents estimates of the dynamic relationship between the difference in the number of donors to Republican candidates and to Democratic candidates for House elections and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of this relationship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

Figure 7: Migration Flows and Opioid Epidemic Exposure



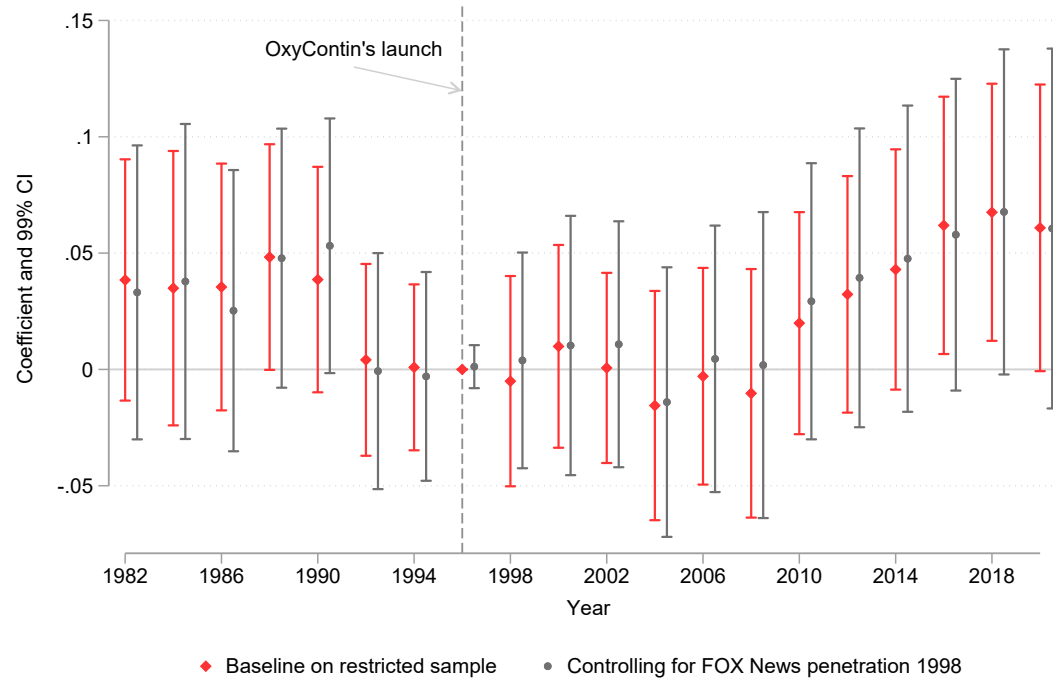
Notes: This figure presents estimates of the dynamic relationship between (i) out-migration (dark red) and (ii) in-migration (light red) and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. The IRS SOI data are available for years starting in 1990. This figure is referenced in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

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



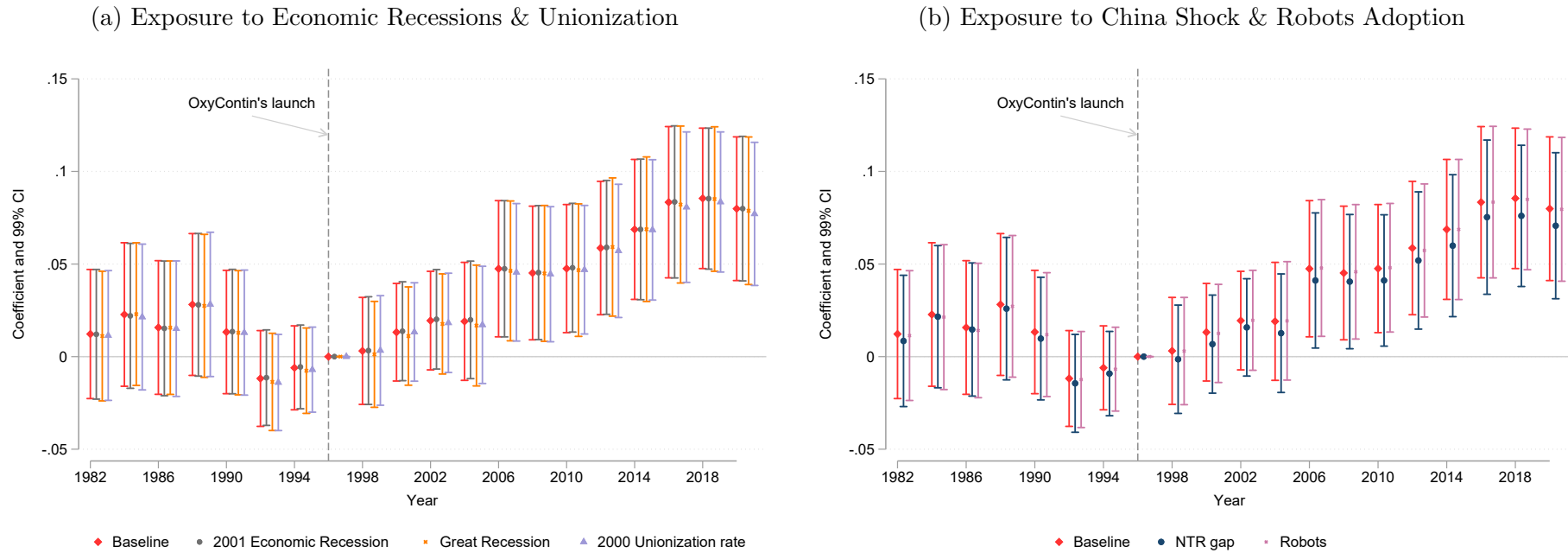
Notes: This figure presents two placebo checks. Panel (a) presents estimates of an out-of-sample dynamic reduced-form analysis for our pre-period. It provides evidence that lagged cancer mortality is not a predictor of future Republican vote share. Panel (b) presents estimates of the dynamic relationship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

Figure 9: Robustness Checks – House Elections and 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 early exposure to Fox News. We use data from DellaVigna and Kaplan (2007). These data cover only 60% of our CZs, so there is a substantial shrinkage of sample size. Thus, we present estimates of the baseline equation restricting the sample to those CZs included in their data; we label this “Baseline on restricted sample”. This figure is referenced in Section VI.b.

Figure 10: Robustness Checks – House Elections and Economics Shocks



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 CZ. Similarly, we use [Yagan’s \(2019\)](#) measure of severity of the great recession and CZ-level unionization rates in 2000 as 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 PNTR with China—termed the “China shock” in the trade literature—and exposure to robot adoption. 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 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](#).

IX. Tables

Table 1: Summary Statistics

	1982–1995			1996–2020		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
Exposure to opioid epidemic and mortality measures						
Doses of prescription opioids per capita ^(a)				5.9293	4.9612	4.9227
Cancer mortality per 1,000 (1996)				2.5466	2.5369	0.7606
Cancer mortality per 1,000	2.4185	2.4100	0.5834	2.4907	2.4994	0.5840
Prescription opioids mortality per 10,000 ^(b)	0.0652	0.0000	0.1320	0.3537	0.2410	0.4424
Voting outcomes and political views						
<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
Turnout rate ^(c)	0.6587	0.6853	0.1169	0.6397	0.6405	0.0987
<i>Donations to House candidates per 1,000 voting-age population^(d)</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) Turnout rates are computed for presidential elections years. House members' ideology is measured with the Nokke–Poole first-dimension estimate; positive values in this category indicate more conservative views. (d) Statistics from 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

	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 noncancer 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 CZ level. Standard errors are robust to heteroskedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table is referenced in Section III.

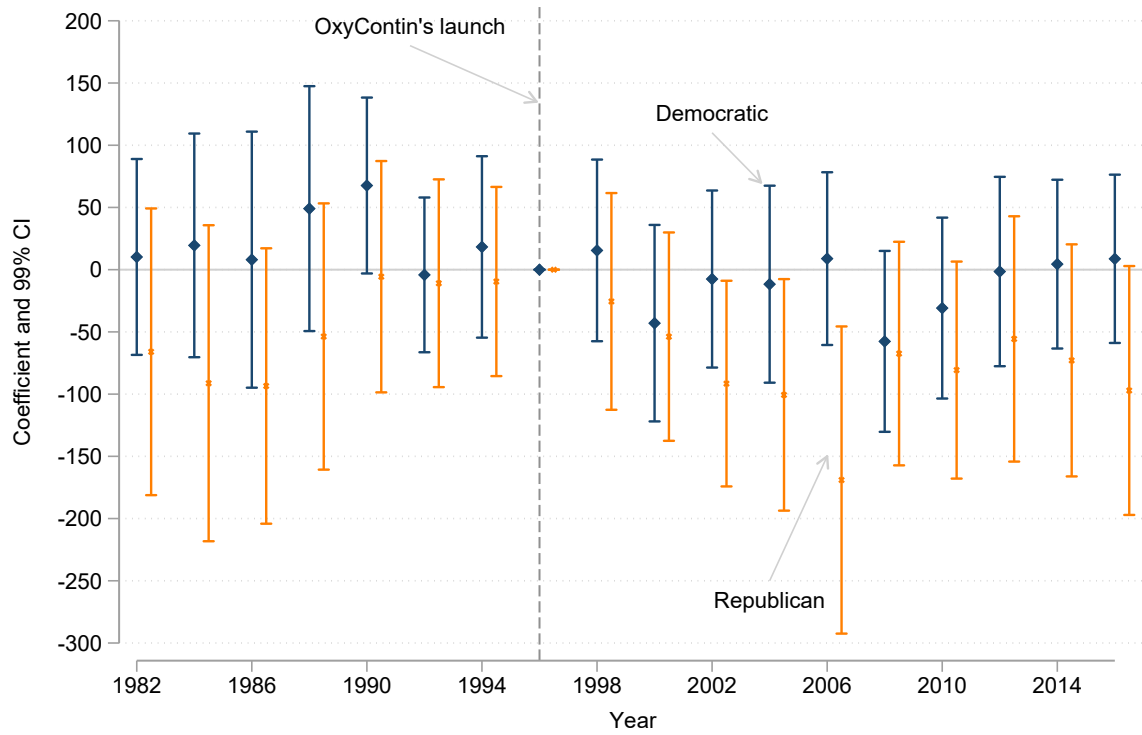
Table 3: Mid-1990s Cancer Mortality and Preferences

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
CZs	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
CZs	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," where 1="Very conservative" and 5="Very liberal". Police questions: "Increase police officers on the street by 10 percent." 1="Support", 0="Oppose". "The police makes me feel safe": 4="Mostly safe", 3="Somewhat safe", 2="Somewhat unsafe", and 1="Mostly unsafe". Higher levels of affective polarization translate to higher polarization measured as the distance between feelings about own party versus the opposition party. Fox News is a dummy variable equal to 1 when respondents report watching Fox News. *Post* takes value one for electoral years after the onset of the opioid epidemic. All regressions include a set of control variables at CZ level and individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table is referenced in Sections V.b. and V.c.

A Additional Figures

Figure A1: House Campaign Median Donation Amounts



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

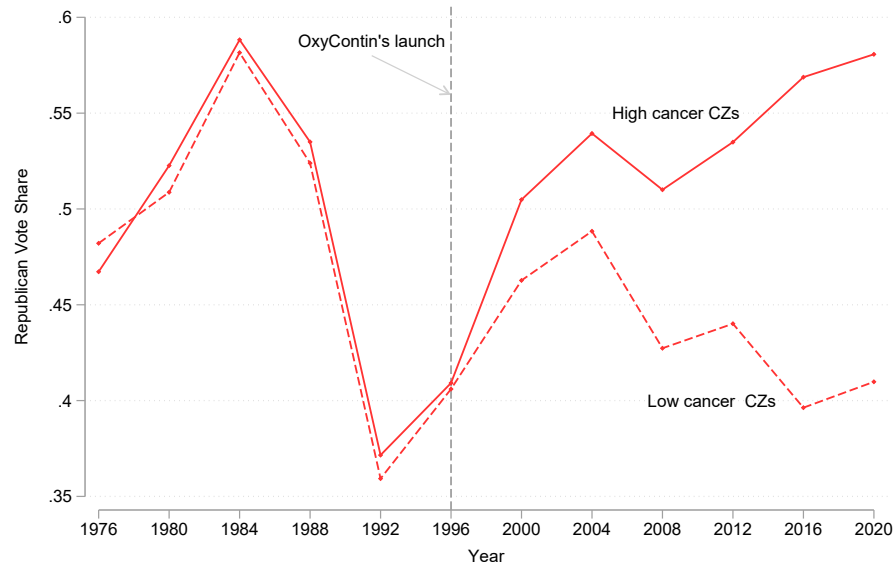
Figure A2: Conservative–Liberal Ideology: Roll-Call Votes of House Members



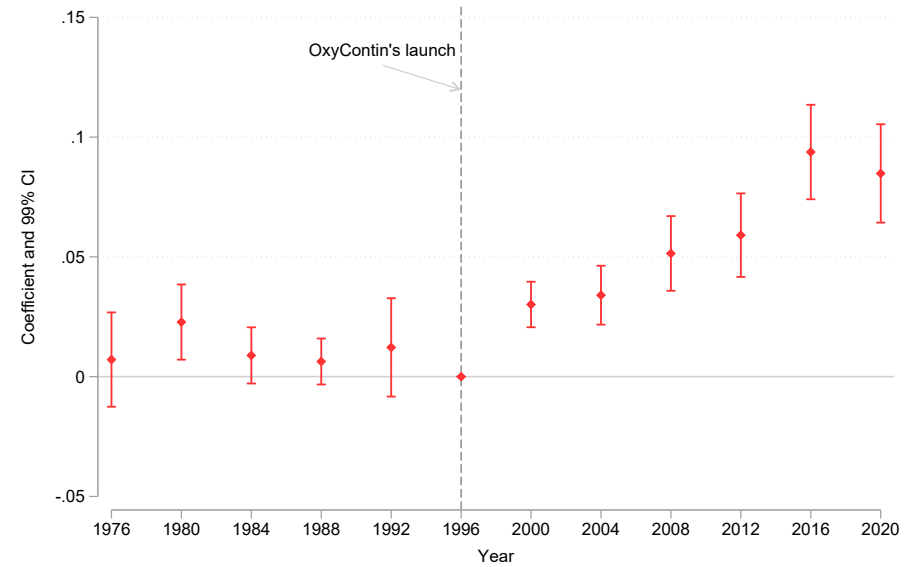
Notes: This figure presents estimates of the dynamic relationship between candidate ideology in roll-call votes and mid-1990s cancer mortality. Panel (a) shows the main effects, and Panel (b) splits the sample by initial Republican vote share in House elections. Panels (c) and (d) show candidates' probability of being in the top and bottom percentiles of the Nokken–Poole measure. This figure is referenced in Section V.a.

Figure A3: Republican Vote Share: Presidential Elections

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

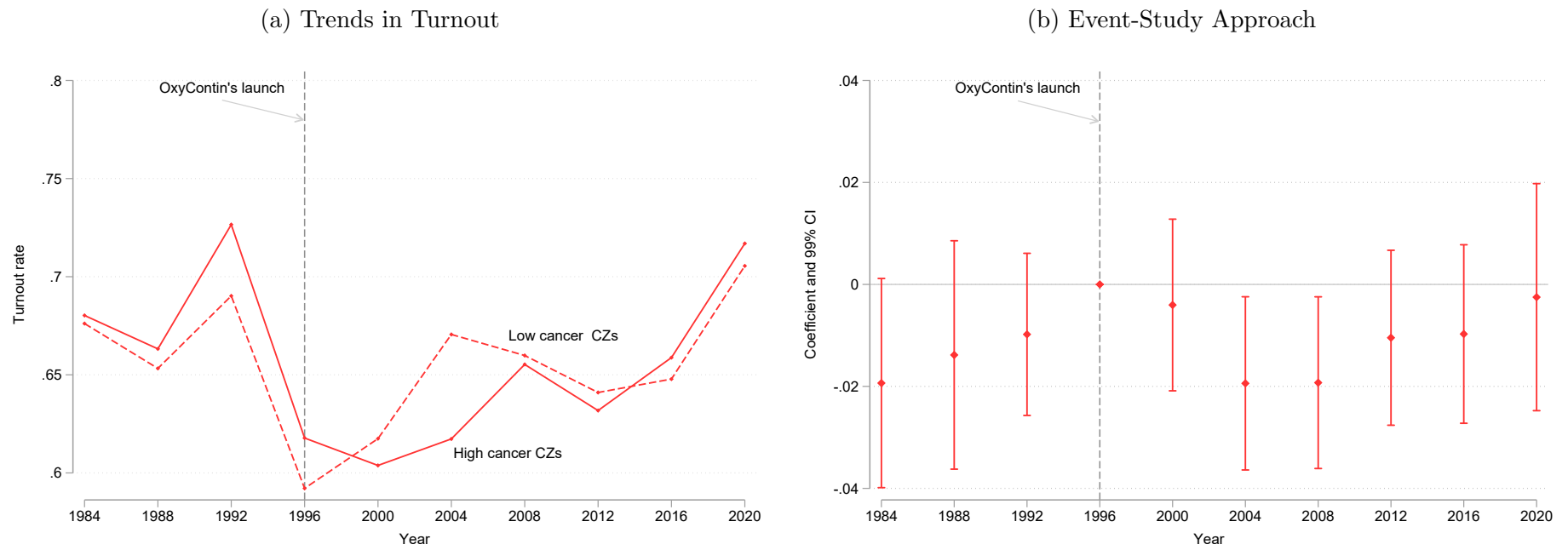


(b) Effects of Mid-1990s Cancer-Market Targeting



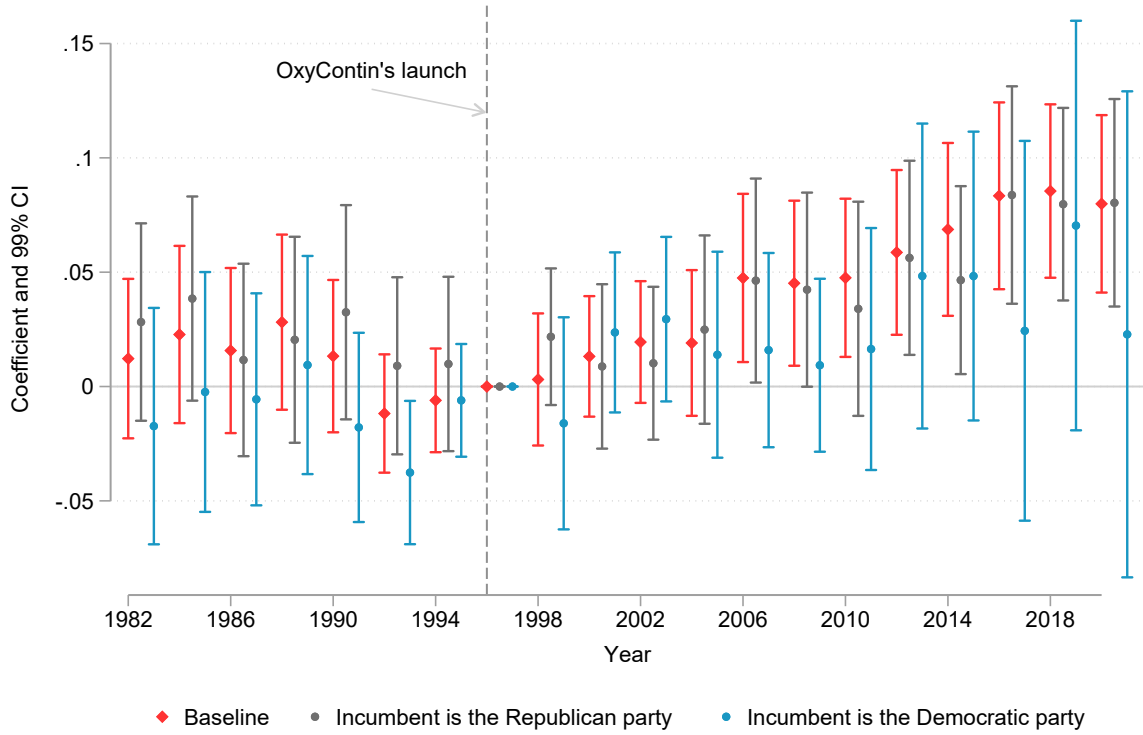
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections in the bottom (dashed line) and top (solid lines) quartiles of the cancer mortality distribution before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship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

Figure A4: Turnout Rates



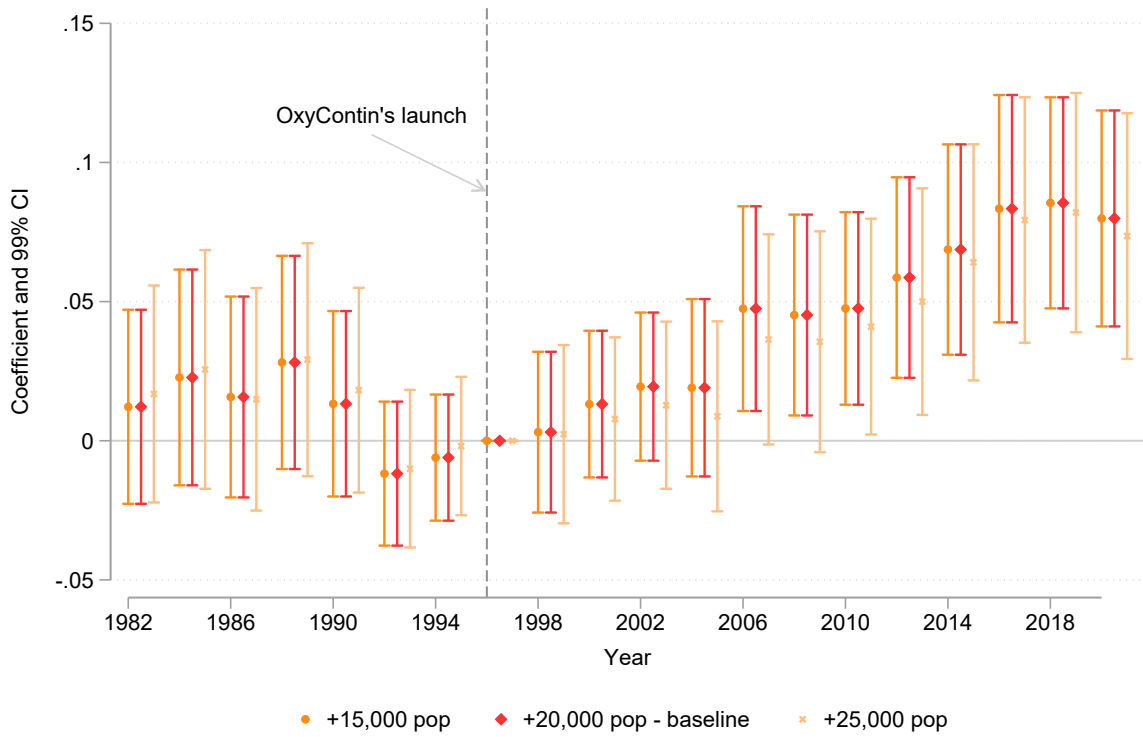
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turnout rates and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.a.

Figure A5: Effects on Republican Vote Share by Incumbent Party



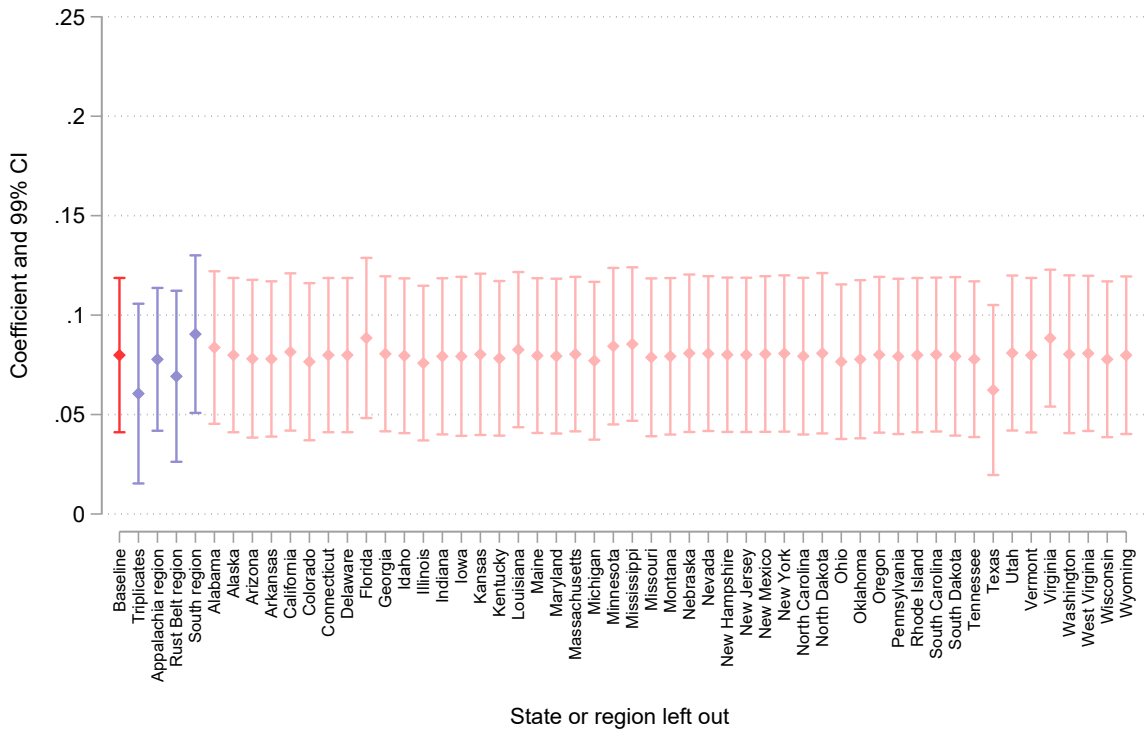
Notes: This figure presents estimates of the effects of opioid epidemic exposure on vote share with the sample CZs split by whether they had a Republican or Democrat incumbent at the time of the election. This figure is referenced in Section V.c.

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



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

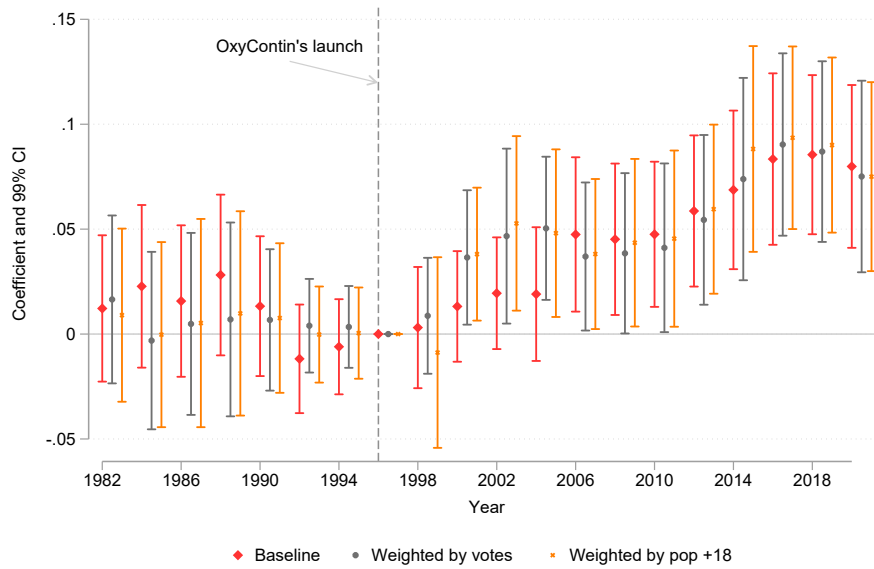
Figure A7: 2020 Coefficients – Leaving One State Out



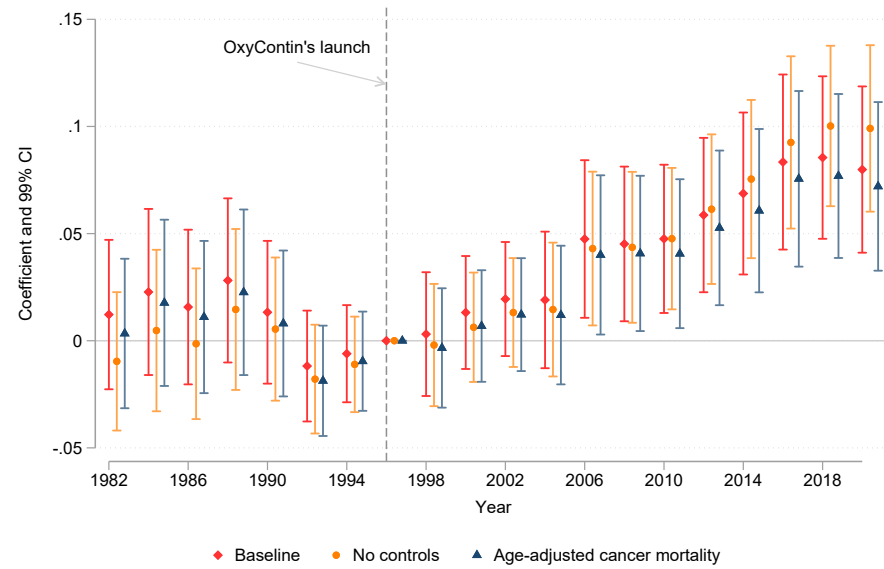
Notes: This figure presents estimates of the 2020 coefficients from an event study similar to that in Equation (1) run on a sample that excludes all CZs in the state indicated on the horizontal axis. That is, the x-axis label indicates the state left out of the estimation. This figure is referenced in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

Figure A8: Robustness Checks: Weighted Estimations, Alternative Specifications, and Age-Adjusted Regressions

(a) Population-Weighted Estimations

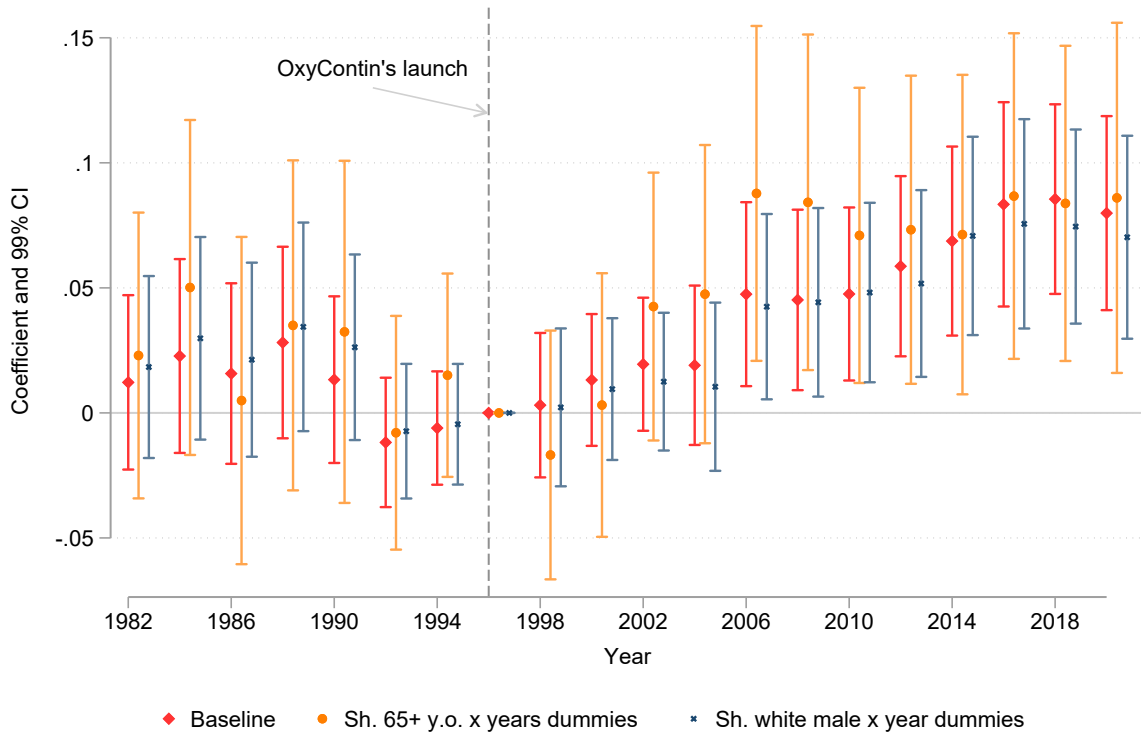


(b) Alternative Controls and 1996 Age-Adjusted Cancer Mortality



Notes: Panel (a) of this figure replicates our estimates from Figure 3 and adds weighted versions, where the 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×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 population aged 65 and older 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.