Republican Support and Economic Hardship: The Enduring Effects of the Opioid Epidemic*

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Abstract

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 partisanship and polarization. Drawing on unsealed records from litigation against Purdue Pharma, we uncover rich geographic variation in the marketing of prescription opioids that serves as a quasi-exogenous source of exposure to the epidemic. We use this variation to document significant increases in opioid-related mortality and greater reliance on public transfer programs. This induced economic hardship led to substantial changes in the political landscape of those communities most affected by the opioid epidemic. We estimate that from the mid-2000s to 2020, exposure to the opioid epidemic continuously increased the Republican vote share in House, presidential, and gubernatorial elections. By the 2020 House elections, a one-standard-deviation increase in our measure of exposure led to a 4.6 percentage point increase in the Republican vote share. This higher vote share in the House translated into Republicans winning additional seats from 2012 until 2020.

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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). Since its onset in 1996, exposure to the epidemic has led to increased opioid addiction, mortality, and fiscal strain on local governments (Maclean et al., 2021; Cornaggia et al., 2022). The unfolding of the epidemic coincides with a historical moment of enhanced partisanship and polarization in the United States. Political elites, particularly members of Congress in both parties, increasingly disagree on policy issues (McCarty et al., 2016), and the content of political speech has become more polarized (Gentzkow et al., 2019; Card et al., 2022). During this period, the Democratic Party has focused on promoting social justice for marginalized and disadvantaged groups, whereas the Republican Party has advocated for solutions to the economic and social hardship of working-class Americans (Hochschild, 2018; Skocpol and Williamson, 2016; Gest, 2016).

In this paper, we document how the opioid epidemic transformed the political landscape in communities that faced the most severe impacts of the crisis in terms of mortality and economic hardship. To do so, we uncover rich geographic, quasi-exogenous variation in exposure to the opioid epidemic originating from detailed features of the initial marketing of prescription opioids. We obtain this information from unsealed court records drawn from litigation against Purdue Pharma—the manufacturer of OxyContin, the prescription opioid at the center of the epidemic. These records show that at the dawn of the opioid epidemic in 1996, pharmaceutical marketing efforts were concentrated on the cancer pain market, with a plan to quickly expand within the *same* geographic areas to the much larger noncancer pain market. This targeting implies that noncancer patients in high-cancer areas were disproportionately exposed to the opioid epidemic and the unfortunate chain of events that followed. Drawing on these insights, we exploit the geographic variation in cancer mortality in 1996 at the commuting zone (CZ) level as a proxy for the cancer pain market served by pharmaceutical companies and use it as a quasi-exogenous measure of exposure to the crisis.[1]

We start by showing the link between Purdue Pharma's marketing for the introduction of OxyContin and the future growth in prescription opioids. Specifically, we estimate a strong positive relationship between higher cancer mortality in 1996 and the rise in prescription opioids following the launch of OxyContin. By 2012, the year when prescription rates peaked, a one-standard-deviation increase in the 1996 cancer mortality rate led to an additional 0.75 opioid doses prescribed per capita—50.6% higher than the baseline mean. This rise in the level of opioid prescriptions in the population translated into an increase in mortality. We show that for the same period, a one-standard-deviation

[1]CZs are geographic areas defined to capture local economic markets. There are 720 CZs in the US, and these encompass all metropolitan and nonmetropolitan areas (Tolbert and Sizer, 1996).

increase in mid-nineties cancer mortality causes a 101% increase in prescription opioid deaths compared to the average before the epidemic. Considering overall drug mortality, which includes fatal overdoses from heroin and fentanyl—categories that gained importance after 2012—we find that by 2017, mortality had increased by 39.8% relative to the pre-epidemic average. These deaths are concentrated predominantly among young and middle-aged adults, with no significant effects observed for individuals aged 55 and older.

Beyond impacts on overdose mortality, the opioid epidemic induced significant economic hardship. We document an increase in the number of individuals participating in public assistance and social insurance programs. By 2020, a one-standard-deviation increase in 1996 cancer mortality corresponded to a 9.2% increase in the proportion of the population receiving SNAP benefits, equivalent to an increase of 0.16 standard deviations. For the same period, we document that such higher exposure to the epidemic increased the populations receiving SSDI and SSI benefits by 10.2% and 5.7%, respectively. We find no statistically or economically significant effects on unemployment.

Communities that endured increases in mortality and reliance on public transfer programs, became increasingly aligned with the Republican Party. We find that exposure to the crisis increased the Republican vote share in House, presidential and gubernatorial elections. The relationship between cancer mortality and Republican vote share emerged soon after the onset of the opioid epidemic. This relationship continuously strengthened over the following years, and by the 2020 House elections, a one-standard-deviation higher 1996 cancer mortality rate yielded an increase in the Republican vote share of 4.6 percentage points. This shift toward the Republican Party and away from the Democratic Party is similar across age, gender, race, and education levels and we find no effects on turnout rates.

The unfolding of the opioid epidemic coincided with a period during which the Republican Party and conservative media, particularly Fox News, emphasized a narrative around the economic hardship experienced by working-class America (Peck, 2019). The Republican Party's new *ownership* of this topic positioned them as the advocates for "forgotten America" and the "America left behind" (Gest, 2016; Hochschild, 2018; Peck, 2019). We ask whether the economic hardship induced by the epidemic sway voters towards the Republican party. Indeed, we document that larger treatment effects of the epidemic on health and economic outcomes predict larger effects on the Republican vote share.

It took several election terms for the incremental gains to change election outcomes. 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 the House. We also observe a decline in donations to Democratic candidates. When we look at presidential and gubernatorial elections, the results follow the same pattern as that for the House elections. Specifically, a one-standard-deviation increase in the 1996 cancer mortality rate increased the vote share by 4.9 percentage points in presidential elections and by 3.7 percentage points in gubernatorial elections, respectively.

We show that the observed effects are not due to changes in the composition of the population or to anti-incumbent responses. Areas with high versus low exposure to the opioid epidemic do not exhibit differential trends in terms of inflow or outflow migration.[2] Additionally, we can rule out 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. Furthermore, we find no evidence that our results are driven by anti-incumbent sentiment, consistent with the fact that voters do not hold the government or any specific party accountable for the opioid epidemic (YouGov, 2022).

Next, we study how the opioid epidemic was framed and addressed by political actors and the media. We find that House members and candidates from both parties barely engaged with the opioid epidemic during the first two decades of the crisis. Using data from House speeches and campaign advertisements, we document that discussions about the epidemic were mostly absent until 2015 and 2020, respectively.[3] To study the role of the media we assemble a new dataset on the coverage of the epidemic by local newspapers and national television networks. We collect archival data and show that the media did report on the crisis from its onset. We find that conservative-leaning media covered the epidemic at a higher rate and that this coverage correlated strongly with local exposure. Moreover, there are notable differences in the content of this coverage: Conservative media emphasized economic hardship, crime and the illegal aspects of the epidemic, topics where the Republican Party has an electoral advantage.[4]

Finally, we also document that the perceived effectiveness of the Republican approach to addressing the opioid epidemic, in comparison to the Democratic approach, benefited the former. Republicans supported increased law enforcement to curb drug trafficking and crime, while Democrats advocated for harm reduction policies and funding increases for opioid abuse treatment and recovery. We find that higher exposure to the crisis predicts greater support for police presence and an increased sense of safety around police. By contrast, the effectiveness of some harm reduction policies has been questioned, and we find that exposure to the opioid epidemic predicts lower support for marijuana legalization on state ballot initiatives.[5]

[2]This result is in line with findings of low migration responses to adverse economic shocks. See Yagan (2019), Autor and Dorn (2013), and Choi et al. (2024).

[3]Data come from Gentzkow et al. (2018) and Fowler et al. (2023).

[4]Stokes et al. (2021) find no evidence that Republican politicians engaged more with the opioid epidemic on social media.

[5]Recent evidence shows that policies such as the decriminalization of drugs in Oregon and access to clean syringes do not decrease drug use or mortality (Spencer, 2023; Packham, 2022).

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 opioid marketing, areas with higher cancer mortality in 1996 would have exhibited the same trends in health, economic and political variables as areas with lower cancer mortality. To support this assumption, we present estimates of reduced-form event studies of the relationship between our outcome variables and 1996 cancer mortality and test for differential trends in the pre-period. We find no relationship between our measure of epidemic exposure and the outcome variables before the introduction of OxyContin and the start of the opioid epidemic. In addition, we perform an out-of-sample exercise using 1976 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 opioid mortality, SNAP recipiency rates or 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, which are unconnected to the opioid epidemic but measure the underlying health of the population.

We rule out several alternative explanations that could drive our results. We control for geographic exposure to economic, political, media, environmental and health shocks as well as for political realignment in rural areas and among demographic and religious groups, which have been documented to affect the outcome variables during this period. Specifically, these shocks include the increase in competition from Chinese imports, the North American Free Trade Agreement (NAFTA), the Republican Revolution of 1994, the 2001 economic recession and the Great Recession, the decline in unionization rates, robot adoption, the introduction of Fox News, and the increase in deaths of despair. We also test to determine whether the political realignment of the south, rural areas, the population aged over 65 years, and evangelicals in favor of the Republican Party confound our results. Our estimates remain robust when we account for exposure to these shocks and trends.

In this paper, we contribute to the understanding of the socioeconomic determinants of political preferences. 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; Guriev and Papaioannou, 2022; and Choi et al., 2024). Less attention has been paid to the effects of health crises on political preferences. Voigtländer and Voth (2012), Galofré-Vilà et al. (2022) and Blickle (2020) document the association between 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 is the first paper to document a causal relationship between the opioid epidemic and the growing divide in political partisanship and polarization. We show how the disparate community effects of this major public health crisis on mortality and economic hardship have led to divergent political preferences and support for the Republican Party.

We extend the literature on the opioid epidemic in two ways. First, we propose a new source of within-state variation in exposure to the crisis. Our proposed design accounts for important state and year-level confounders– e.g., implementation of PDMPs, regulation of "pill mills"– and serves as a rich instrument for future work on the epidemic. Second, we conduct the first comprehensive community-level examination of how the opioid epidemic has shaped the economic, health, and political outlooks of the hardest-hit communities. We document its direct effects on new outcomes such as increased reliance on public transfer programs and shifts in political preferences, shedding light on how the crisis may continue to shape the future trajectories of these communities. In doing so, we contribute to the rich literature on the opioid epidemic; one strand of this literature has evaluated the efficacy of policy responses intended to curb the crisis—such as the reformulation of OxyContin and the introduction of PDMPs (Meara et al., 2016; Mallatt, 2018; Buchmueller and Carey, 2018; Kim, 2021; among others). A second strand of the literature exploits the variation induced by such policies to study effects on disability, labor supply, foster care, child maltreatment, and infant health; indirectly quantifying the costs of the opioid epidemic (Evans et al., 2020; Ziedan and Kaestner, 2020; Park and Powell, 2021; Gihleb et al., 2022). Closer to our work, a smaller literature has exploited state-level variation to look at the direct effects of the opioid epidemic on drug mortality and child outcomes (Alpert et al., 2022; Buckles et al., 2022).

II. The Unfolding of the Opioid Epidemic

The United States is experiencing an unprecedented crisis related to the misuse of and addiction to opioids. As of 2022, over 700,000 lives have been lost to opioid overdoses (CDC, 2023). During the last decade, a body of research has studied the origins of the opioid crisis and the factors that shaped its evolution and propagation. This literature has shown that the pharmaceutical industry, physicians, and access to healthcare played a critical role in the origins of the crisis (Eichmeyer and Zhang, 2020; Miloucheva, 2021; Alpert et al., 2022). In particular, these potent opioids, with their high potential for addiction, were aggressively and deceptively marketed to physicians in a setting that provided financial incentives for them to increase prescriptions in conjunction with weak monitoring, thereby creating the perfect platform upon which the crisis could unfold.

The origin of the opioid epidemic can be traced to the 1996 introduction of OxyContin by Purdue Pharma (Quinones, 2015). This prescription opioid redefined pain management practices for noncancer and nonterminal conditions in the United States. Before OxyContin, opioid therapy was primarily reserved for cancer and end-of-life care due to concerns about addiction risks for chronic nonterminal pain patients (Melzack, 1990). Before 1996, MS Contin, a drug also produced by Purdue Pharma, was the gold standard for cancer pain treatment. The development of OxyContin aimed to counter the generic competition expected after MS Contin's patent expired in 1996 (Radden Keefe, 2021). As Purdue stated: *"Because a bioequivalent AB-rated generic control-release morphine sulfate is expected to be available sometime during the latter part of 1996, one of the primary objectives is to switch patients who would have been started on MS Contin onto OxyContin as quickly as possible"* (OxyContin Launch Plan, September 1995).

The objective for OxyContin was not only to take over MS Contin's market but also to gain ground in the much larger noncancer pain treatment market, in which opioids were almost absent. However, establishing the use of OxyContin for moderate and chronic pain was not an easy task; it was clear to Purdue that they would face pushback when expanding to the noncancer market. Specifically, based on physician focus groups in 1995, Purdue concluded that *"there is not the same level of enthusiasm toward this drug for use in non-cancer pain as we identified in cancer pain"* (Purdue Pharma, 1995). The two main barriers Purdue Pharma faced were (i) the fear and stigma related to the use of opioids for nonterminal or noncancer pain and (ii) the administrative barriers physicians and pharmacies had to overcome to prescribe and sell Schedule II drugs.[6]

To overcome these obstacles, Purdue deployed a comprehensive marketing and lobbying strategy. First, they pushed a message of an untreated *"pain epidemic"* that affected millions of Americans on a daily basis, and this message urged for the application of opioids to a wider range of conditions. Pain was introduced as the fifth vital sign, with the goal of encouraging the standardized evaluation and treatment of pain symptoms (Jones et al., 2018). This messaging also included deliberate deceptions—for instance, that opioid addiction rates were lower than 1%. Second, OxyContin was promoted directly to physicians by the largest and highest-paid sales force in the industry.[7] OxyContin was continuously promoted through advertisements, gifts, and promotional medical literature delivered during repeated visits and calls to physicians.[8] Furthermore, the marketing team carefully tracked physician prescription habits to optimize and personalize their detailing messages.[9] These promotional efforts quickly translated into a growing number of prescriptions for OxyContin (Figure A1).

[6]Schedule II drugs are substances that have a high potential for abuse, which may lead to severe psychological or physical dependence, but also accepted medical uses with strict restrictions. This classification is performed by the Drug Enforcement Administration (DEA) in collaboration with the Food and Drug Administration (FDA) in the United States.

[7]The average sales representative's annual salary of $55,000, was complemented by annual bonuses averaging $71,500, with a range of $15,000 to nearly $240,000 (Van Zee, 2009).

[8]A large body of work documents the positive effects of pharmaceutical marketing and detailing on physician prescribing practices (Mizik and Jacobson, 2004; Manchanda and Honka, 2005).

[9]From 1996 to 2000, Purdue increased its total physician call list from approximately 33,400 to approximately 70,500 physicians; United States General Accounting Office (2003). See Figure A2 for details on the targeting of top-decile prescribers by Purdue Pharma.

Soon after the introduction of OxyContin, reports of abuse and addiction started to be covered by the media.[10] By 2001, West Virginia, Virginia, Ohio, and Kentucky were pursuing class-action lawsuits against Purdue Pharma and other pharmaceutical companies. During this time, United States Attorneys for Maine and Virginia, physicians, and community leaders raised concerns to the FDA and Congress about the level of OxyContin abuse (Meier, 2018). Between 2007 and 2013, 17 states implemented Prescription Drug Monitoring Programs for the first time but did not require providers to access them (Buchmueller and Carey, 2018).[11] The prescription of opioids continued to increase during this decade with limited restrictions. At their peak in 2012, opioid prescriptions numbered 81.3 prescriptions per 100 persons (CDC, 2020). The rate 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., 2021).

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 with 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 overall reduction in the combined heroin and opioid death rate (Evans et al., 2019).

It took many years for this issue to become a matter of national interest. President Obama first referred to the opioid crisis in October of 2015, and it was not until 2016 that Congress passed its first legislation targeting the crisis. This law, however, did not include any restrictions or controls on prescribing opioids, and increases in funding for addiction were very limited. At the time, Obama administration officials said they were trying to strike a balance between controlling the harms of opioids and keeping them available for patients—a narrative closely aligned to the *"epidemic of pain"* campaign that Purdue funded during the previous two decades (Whyte and Ernsthausen, 2016).[12] This initial legislation occurred in a context where, from 2006 to 2015, the pharmaceutical industry spent over 800 million dollars lobbying Congress, federal agencies, and all 50 state legislatures on issues related to restrictions and controls for prescribing opioids (Whyte and Ernsthausen, 2016).

From 2016 to this day, the epidemic has been characterized by surging deaths re-

[10] The first mention of the misuse of OxyContin in local media dates back to June 10th, 1997, when the San Angelo Standard-Times, in Texas, covered the story of a doctor who lost his medical license as a result of OxyContin misuse.

[11] State programs have evolved over time and continue to vary along several dimensions, including the extent to which medical providers are mandated to access data on a patient's prescribing history. The effectiveness of PDMP initiatives vary.

[12] In 2012, pain advocacy groups funded by the opioid industry sent a letter to United States Senators promoting a hearing on an influential report about a "crisis of epidemic proportions": pain in America.

lated 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.[13] 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 said that the federal government should be doing more about opioid addiction.[14] However, there is no attribution of responsibility for the epidemic to the government or to one specific party. According to a 2022 YouGov survey among adult Americans, both Democrats (66%) and Republicans (74%) predominantly consider drug dealers who illegally sell opioids to be responsible for the opioid epidemic (YouGov, 2022). Among Democrats, the next most culpable parties are considered to be pharmaceutical companies and physicians. In contrast, Republicans next attribute blame to the people addicted to opioids and pharmaceutical companies. Neither Republican nor Democrat respondents see the government as the primary culprit for the epidemic.

III. Data and Descriptive Statistics

This section briefly describes the primary data sources leveraged in the empirical analysis. Appendix B. provides further details.

III.a Prescription Opioids

We digitize historical records from the DEA's Automation of Reports and Consolidated Orders System (ARCOS).[15] 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. We report all ARCOS measures in morphine-equivalent doses, which are equal to 60 morphine-equivalent mg. Figure A3 presents the time evolution of shipments of all prescription opioids and of the three main controlled substances: oxycodone, hydrocodone, and morphine. This figure shows the rapid growth of prescription opioids over time and the dominant role of oxycodone—the active ingredient of OxyContin—in such growth. Figure A4 shows the geographic varia-

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

[14] 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.

[15] The ARCOS data are available only from 1997 forward, so the analyses using this measure are restricted to this period.

tion in the level of prescription opioids per capita in 2010, the year the abuse-deterrent formulation of OxyContin was introduced.

III.b Mortality Measures

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

We construct two measures of opioid-related mortality. Prescription opioid mortality includes deaths whose underlying causes are substances usually found in prescription painkillers, e.g., hydrocodone, morphine, and oxycodone. Since drug overdose deaths can be hard to categorize, especially when using data that spans more than one version of the ICD codes, as in our case, we construct a measure of drug-induced deaths. This alternative measure has an advantage in that comparisons across years are less affected by changes in the ICD classification, and it includes a broader set of drugs as causes of death, e.g., deaths from heroin and synthetic opioids such as fentanyl.[16] Panel (b) of Figure 1 shows the geographic distribution of prescription opioid mortality from 1999 to 2020.

III.c Economic Outcomes

We construct a measure of SNAP benefit recipiency rates at the CZ level using data from the Food and Nutrition Service of the Department of Agriculture. In particular, we use data on county-level participation in the month of January for all years spanning 1989-2020, focusing on beneficiaries of Food Stamps (FSP) and Electronic Benefit Transfers (EBT) in the context of the program. We then aggregate the county-level counts to compute the share of beneficiaries in the population at the CZ level.[17] We include two measures of disability benefit recipiency, constructed as the share of the population that receives Supplemental Security Income (SSI) and who is blind or disabled and the share of the population 18 to 65 that receives Social Security Disability Insurance (SSDI). Information on the total number of SSI recipients in each county is based on SSI Annual Statistical Reports and Old Age, Survivors, and Disability Insurance (OASDI) reports prepared by the National Social Security Administration, which we aggregate at the CZ level. These data are available starting in 1999 for the SSDI program and 1998 for the

[16] The drug-induced deaths category includes deaths from poisoning and medical conditions caused by the use of legal or illegal drugs, as well as deaths from poisoning due to medically prescribed and other drugs.

[17] When information at the local level is not available, we impute the state-level share of SNAP recipients.

SSI program.[18] We use county-level estimates of the unemployment rate from the Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics.

III.d Political Outcomes

Voting. We obtain data on election outcomes from Dave Leip's Atlas of US Elections (Leip, 2022) and combine these data with the United States Historical Election Returns Series developed by the ICPSR. We construct the Republican vote shares for governors, House representatives, and presidential candidates and the voter turnout for these elections.[19] Panel (c) of Figure 1 shows the distribution of the Republican vote share in House elections in 1996. This figure suggests widespread variation in support for the Republican Party in the mid-1990s. Panel (d) shows changes in the Republican vote share for 2020 relative to 1996. Table 1 shows summary statistics in the pre- and post-periods for Republican vote shares for House, Presidential, and gubernatorial elections. Throughout this period, Republicans increased their representation, particularly in the House, where the average vote share increased from 45% to 56%. Turnout remained generally stable, experiencing a modest decline from 66% to 64%.

Campaign contributions. We use the Database on Ideology, Money in Politics, and Elections (DIME) from Bonica (2023) to capture campaign donations to House races from 1982 to 2016.[20] We aggregate the count of individual campaign contributions directed toward Republican or Democrat candidates in House races and divide these totals by the voting-age population.

House members' ideology. Data on House members' ideology comes from Lewis et al. (2023). This repository includes information on all individual roll call votes cast by members of Congress, along with an estimation of that member's ideology. We use the Nokken–Poole estimate of ideology, which places each member along a liberal–conservative axis based on preferences towards taxation, spending, and redistribution. This model generates ideological positions, allowing each Congress to hold different positions. Thus, it is well suited for measuring how members of Congress's ideological positions may have changed over time.

Our main estimation sample consists of a panel of 625 CZs from 1982 to 2020. We choose CZs as the geographic unit of analysis because they are designed to capture local economic activity. As a result, CZs better reflect the market definition used in phar-

[18] We observe the number of beneficiaries at a given point in time but do not observe the number of beneficiaries entering or exiting the programs. Thus, we cannot speak to the question of whether a change in the stock is due to people entering more quickly or receiving benefits for a longer time.

[19] For gubernatorial and presidential elections and turnout, we study the period 1976-2020. For House elections, we study the period 1982-2020; the analysis window for House elections is different due to data availability. Leip's Atlas only includes House elections since 1990, we use the ICPSR dataset to obtain a longer window to test for pre-trends.

[20] We exclude data for 2018 and 2020 from our analysis because donation patterns changed significantly during these election cycles, rendering the data incomparable.

maceutical companies' marketing strategies and allow for more accurate measurement of exposure to the epidemic. 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.[21]

IV. Measuring Exposure

In this section, we explain the rationale for using mid-nineties cancer mortality as a measure of exposure to the opioid epidemic and provide empirical support for this approach.

IV.a The Introduction of OxyContin and the Spread of the Epidemic

Purdue's success in introducing OxyContin to the broader noncancer pain market relied on their ability to overcome both the stigma associated with the use of opioids for nonterminal, nonmalignant pain among patients and physicians. To address this challenge, Purdue focused its initial marketing efforts on the physicians who faced less stigma around opioids: those in the cancer pain market. On repeated occasions, Purdue stated clearly that *"OxyContin tablets will be targeted at the cancer pain market."* (OxyContin Team Meeting, April 1994). *"OxyContin primary market positioning will be for cancer pain."* (OxyContin Team Meeting, March 1995). *"At the time of launch, OxyContin will be marketed for cancer pain."* (OxyContin Launch Plan, September 1995). This approach, however, was only intended as a path to enter the larger noncancer pain market. Purdue explicitly stated that

> *"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 nonmalignant pain patients also seen by the family practice specialists"* (OxyContin Launch Plan, September 1995).

That is, Purdue exploited its previously established network of cancer patients and their physicians to introduce its newest product to the broader pain market. This strategy also solved additional logistical barriers related to the sales of Schedule II drugs, such as OxyContin. At the time of launch, only about half of the pharmacies in the country had the paperwork required to sell Schedule II drugs, and because *"pharmacists are generally reluctant to stock Class II opioids"*, Purdue decided that their *"initial targets will be the 25,000 stores who stock MS Contin"*, as no additional paperwork or training would be required for these pharmacies to stock OxyContin.

Once the marketing strategy aimed at eliminating the stigma surrounding opioid use for noncancer pain succeeded, Purdue shifted its efforts away from the cancer pain market

[21]Details on the geographic harmonization are included in Appendix B.

and into the larger noncancer pain market. In their words, there was a *"determination to avoid emphasizing OxyContin as a powerful cancer pain drug,"* due to *"a concern that noncancer patients would be reluctant to take a cancer drug."*[22] Purdue went so far as to perpetuate the belief that oxycodone, the active ingredient in OxyContin, was weaker than morphine, when in fact it is 1.8 times more potent. They said, *"We are well aware of the view held by many physicians that oxycodone is weaker than morphine. I do not plan to do anything about that."* They also stated, *"It would be extremely dangerous at this early stage in the product's life to make physicians think the drug is stronger or equal to morphine"*.[23]

Purdue's marketing strategy succeeded in making the use of highly addictive opioids standard practice in the treatment of moderate and chronic pain for a wide range of conditions. By 2003, nearly half of all physicians prescribing OxyContin were primary care physicians (Van Zee, 2009). This strategy also opened the door for other pharmaceutical companies to follow Purdue's leadership and promote their prescription opioids beyond the cancer market. These companies—Janssen, Endo, Cephalon-Teva, Actavis, Insys, and Mallinckrodt—which are also targeted by dozens of lawsuits for their role in the opioid epidemic, closely shadowed OxyContin's marketing, intending to grow by reducing OxyContin's market share: *"Success means increasing Duragesic share at the expense of OxyContin"* (Sales Force Memorandum, 2001, Janssen Exhibit S0510, State of Oklahoma v. Purdue Pharma et al.).[24]

Finally, Purdue's later strategy to promote only to top opioid-prescribing physicians, those in the highest three deciles of the distribution (Figure A2), meant that areas receiving high initial promotion as a result of the cancer market focus, were also subject to higher future promotion when Purdue's plan shifted to the broader pain market.[25] This created a path dependency that kept the initial targets relevant even as the distribution of opioids expanded.

IV.b From the Marketing Documents to the Identification Strategy

The pharmaceutical industry's marketing strategy meant that areas with a higher incidence of cancer at the time of OxyContin's launch consistently received a disproportionate amount of marketing and prescriptions for OxyContin and other opioids. In practice, this created a spillover in high-cancer communities from cancer patients to noncancer patients through their common physicians. In this context, the ideal instrument is a measure of

[22]Email from Michael Friedman to Richard Sackler in May of 1997, released as part of the evidence involved in the Deposition of Richard Sackler in 2015. Link

[23]Deposition-Richard Sackler EXHIBIT NO. 11

[24]Duragesic is a fentanyl patch manufactured by Janssen, the pharmaceutical company of Johnson& Johnson.

[25]Other pharmaceutical companies followed this strategy. For example, Janssen referred to *high decile prescribers* as their *highmost important customers* in a Sales Force Memorandum for Duragesic in 2001.

the cancer market Purdue Pharma was serving with MS Contin prior to the introduction of OxyContin. In fact, panel (a) of Figure A5 shows that 1994 MS Contin prescription rates are strongly correlated with 1996-1998 OxyContin prescription rates. This figure uses state-level data for prescriptions covered by Medicaid. Unfortunately, for the period of our analysis, county- or CZ-level data on prescription rates are not available.[26]

We proxy the market served by Purdue Pharma using cancer mortality in 1996. This variable is available at the county level and is accurately and consistently measured throughout the period. This measure has a close connection to the rates of cancer patients who are using opioid painkillers to manage cancer pain (e.g., MS Contin), especially in the later stages of cancer treatment.[27] Indeed, panel (b) of Figure A5 documents the strong relationship between MS Contin prescription rates and mid-nineties cancer mortality prior to the launch of OxyContin at the state level.[28]

Next, we provide graphical evidence of the relationship between cancer mortality in 1996 and future prescription rates of opioids. In panel (a) of Figure 2, we divide CZs into quartiles according to their level of cancer mortality before the launch of OxyContin and trace the evolution of all prescription opioids and oxycodone—the active ingredient of OxyContin. It is clear from the graph that communities with high rates of cancer experienced a much larger influx of prescription opioids (solid lines) than low-cancer communities (dashed lines), even though the two groups started the period with comparable prevalence. Oxycodone accounts for the largest share of this growth. Specifically, between 1997 and 2010, areas in the highest quartile of cancer incidence saw an increase in oxycodone gm per capita of 2,900%, while areas in the lowest quartile experienced a growth that was one-third of that, even though the incidence of cancer varied equally across the two groups (Figure A6).

It could be expected that, in the absence of this marketing strategy, areas with high cancer mortality would have had higher rates of OxyContin use as cancer patients were switched from MS Contin to OxyContin. However, this does not explain the observed trends. If this were the case, we would not see an increase in the overall amount of opioids dispensed, measured in morphine equivalent units, since the market was already being served by an equivalent opioid, MS Contin. Instead, the data show that communities with higher cancer rates did adopt OxyContin at higher rates, but this adoption extended far

[26] From reading court litigation documents, we know that at that time, Purdue had access to extremely granular prescription drugs data through a firm called IMS (later called Xponent, and today called IQVIA). We contacted IQVIA to inquire about these data, and they stated that they do not keep historical data records. A plausible alternative instrument is the number of oncologists per capita. This measure, however, is far too concentrated in the largest CZs.

[27] An additional measure of cancer incidence is the rate of cancer patients in the population. Unfortunately, incidence measures reported by the CDC and the Surveillance, Epidemiology, and End Results (SEER) program are aggregated at the state level. Importantly, the two measures are highly correlated: The correlation coefficient is 0.88.

[28] In Appendix C., we provide evidence of the link between the marketing efforts and spending of Purdue Pharma and other opioid-producing pharmaceutical companies and the size of the cancer market.

beyond what was necessary to serve the cancer market (Figure A6).

V. Empirical Strategy and Effects on Health and Economic Outcomes

The relationship between cancer mortality and opioid prescription rates uncovered above motivates an empirical strategy in which we interact 1996 cancer mortality with year dummies to evaluate the presence of pre-trends and to graphically display its effects on our set of outcomes. Variation in 1996 cancer mortality across locations is not random; rather, it depends on demographic, environmental, and socioeconomic variables. In Table 2, we find that cancer mortality is strongly related to share of the population over 65, negatively associated with the share of Hispanic population, and positively associated with mortality from other causes of death. There is not, however, a cross-sectional correlation with relevant economic variables such as income, employment rate or education.

The validity of our identification strategy does not require that cancer be randomly distributed across areas, but rather that in the absence of the opioid epidemic, areas with higher cancer mortality exhibit the same *trend* as areas with lower cancer mortality in terms of our health, economic and political outcome variables (Goldsmith-Pinkham et al., 2020). In this section, we outline the details of the empirical strategy and discuss our results in terms of the supply of prescription opioids, mortality and economic hardship. We provide evidence in support of the exogeneity assumption and exclusion restriction in Section VIII.a.

V.a Supply of Prescription Opioids

We start by running the following specification over our sample of CZs:

$$\Delta\ Opioids_{ct} = \alpha_1 + \sum_{\tau=1998}^{2020} \phi_\tau\ CancerMR_{ct_0} \mathbf{1}(Year = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + \upsilon_{ct}\ , \tag{1}$$

where c indexes the CZ, 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 $\Delta\ X_{ct}$ that represents the long changes in the time-varying control variables. These are contemporaneous cancer mortality, the white and female population shares, the shares of the population aged 18–29, 30–49, 50–64, and above 65 years, and the share of the population aged under 1 year; all of these are measured at the CZ level.

$CancerMR_{ct_0}$ is the cancer mortality rate in CZ c in 1996 (t_0), and it is interacted with a full set of year dummies indexed by τ. The coefficients ϕ_{1998}, ϕ_{1999} , to ϕ_{2020}

measure the effect of higher cancer mortality in 1996 on opioid shipments.

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 and 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[29]—as well as the evolution of our outcome variables.

In panel (b) of Figure 2, we find that starting in 1998, the second year prescription opioids data are available, and continuing until 2020, there is a positive relationship between cancer mortality rates and prescription opioids per capita. This relationship peaks in 2012 and continues to be statistically significant until 2017.[30] By 2012, the year in which prescription rates peaked, a one-standard-deviation increase in the 1996 cancer mortality rate led to an additional 0.75 opioid doses prescribed per capita, which is 50.6% higher than the baseline mean. These results are similar in magnitude to the triplicate state variation used in Alpert et al. (2022), who find that opioids distribution was approximately 50% lower in triplicate states in the years after the launch of OxyContin.

V.b Prescription Opioids and Drug Mortality

We next turn our attention to drug mortality effects. When we inspect the raw data, panels (a) and (b) of Figure 3 show that areas in the top and bottom quartiles of cancer mortality experienced a similar evolution in prescription opioid and drug-related mortality before the launch of OxyContin. In contrast, for the years after 1996, strong patterns emerge, and the mid-1990s cancer mortality starts to predict opioid and drugs-related mortality. Communities in the top cancer areas drift apart from those in the bottom, and by 2020, mortality rates in high cancer CZs are 47% and 54% higher for prescription opioids and drug induced mortality, respectively.[31]

We continue by estimating a regression similar to that presented in Equation 1. Since the mortality data go further back, we can estimate coefficients since 1989:

$$\Delta\ Mortality_{\ ct} = \alpha_1 + \sum_{\tau=1989}^{2020} \phi_\tau\ CancerMR_{ct_0}\mathbf{1}(Year = \tau) + \alpha \Delta X_{ct} + \gamma_{st} + \upsilon_{ct}\ , \qquad (2)$$

This 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_{1989}, ϕ_{1990}, to ϕ_{1995}, test whether mortality followed similar trends in areas with higher and

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

[30]Our first-stage analysis underestimates the impact of the initial marketing of opioids on the overall level of both legal and illegal opioid use because we lack data for the latter.

However, previous research has established a strong causal link between prescription opioid use and illegal opioid use (Alpert et al., 2018; Evans et al., 2019).

[31]In Appendix Figure A7, we present a similar analysis by splitting data into octiles of cancer mortality and observe consistent patterns.

those with lower cancer mortality before the launch of OxyContin. The main coefficients of interest, i.e., ϕ_{1997}, ϕ_{1998} , 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 rest of the variables are defined as in Equation 1.

Estimates using this reduced-form approach are presented in panels (c) and (d) of Figure 3. We confirm the absence of trends prior to 1996 and estimate that, after the launch of OxyContin, a strong relationship develops between mid-nineties cancer mortality and increases in opioid-related and drug-related mortality.[32] As the epidemic progressed from its first wave, primarily involving prescription opioids, to a second wave focusing on heroin, we observe that these effects begin to wane in the latter half of the 2010s. Nonetheless, the correlation with overall drug mortality remains positive and stable until around 2017.[33]

Our estimates indicate that, at its peak in 2012, a one-standard-deviation increase in mid-nineties cancer mortality causes a 101% increase in prescription opioid deaths relative to the pre-epidemic average. In terms of overall drug mortality, we find that by 2017, mortality had increased by 39.8% relative to the pre-epidemic average. These results are similar in magnitude to those in Alpert et al. (2022), who find that non-triplicate states would have had an average of 34% fewer drug overdose deaths from 1996 to 2017.

The excess drug-related mortality induced by the marketing of prescription opioids by and large comprises young and middle-aged adults and at the beginning of the epidemic is driven mainly by white adults. In Figure A9, we present event studies for three age groups, and we also split the data by race. The analysis by age shows (i) no evidence of pre-trends on mortality for any of these groups and (ii) mortality increases that are concentrated among individuals aged less than 55 years old. Furthermore, different from the trends in prescription opioids mortality, for the case of drug mortality—which adds deaths from heroin and fentanyl—the effects are persistent even in the last years of our sample for those under 55.

Case and Deaton (2017) document a dramatic decline in life expectancy for white non-Hispanic Americans, which is mostly driven by deaths of despair such as drug overdoses, suicides, and alcohol-related liver mortality, and point to a possible connection to the opioid epidemic. We explore this connection by studying the effects of exposure to the opioid epidemic on *nonopioid-related* deaths of despair. In panel (a) of Figure D1, we show that there is only a weak link between the opioid epidemic and suicides.

[32] We estimate a statistically significant relationship starting in 2000 (significance level at 5%). In Appendix Figure A8, we replicate this analysis for any type of opioid mortality and document similar trends.

[33] Previous studies have demonstrated the causal relationship between the first and second waves of the opioid epidemic (Alpert et al., 2018; Evans et al., 2019); however, less is known about the geographical variation in the third wave.

V.c Economic Hardship

Families and communities affected by the opioid epidemic may face economic hardship due to reduced working capacity, healthcare costs, and the overall health toll associated with addiction and mortality. This economic strain can increase the need of public transfer programs to help meet basic needs. In this section, we analyze the impact of access to potent opioids on adult wellbeing, focusing on how the associated risks of addiction and mortality have influenced the demand for social insurance, welfare programs, and unemployment rates.

We document a strong link between the opioid epidemic and an increase in the take-up of SNAP. Panel (a) of Figure 4 shows how 1996 cancer mortality predicts a continuous increase in the take-up of SNAP in the subsequent two decades. By 2020, a one-standard-deviation increase in 1996 cancer mortality corresponded to a 9.2% increase in the proportion of the population receiving SNAP benefits, equivalent to an increase of 0.16 of a standard deviation.

Next, we evaluate whether the opioid crisis induced changes in disability rates. Take-up of these programs can increase through at least two channels. First, it can increase directly from increased access to opioids. For instance, Savych et al. (2019) find that long-term opioid prescribing behavior leads to a considerably longer duration of temporary disability, and Park and Powell (2021) document that the rise in heroin access and consumption increased disability applications. Second, increased take-up can result from the economic hardship induced by the opioid crisis, where workers with marginal health issues but still capable of working seek disability for income support, as documented in Choi et al. (2024) and Autor and Duggan (2003). Due to data availability constraints regarding sub-state records for SSI and SSDI, we cannot test for the presence of pre-trends. However, in the post-period, we see that 1996 cancer mortality predicts a continuous increase in the take-up of these programs in the subsequent years. By 2020, a one-standard-deviation increase in cancer mortality led to a 10.2% rise in the population receiving SSDI benefits and a 5.7% rise in the population receiving SSI benefits.

Finally, we examine whether exposure to the epidemic and the increase in the take-up of social insurance and welfare programs were accompanied by changes in unemployment rates. Panel (b) of Figure 4 illustrates the effects of the year interaction with our measure of epidemic exposure and shows no discernible pattern in the data.[34] This result is in line with Currie et al. (2019), who document little relationship between the employment-to-population ratio and opioid prescriptions across United States counties.

As Choi et al. (2024) and Autor et al. (2020) have shown, economic disruption–such

[34] The Local Area Unemployment Statistics (LAUS) from the BLS employs statistical models to generate estimates for counties and other sub-state areas. These models incorporate data from the CPS, CES, and state UI systems. A significant part of the variation is at the state level, which in our case will be absorbed by the state-year fixed effects.

as those caused by NAFTA and the China shock–can reshape political landscapes by altering voter behavior and increasing polarization. In the next section, we explore the political changes that unfolded.

VI. Effects on Political Outcomes

As the opioid epidemic deteriorated the fabric of communities through increased mortality, poverty, and disability, the Republican Party underwent a significant narrative shift. This new narrative spoke directly to the experiences of communities that witnessed a decline in their socioeconomic standing, partly due to external factors. During this period, the Republican Party took political *ownership* of the topic of working-class economic hardship (Peck, 2019) and positioned itself as the advocate for "Forgotten America" and the "America left behind" (Hochschild, 2018; Gest, 2016).[35] For communities that experienced higher exposure to the opioid epidemic, this message may have resonated particularly well. In this section, we evaluate the political effects of the opioid epidemic. Our main focus is on House elections: Given the local nature of these races, they allow for within-state differences in seats won, heterogeneity in candidates elected, and campaign donations. However, we also study presidential and gubernatorial elections.

We turn to a specification in which our endogenous variable corresponds to measures of political outcomes such as Republican vote share in House elections. For each outcome variable, we consider the following specification, which is run over our sample of CZs:[36]

$$\Delta\, y_{ct} = \alpha_1 + \sum_{\tau=1982}^{2020} \phi_\tau \; CancerMR_{ct_0} \mathbf{1}(Year = \tau) + \alpha\; \Delta\; X_{ct} + \gamma_{st} + \upsilon_{ct}\;, \tag{3}$$

This regression follows the same notation and definitions as those for Equation (1). The coefficients that capture potential pre-trends are ϕ_{1982}, ϕ_{1984}, to ϕ_{1994}; 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.

VI.a 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 and splitting CZs into quartiles

[35] This Republican "ownership" is within a context in which Democrats "own" the topics of income inequality and Republicans "own" crime.

[36] We refrain from conducting an instrumental variable analysis, as we view our political outcomes as the result of the complex and dynamic consequences of increased exposure to the opioid epidemic, rather than the direct and contemporaneous effects of higher levels of prescription opioids or higher mortality from prescription opioids. There is no single endogenous variable that we could instrument to adequately capture the evolving effects over the 24 years of the epidemic.

based on cancer incidence in 1996. Panel (a) of Figure 5 shows no difference in the pre-1996 Republican vote share between areas with high and those with 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 yielded 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) increased the vote share by 4.6 percentage points (see panel (b) of Figure 5). These increases in vote share are not driven by differential changes on the extensive margin as measured by turnout: In Figure A10, we document no notable changes along this margin.[37]

We use CCES survey data from 2006 to 2020 to examine heterogeneity in the effects along voters' sociodemographic characteristics.[38] We start by replicating our baseline result on voting Republican using the CCES data. Column (1) of Table 3 shows very similar results from this alternative data source. Next, we divide the sample by gender, age, race, and educational attainment level. Columns (2) through (9) show that along all of these subsamples, we estimate a higher Republican vote share in communities with higher exposure to the epidemic. Although these differences are not statistically significant, the estimates are larger for the population under 50 years old and for non-whites, while the estimated effects are very similar across the gender and educational attainment samples.

Whether increases in the Republican vote share translate into election wins depends on how contested the districts are and how much the vote increases. We show that even though the Republican vote share starts to increase in 2006, it is only starting in the year 2012 that we observe evidence of an increase in the probability of a Republican win (panel (a) of Figure 6). The main reason for this pattern is that the initial increases in vote share are concentrated in communities with a low baseline Republican vote share (panel (b) of Figure 6). Starting in 2014, the vote share in communities that began at a median level also begin to increase, contributing to the rise in a seat's likelihood of flipping in the election.

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 CZ level.

[37]We do not report turnout pre-trends or effects for House elections, as data are not available for midterm elections from 1990 to 1998. Our analysis of turnout rates is limited to documenting net changes, which could mask potentially important compositional variation. Unfortunately, with the data available, we cannot shed light on this important margin of adjustment.

[38]When 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 in which the CCES data are available—to 2020. In Table 3, we report the coefficients of 1996 cancer mortality rates without time interactions to maximize power. The outcome of interest is defined in levels due to the lack of baseline data to compute long changes.

In Figure A11, we replicate Equation (3) 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 results from a 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 A11). These results, however, 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.

The changes in vote share and additional seats won by the Republican Party translate 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 A12, we document that opioid epidemic exposure increases conservative views in the House, particularly among representatives from districts with lower baseline Republican support (panel (b)). However, this shift originates 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 A12) but rather from a change in the composition of the House.

VI.b Gubernatorial Elections

We next turn our attention to gubernatorial elections, where we also find a shift towards the Republican Party resulting from exposure to the epidemic. All states except New Hampshire and Vermont hold elections every four years. Nonetheless, these elections do not necessarily happen at the same time. For example, out of the 50 states in the United States, 35 have gubernatorial terms ending in 2027.[39] Thus, to estimate the effects of exposure to the opioid epidemic, we normalize time relative to the most recent election in state s that occurred before 1996 and count elections before and after this date. For example, Idaho elected a governor in 1994; this election is assigned *event time* zero, and the election held in 1998 is assigned event time one. In contrast, Indiana elected a governor in 1996 and 2000; the former is assigned event time zero and the latter event time one. Using this approach, the estimates of the coefficient on cancer mortality are interpreted as the effect seen t (or τ) elections after the start of the opioid epidemic.

Figure 7 presents these results. The raw data patterns and pre-trend estimates indicate that CZs show similar trends before 1996, but four elections after the start of

[39] These states are Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Iowa, Kansas, Maine, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, Nevada, New Hampshire, New Mexico, New York, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Vermont, Wisconsin, and Wyoming in Jan 2027 and Kentucky in December 2026. See The Council of State Goverments (2024) for details.

the opioid epidemic, statistically significant differences emerge. We estimate that in six elections—i.e., those between 2017 and 2020—a one-standard-deviation increase in cancer mortality translated to a 3.7-percentage-point increase in the Republican vote share. These estimates are comparable in magnitude to the decline in the Democratic vote share resulting from a 3-percentage-point increase in the employment rate. In particular, Brunner et al. (2011) find that such an increase would lead to a 3.9-percentage-point decrease in votes for a Democratic governor and a 3.3-percentage-point decrease in support for party-endorsed ballot propositions.

VI.c Presidential Elections

The epidemic's effects 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 8). By the 2000 election, a wedge had emerged in terms of Republican support that widened as time went on, such that by 2020, the gap in the GOP vote share between areas with high and those with low cancer mortality was greater than 15 percentage points. We estimate that an increase of one standard deviation in cancer mortality in the baseline period increases the share of votes for a Republican candidate in presidential elections by 4.9 percentage points. This effect is comparable to the increase in Republican vote share when moving from the top quartile to the bottom quartile of NAFTA vulnerability (Choi et al., 2024).

VI.d Accountability and Anti-Incumbent Responses

Traditional models of political accountability argue that voters hold elected officials and parties responsible for economic and social outcomes, rewarding or punishing them in elections based on their perceived performance (Persson et al., 2000; Ashworth, 2012). Furthermore incumbents are often hold accountable for crises, even when these are exogenous (Healy and Malhotra, 2009; Achen and Bartels, 2017).

In the context of the opioid epidemic, multiple factors obscure the assignment of blame and responsibility, making it difficult to attribute the crisis's origin and progression to any specific candidate, political party, or government entity. One reason for this is the involvement of multiple levels of government in the origins and developments of the epidemic. For example, federal agencies such as the FDA and DEA are responsible for regulating the prescription and distribution of opioids, state legislators have policy tools like the implementation of Prescription Drug Monitoring Programs (PDMPs), and local authorities oversee crime related to illegal drug sales and are in charge of emergency responses to drug overdose incidents. Despite this shared responsibility, the crisis was, for many years, primarily perceived as stemming from individual addiction issues, physicians' behavior and secular trends in local socio-economic conditions. A second factor is that neither political party took ownership of addressing the crisis or held the opposition accountable for it, similarly the media did not attribute blame to any party. As a result, voters do not hold the government or any political party responsible for the opioid epidemic, as evidenced by survey data (YouGov, 2022).

Nonetheless, we assess whether our results may partly stem from anti-incumbent responses, as incumbents who were in office at the onset of the epidemic or who managed the crisis and its aftermath unsuccessfully could be held accountable. In panel (a) of Figure A13, we split the sample by party according to who is in power at the time of each election and replicate our baseline estimation.[40] The results of this analysis are noisy, particularly in the later years, due to the decreasing proportion of CZs with Democratic incumbents. We find that changes in Republican vote share are not statistically different depending on whether the incumbent was a Republican or a Democrat. In panel (b), we conduct a second exercise, defining our outcome variable as the incumbent's vote share. We do not find evidence of changes in the incumbent party's ability to be re-elected for most of the period studied. If anything, after 2016, there is a slight increase in the likelihood of staying in power. These exercises show that there is no empirical support for the hypothesis that the increases in Republican vote are a response to anti-incumbent sentiment when Democrats are in power.

VI.e Composition of the Electorate

To investigate whether our results are driven by changes in the composition of the electorate, we first examine the role of migration. We collect data on county-to-county migration flows from the IRS Statistics of Income (SOI) Tax Stats and calculate total out-migration and in-migration flows at the CZ level. Figure A14 estimates Equation (3) 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 do 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). Nonetheless, this result is consistent with previous evidence suggesting that migration provides very little insurance against adverse economic shocks (Autor and Dorn, 2013; Yagan, 2019; Choi et al., 2024).

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

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

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 given a one-standard-deviation increase in 1996 cancer mortality.

VII. Mechanisms: How the Epidemic Led to Republican Gains

The evidence presented before illustrates a narrative in which the initial marketing of opioids is linked to future opioid prescriptions and drug overdose deaths, which in turn lead to increased reliance on welfare and social insurance, as well as greater support for the Republican party. This unfolded in a period, in which the Republican party and conservative media became the voices of the economic hardship of working-class America, and their narrative might have resonated particularly well with those most affected by the epidemic. In this section, we first evaluate whether the communities that experienced the strongest effects in terms of economic hardship are also those that shifted their support towards the Republican Party. Second, we look into how politicians and the media framed and engaged with the opioid epidemic, as well as the role of preferences for policy solutions proposed by Republicans and Democrats.

VII.a Where Are Republican Gains Concentrated?

We start by examining the geographical variation in the effects of the epidemic on economic hardship and Republican support. With this objective, we run a modified version of Equations (2) and (3) in which we add state indicators to the 1996 cancer-year interactions as follows:

$$\Delta\, y_{ct} = \alpha_1 + \sum_{s=1}^{s=50} \sum_{\tau=1989}^{2020} \phi_{\tau,s}\; CancerMR_{ct_0} \mathbf{1}(Year = \tau \;\&\; State = s) + \alpha \Delta X_{ct} + \gamma_t + \upsilon_{ct}, \quad (4)$$

This specification allows for the identification of state-level treatment effects over time for our different outcome variables. In Figure 9, we plot the treatment effects for SNAP in 2006 against the treatment effects for Republican vote share in the House from 2008 to 2018.[41] We observe a strong positive correlation between these two estimates across the years. Notably, this correlation is highest with a delay; specifically, the 2006 SNAP treatment effects are the most predictive of the 2016 vote share effects. That is, the communities that endured the worst effects in terms of increased reliance on SNAP, are those same communities that saw later, the largest gains in terms of Republican vote share. In Figure A16, we replicate this analysis for mortality, SSI, and SSDI, finding

[41] In Figure A15 we show the same excercise for a different group of years.

similar positive correlations. This evidence suggests that the economic hardship induced by the epidemic may be mediating the effects on political outcomes.[42]

VII.b Engagement with the Epidemic: House of Representatives

Next, we document the engagement of House members with the opioid epidemic and explore how partisan differences in policy solutions might have swayed voters towards the Republican party.

The opioid epidemic was mostly absent from discussion in the House until 2015. Prior to this year, records from House speeches indicate that Republican representatives spoke more about this issue (see Figure A17), but the level of discussion was too low to be influential. We observe further evidence of this low engagement by examining the topics covered in campaign advertising, where the opioid epidemic only started to be systematically mentioned in 2020 (Fowler et al., 2023). 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. They find that the volumes of Democrats' and Republicans' opioid-related posts were equally correlated with state overdose death rates. These findings suggest no differential political engagement surrounding the opioid epidemic that could have driven vote share movements in one direction or the other.

In terms of policy responses, there are stark differences between the parties' approaches to the crisis. The Republican Party favors law enforcement and tighter immigration policies, while the Democratic Party advocates for rehabilitation, addiction treatment, and harm reduction initiatives. 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 have gravitated toward the Republican Party, which is perceived as advocating for a larger police force and stricter law enforcement measures; they may have seen these policies as tools that could curb the crisis. Furthermore, previous work documents that the increased salience of crime has provided electoral benefits for Republican candidates (Jacobs and Tope, 2008; Boldt, 2019). Using 2020 CCES data, we find that mid-1990s cancer mortality is indeed positively correlated with an expressed preference for increasing the number of police officers on the street and a reported sense of safety around law enforcement agents (see columns (1) and (2) of Table 4), which suggest a preference for the policy response favored by the Republican Party.

In contrast, the types of harm reduction policies primarily promoted by Democratic politicians, such as drug legalization and syringe exchange programs, have faced increased skepticism. Recent evidence indicates that these policies may contribute to an increase

[42] A standard mediation analysis is not well-suited for our case given the sequential chain of effects. For example, by 2020, our instrument no longer predicts prescription opioid mortality and thus cannot mediate any effect on SNAP or vote share. However, lagged prescription opioid mortality does predict future SNAP effects and political outcomes. Recent work by Bugni et al. (2023) extends mediation analysis for such a delayed setting, but only in the context of a binary treatment.

in drug mortality (see Doleac and Mukherjee, 2019; Packham, 2022; Spencer, 2023). We evaluate whether support for the legalization of marijuana possession and recreational use, an example of such harm reduction policies generally supported by the Democratic Party, varies based on the level of exposure communities have had to the opioid epidemic. To do so, we collect data for 18 out of the 19 states that have put forward a ballot initiative to legalize marijuana between 2012 and 2023. In column (3) of Table 4, we find that indeed, exposure to the opioid epidemic predicts lower support for marijuana legalization.[43] These results indicate that in the policy sphere, exposure to the epidemic is associated with a preference for Republican Party policies and a disapproval of Democratic Party initiatives.

VII.c Media: Newspapers and Television

In this section, we examine the differential coverage of the opioid epidemic by local newspapers and national television networks. Previous work has documented the importance of media coverage in shaping public understanding of events and influencing political preferences. On the extensive margin, differential levels of coverage of the opioid epidemic could alter media consumption patterns, directing audiences toward outlets that focus more on this issue and that consequently realign consumers' political preferences (DellaVigna and Kaplan, 2007; Clinton and Enamorado, 2014; Martin and Yurukoglu, 2017). On the intensive margin, the nature of media coverage is also important. For example, during the crack epidemic, the media's fear-driven narrative played a key role in promoting right-wing policies and legislation that resulted in a more punitive criminal justice system (Reinarman and Levine, 1989).[44]

We create a novel database of news articles mentioning the word "opioids" from local newspapers for the years 1995 to 2020, using the archive from *newspapers.com*. We assign political affiliations to these outlets (Democrat, Republican, or independent) leveraging the classification developed by Gentzkow and Shapiro (2011) for 1994. In Figure A18, we document that, consistently over the period of the opioid epidemic, Republican-identified newspapers provided greater coverage of the opioid epidemic. Furthermore, in Table A1, we find that this coverage by Republican media responds to the local incidence of the crisis. This regression examines the relationship between local mortality rates and the level of coverage of the opioid epidemic over different periods. For Republican media, we estimate a consistently strong positive relationship, whereas for Democratic media, there is no correlation between local exposure and opioid coverage.

[43] The list of states in chronological order from most recent to the first are Ohio, Oklahoma, South Dakota, Arkansas, Maryland, Missouri, North Dakota, New Jersey, Arizona, Montana, Michigan, California, Nevada, Maine, Massachusetts, Oregon, Alaska, Colorado and Washington. We could not obtain county-level data for Alaska.

[44] Inducing fear is an effective way to create support for law-and-order policies, as psychological adaptations to cope with collective threats favor such politics (Gelfand, 2021; Roos et al., 2015; Gelfand, 2019). Past drug epidemics serve as examples where perceived threats have led to the implementation of "tighter" and more punitive policies.

Next, we examine the content of the coverage. We collect the headlines of a random subsample of these articles written between 2000 and 2018 (9,044 out of 118,210) to analyze whether there are differences in how they cover the epidemic. We focus on five categories: (i) drug trafficking, cartels and crime; (ii) fear, panic, and alarm; (iii) economic hardship; (iv) rehabilitation and addiction treatment; and (v) policy solutions. We define keywords for these categories and compare their relative frequencies.[45] Our findings in Table A2 indicate that Republican-leaning newspapers place greater emphasis on economic hardship, with a 23% higher frequency of related keywords, 19% higher for illegal activities, and 22% higher for rehabilitation/treatment compared to Democratic-leaning newspapers.

Similar to the trend we document for local print media, the opioid epidemic receives more attention from Fox News than from more liberal media outlets such as CNN and MSNBC. Specifically, using data from the TV News Internet Archive, which has collected TV clips since 2009, we find that Fox News covers opioid epidemic stories at a rate that was 1.5 and 1.7 times higher than CNN and MSNBC, respectively. Their coverage is also different, with Fox News emphasizing stories about crime, drug trafficking, and cartels at double the frequency of the more liberal news outlets. We do not find any other systematic differences.

Such differences in the extensive and intensive margins of coverage may have favored the Republican Party. First, the higher coverage of the epidemic by Republican-leaning outlets may have increased the preference for conservative newspapers and Fox News in communities more exposed to the crisis. By reporting on the experiences these communities face and thereby growing their audience, these outlets may then have also reinforced support for the Republican Party and conservative ideology among this group (DellaVigna and Kaplan, 2007; Clinton and Enamorado, 2014; Martin and Yurukoglu, 2017). We investigate this hypothesis using CCES data for 2020, a year in which a question on Fox News viewership was included. Indeed, as shown in column (4) of Table 4, we find that exposure to the opioid epidemic predicts Fox News viewership.

Second, the differential content of the coverage may have further aligned preferences with those of the Republican Party. Specifically, the emphasis on economic hardship suits the narrative of the Republican Party during this period. Additionally, the focus on crime and drug cartels could increase preferences for tighter law enforcement and stricter immigration policies, both of which are favored by the Republican Party. As described earlier, in Table 4, we find that communities with higher exposure to the opioid epidemic prefer an increase in the number of police officers, feel safer around the police, and favor tighter immigration restrictions. Moreover, we also observe that exposure to the epidemic predicts conservative views on other topics such as abortion, gun control, and self-reported ideology (see panel B of Table 4).

[45] Appendix B. lists the keywords used for each category.

In short, by creating economic hardship, the opioid epidemic became politically advantageous for the Republican Party, which during this period, repositioned itself as the party advocating for the struggling white working-class America. This connection was further amplified by conservative media covering the epidemic more extensively and framing it around themes like drug trafficking, crime, and economic hardship. On top of this, communities more exposed to the epidemic showed a stronger preference for Republican policies focused on law enforcement while rejecting harm reduction approaches typically supported by Democrats.

VIII. Robustness Checks

In this section, we provide evidence in support of our identification strategy, explore alternative explanations for our findings and test the robustness of our results. Appendix D. discusses additional exercises.

VIII.a Evidence on the Exogeneity Assumption and Exclusion Restriction

The validity of the identification strategy requires that, in the absence of prescription opioid marketing, areas with higher cancer mortality in 1996 would have exhibited the same trends in health, economic and political variables as areas with lower cancer mortality. To support this assumption, we present several exercises. First, we perform an out-of-sample dynamic reduced-form analysis to test if lagged cancer mortality predicts future opioid mortality, SNAP claims, employment in the mining and manufacturing sector, unemployment rate, or future Republican vote share before the onset of the opioid epidemic. That is, we run Equation (1) over a sample of CZs for the years 1982 (or the first available year) to 1995 and estimate if cancer mortality in 1976 predicts any of these health, economic, and political outcomes in the next fourteen years or seven electoral cycles. We present the results of this analysis in Figure 10. These results demonstrate that before the introduction of OxyContin, there is no relationship between our outcome measures or additional economic outcomes and lagged cancer mortality—the estimated coefficients are statistically indistinguishable from zero, and there is no evidence of a pattern.

Second, we test the validity of our design by estimating event-study regressions with placebo instruments—i.e., mid-1990s mortality from causes unrelated to cancer.[46] Finding a good placebo instrument is challenging given that the causes that underlie the incidence of cancer and 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

[46] These placebo instruments are also known as negative instruments (Danieli et al., 2023).

among elderly age groups. With this caveat, in Figure 11, we show placebo instrument regressions for mortality from hypertension and pneumonia, 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 our health, economic and political outcomes.

Third, we enrich the set of covariates to account for health behaviors, access to healthcare and economic factors and the correlation of these with cancer. For example, Dong et al. (2022) document that the share of smokers and the share of adults with overweight are among the main risk factors associated with cancer mortality. We expand the set of controls in our baseline to include the share of smokers, the share of adults with overweight, the share of primary care physicians, and the infant mortality rate, all measured at the CZ level at baseline or the earliest available data point. Panel (a) of Figure 12 and Figure A20 present estimates from a specification where we add these controls, interacting each of these with year dummies. Our results remain unchanged.[47,48]

Similarly, we include a set of economic covariates to our main specification. We interact each economic control measured at baseline with year dummies; these controls include the unemployment rate, the share of employment in the manufacturing sector, income per capita, and the share of the population that has completed some college.[49] Panel (b) of Figure 12 shows that the inclusion of these covariates does not affect our main estimations for prescription opioid mortality and the Republican vote share in House elections. Similarly, panel (a) of Figure A20 presents this analysis for SNAP shares.

In sum, these exercises support the assumption that the variation in 1996 cancer mortality rates was not preceded by or accompanied by drifting health or economic trends. Rather, after 1996, this variation translated into diverging exposure levels to the epidemic.

VIII.b Exposure to Economic Shocks

We consider the geographic exposure to the economic shocks that have been shown to influence our outcome variables during the period of study. In each exercise, we include a measure of exposure to a specific shock interacted with year dummies to flexibly account for its geographical impacts.[50]

[47] Numerous studies have shown that air pollution has a causal effect on both infant and older adult mortality (see, for example, Deryugina et al., 2019). Nonetheless, data on air pollution have limited coverage, expanding only 57% of our sample. In Figures A19 and A20 (panel b), we show that our results remain unchanged when including readings on the level of PM2.5 (in $\mu g/m^3$) in our estimation.

[48] In appendix D. we show that there is no systemic relationship between mid-nineties cancer mortality and overall health trends or despair. Specifically, we find that exposure to the epidemic does not predict suicides or overall mortality neither before or after the introduction of OxyContin.

[49] All of these controls are measured at the CZ level at baseline or the first available year; see Appendix B. for further details.

[50] We follow the literature to construct these measures; Appendix B. provides the details. The correlation between these measures and exposure to the opioid epidemic varies between -0.04 and 0.34. Specifically, these values are NAFTA: -0.04, China shock: 0.18, 2001 recession: 0.05, Great Recession:

Contemporaneous with the unfolding of the opioid epidemic, the United States economy faced increasing import competition from both Mexico and China, experienced the 2001 economic recession and the Great Recession, and was impacted by significant advances in the adoption of robotic technology. Potentially, our results could reflect exposure to these shocks rather than to the effects of the opioid epidemic.

NAFTA is a trade agreement between Canada, Mexico, and the United States that was implemented on January 1, 1994. Its primary goal was to eliminate trade barriers and promote free trade among the three North American nations. Hakobyan and McLaren (2016) and Choi et al. (2024) document that geographies whose 1990 employment depended on industries vulnerable to NAFTA suffered significant and persistent employment and wage growth losses after its implementation. Choi et al. (2024) find that voters in exposed counties increased reliance on SNAP and turned away from the Democratic Party. In panel (a) of Figure 13 and panel (b) of Figure A21, we show that our results remain invariant when we control for the NAFTA vulnerability measure.

In October 2000, the United States Congress granted permanent normal trade relations (PNTR) to China. Regions more exposed to Chinese import competition experienced significant declines in employment, greater uptake of social welfare programs, and increases in fatal drug overdoses (Autor and Dorn, 2013; Adda and Fawaz, 2020; Pierce and Schott, 2020). In panel (a) of Figure 13 and in Figure A21, we use the measure of exposure to trade competition from Pierce and Schott (2020) and show that our results are quantitatively similar to the baseline estimation when controlling for this measure.

Next, we assess whether the 2001 and 2007 economic recessions mediate some of our effects. For each recession, we construct a measure of severity as a function of the change in the CZ unemployment rate. We find that our estimates do not change when controlling for exposure to these economic shocks (see Figure 13 and Figure A21).

Finally, 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 technological change mediates our effects. Panel (a) of Figure 13 shows that our main estimates remain unaffected when we control for this exposure.

VIII.c Political Developments and Group Realignments

Our period of study was also characterized by important political and demographic shifts that could potentially confound our results. In this section we explore several of these changes.

0.02, adoption of robots or automation: 0.10, rurality score: 0.34., 1992 share of votes for Clinton: 0.08, Fox News: -0.03.

Republican Party and rural areas. Mettler and Brown (2022) show that rural voters' support for Republicans was declining before 1996, while it has steadily increased since 2000. This shift is part of a broader, century-long trend of increasing polarization between rural and urban voters (Rodden, 2019). Given that cancer mortality is positively correlated with rurality, it is plausible that our result confounds the differential trends in rural versus urban support towards the Republican Party.[51] To address this concern, we use a measure of rurality from the United States Department of Agriculture in 1993 and add interactions with year dummies to our baseline regression. Panel (b) of Figure 13 shows that our results are robust to the inclusion of this control.

The Republican revolution. In 1994, the Republican Party had a historic victory that resulted in a net gain of 54 seats in the House. This event, referred to as the Republican Revolution or the Gingrich Revolution, could be an alternative explanation for the changes in voting patterns we document in this paper. Brady et al. (1996) show that Democratic losses in the House stemmed from voter rejection of President Clinton's legislative agenda and that this swing was both regionally and ideologically concentrated in marginal districts in the 1992 election. Following these arguments, we flexibly control for the share of votes to Clinton in the 1992 presidential election. We do not find evidence that suggests that our results are driven by this backlash against the Democratic president (see panel (b) of Figure 13).

White and over-65 voters. Cancer mortality in 1996 is correlated with the share of the population over 65, a demographic that has grown over time and tends to lean Republican. In Figure 13, we expand the vector of controls to include interactions between the share of the population over 65 years old in 1996 and year dummies. We find that our conclusions hold when we flexibly add this share as a control. Along the same lines, given that the Republican Party has a significant advantage among white men and that this wedge has widened in recent years, we consider whether communities with larger shares of this demographic group drive our results. To assess this hypothesis, we add to our main specification as an additional control the share of white men in 1996 interacted with year dummies. We find no evidence supporting this explanation: The estimated effects are quantitatively very similar to those from the baseline specification.

The Republican Exodus. One of the largest and most debated partisan shifts in modern democracy is the exodus of white Southerners from the Democratic Party in the second half of the twentieth century (see Kuziemko and Washington, 2018). Given this shift, we ask whether our results are driven by communities in the south. To this end, we run our main specification (Equation 3) while excluding CZs in the south. This analysis does not reveal evidence that our results are driven by this specific region (see panel (b) of Figure

[51]The opioid epidemic has had an unequal impact on rural and urban areas (Rigg et al., 2018). In Figure A21, we reproduce our baseline estimates with interacted year dummies using 1993 rurality measures and find our results remain invariant to these controls.

13).

The introduction of Fox News. The timing of the opioid epidemic coincides with the October 1996 introduction of Fox News to cable programming in selected locations. According to DellaVigna and Kaplan (2007) and Clinton and Enamorado (2014), higher initial exposure to Fox News increased the Republican vote share in the 2000 presidential elections and shifted House representatives toward the Republican Party. 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 Clinton and Enamorado (2014) and replicate our estimates. These data cover only 60% of our CZs, resulting in a significant reduction in sample size and 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 A22).

Appendix D. complements these robustness checks. In addition to the above exercises, we further test for the role of health trends and behaviors, the decline in unionization rates, and the rise of evangelicals' support for the Republican party. We also present a set of exercises where we reproduce the main analysis at the county level, drop individual states, modify the population sample restrictions, and use alternative measures of cancer mortality. Our results are robust to these tests; we reach similar quantitative and qualitative conclusions to the baseline specification.

IX. Discussion

The opioid epidemic stands as one of the most tragic events in recent United States history. Its effects have extended beyond the direct loss of life to impact the economic and political life of the most affected communities. 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 who were treated by the same doctors. A later marketing practice that targeted heavy prescribers created path dependency from this initial exposure. We use 1996 cancer mortality at the CZ level as a measure of this initial exposure. We document that exposure to the epidemic caused an increase in drug deaths as well as economic hardship measured as SNAP and disability take-up. These impacts further differentiated the trajectories of these communities in terms of their political support. By 2020, areas that had looked very similar in the mid-1990s now had substantial differences in their Republican–Democrat preferences as a function of their exposure to the epidemic. We find that the opioid epidemic increased Republican vote shares in house, gubernatorial and presidential elections and in the House started to flip elections by 2012.

In this paper, we explore the complex, long-lasting effects of a public health crisis on the health, economic, and social dimensions of communities, and how these impacts continue to shape them, particularly through their influence on elections. Our findings add to the rich literature on the economic determinants of political preferences, which has examined factors such as inequality, trade, unemployment, and income level but has given less attention to health. We hope that this work inspires further research into the political and long-term consequences of health disparities and health shocks, particularly in a landscape where health policies and guidelines are increasingly divided along party lines (e.g., vaccination rates), as through such differences, disease exposure and mortality have become politicized (Wallace et al., 2023).

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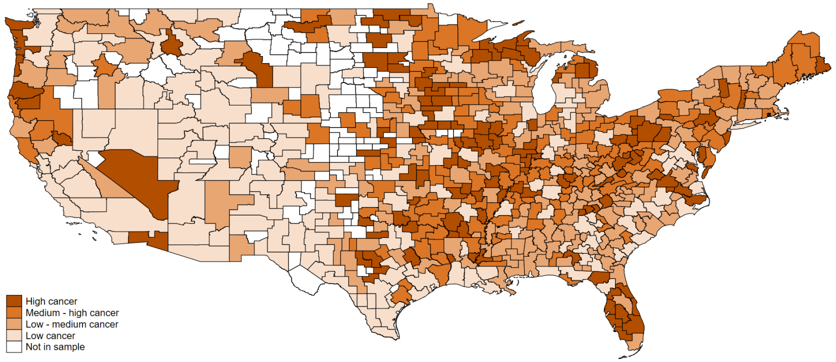
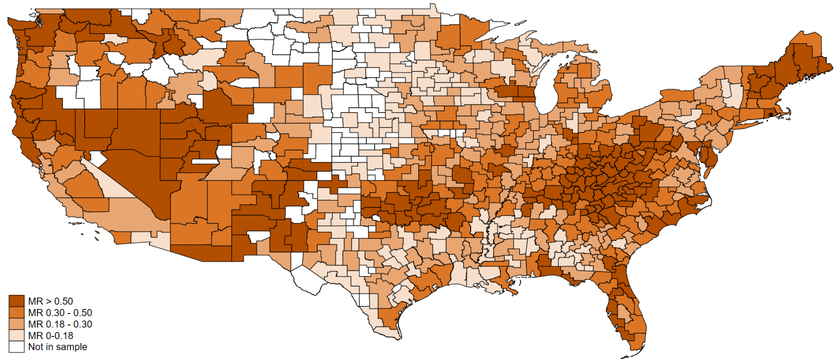
X. Figures

Figure 1: Geographical Variation

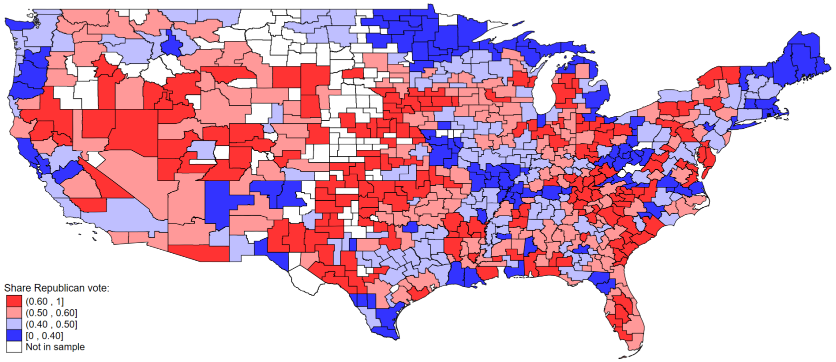
(a) Cancer Mortality Rate, 1996



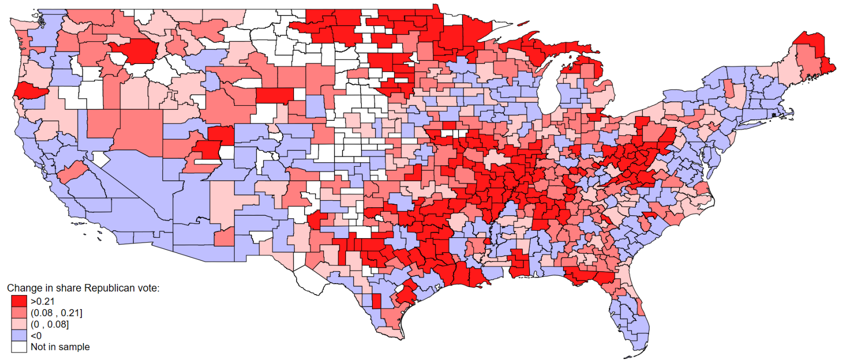
(b) Prescription Opioid Mortality Rate, 1999–2020



(c) Republican Vote Share – House Elections, 1996



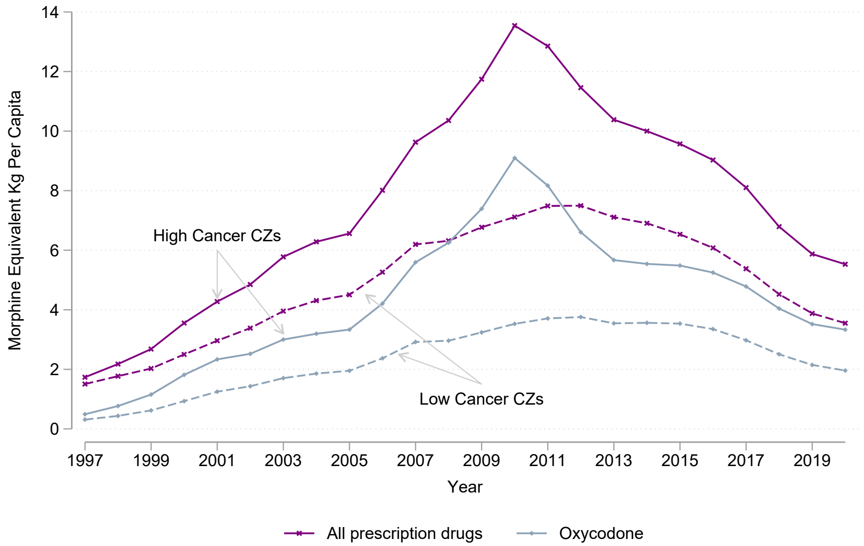
(d) Change in Republican Vote Sh. – House Elections, 2020–1996



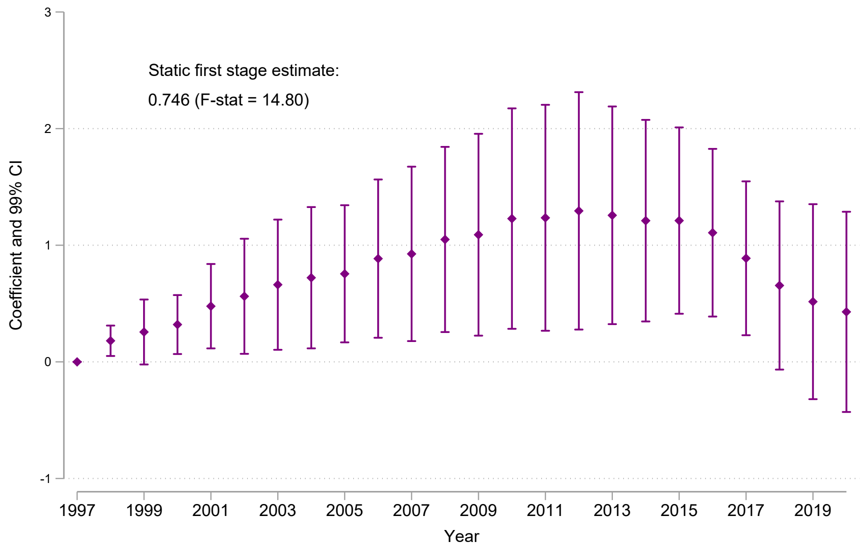
Notes: Panel (a) shows the geographic distribution of our measure of exposure to the opioid epidemic—cancer mortality in 1996—and panel (b) shows the distribution of prescription opioid mortality. Panel (c) shows the geographic distribution of the Republican vote share in House elections, and its evolution between 1996 and 2020 is shown in panel (d). We restrict our sample to areas with more than 20,000 residents; these account for more than 99% of all opioid deaths and 99% of the total population. CZs not included in the sample, i.e., "Not in sample", are white in the figure. This figure is referenced in Section III..

Figure 2: Effects of Cancer-Market Targeting on Opioid Distribution & Mortality

(a) Trends in the Prescription Opioid Distribution



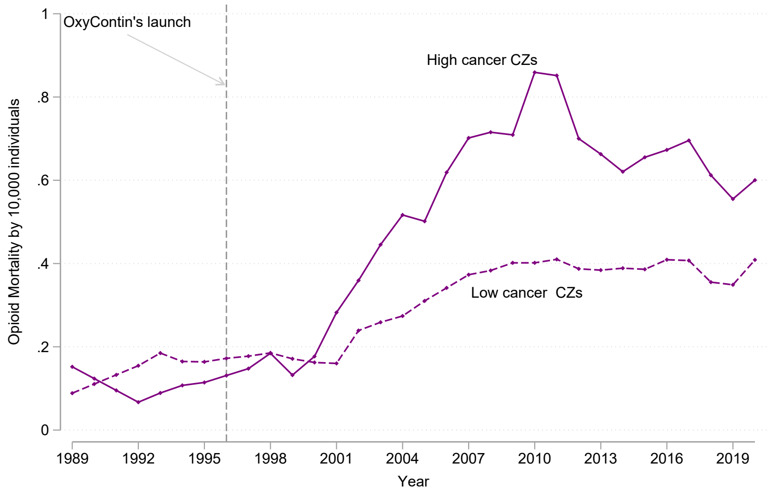
(b) Effects on the Prescription Opioid Distribution



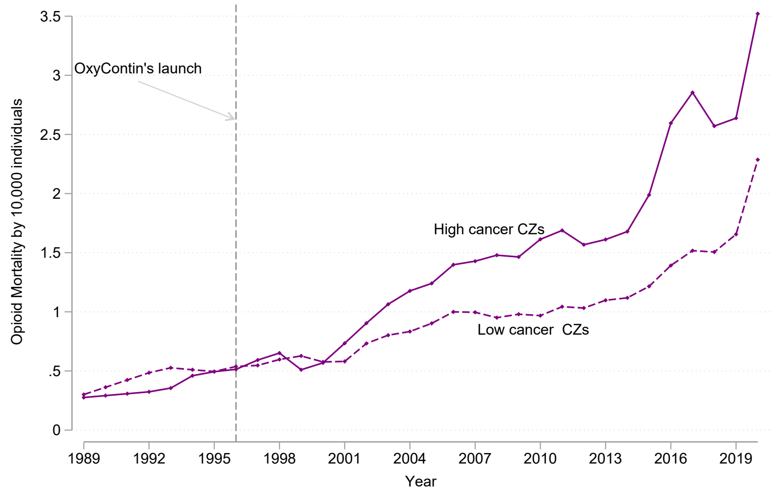
Notes: Panel (a) shows the evolution of the distribution of prescription opioids for the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Oxycodone is OxyContin's active ingredient. Panel (b) shows estimates of the effects of cancer-market targeting on the distribution of prescription opioids, i.e., estimates of the ϕ_τ coefficient in Equation (1). The ARCOS data are available only from 1997 on; thus, we can estimate coefficients only from this date. This figure is referenced in Section IV.b and Section V.a.

Figure 3: Effects of Cancer-Market Targeting on Opioid Distribution & Mortality

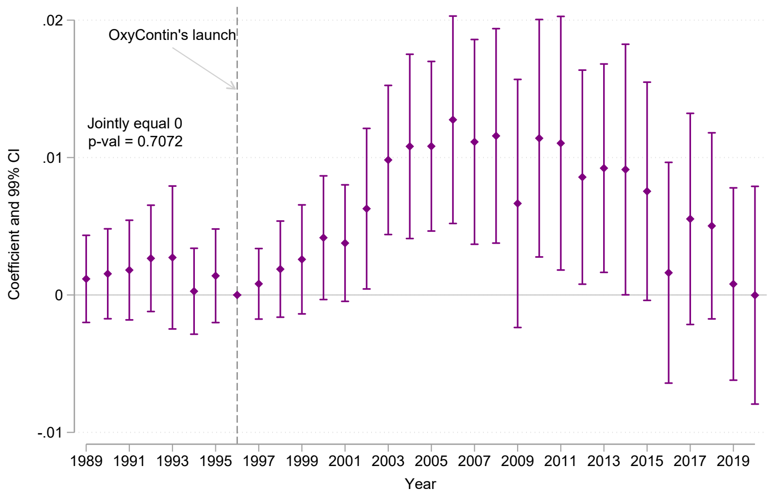
(a) Trends in Prescription Opioid Mortality



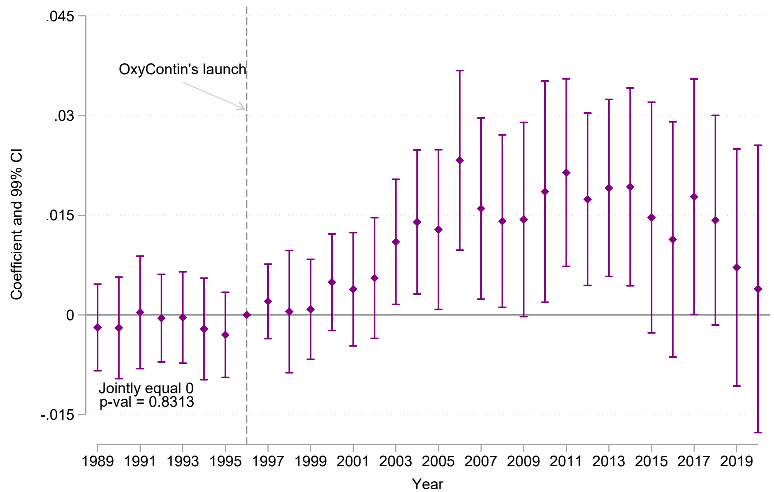
(b) Trends in Drug Induced Mortality



(c) Effects on Prescription Opioid Mortality



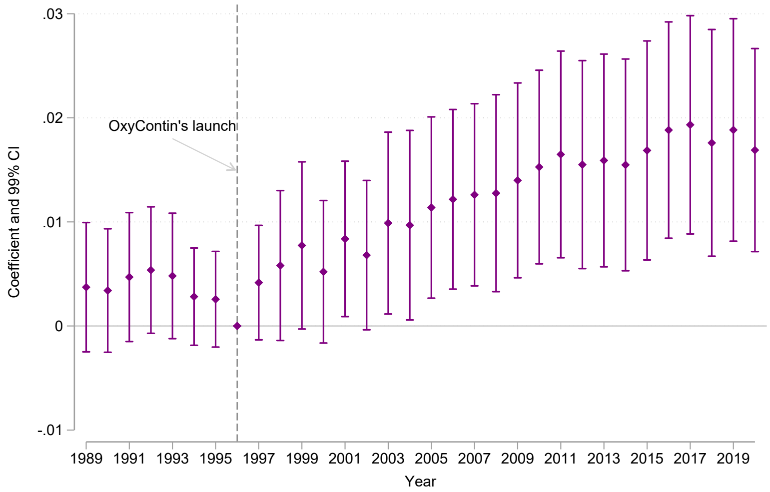
(d) Effects on Drug Induced Mortality



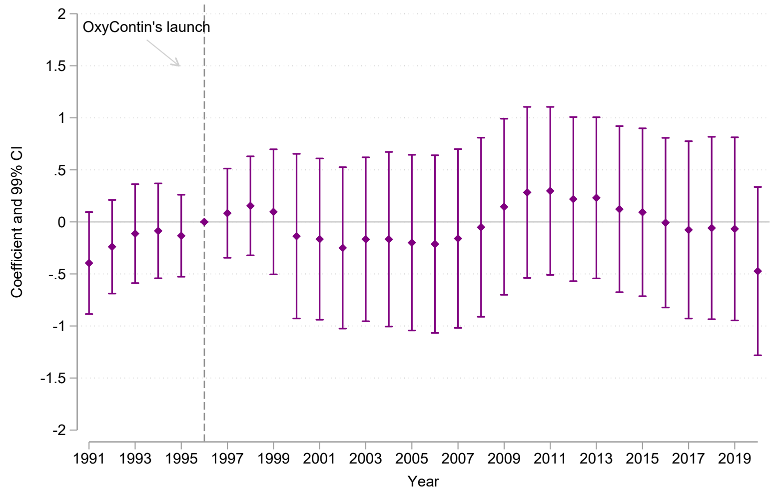
Notes: The top panels show the evolution of opioid-related mortality in CZs in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. The bottom panels show estimates of the effects of cancer-market targeting on mortality measures. We do not reject the null hypothesis that the estimated coefficients before 1996 are jointly equal to zero. This figure is referenced in Section V.b.

Figure 4: Effects of the Opioid Epidemic on Economic Outcomes

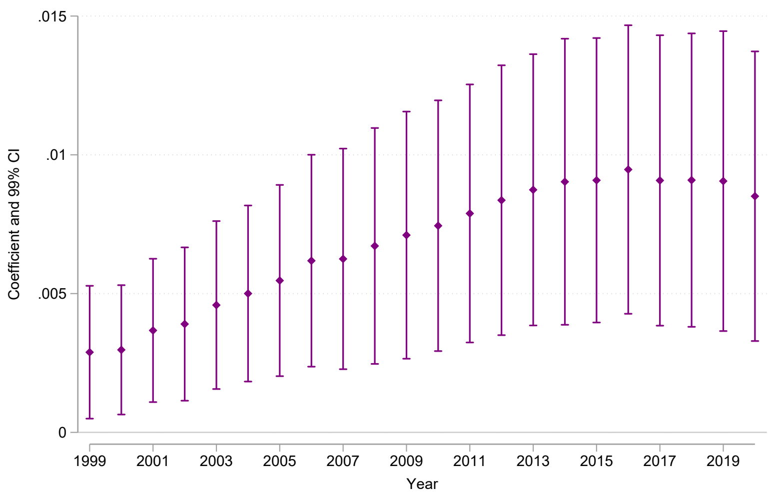
(a) Effects on Claims for SNAP



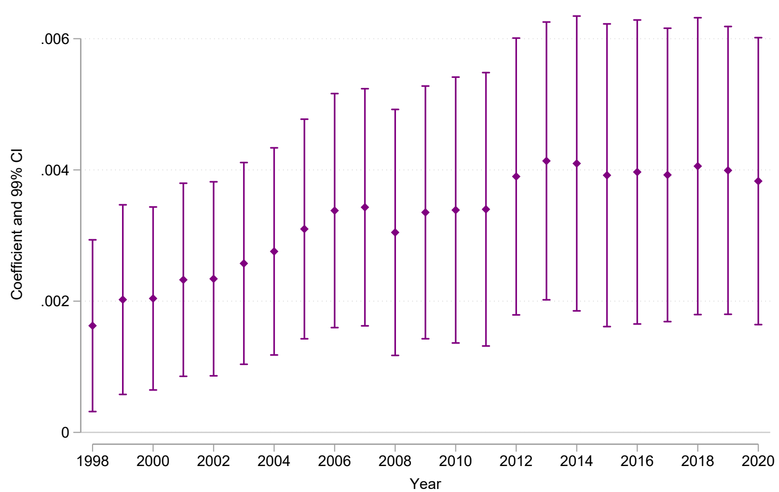
(b) Effects on Unemployment



(c) Effects on Claims for SSDI



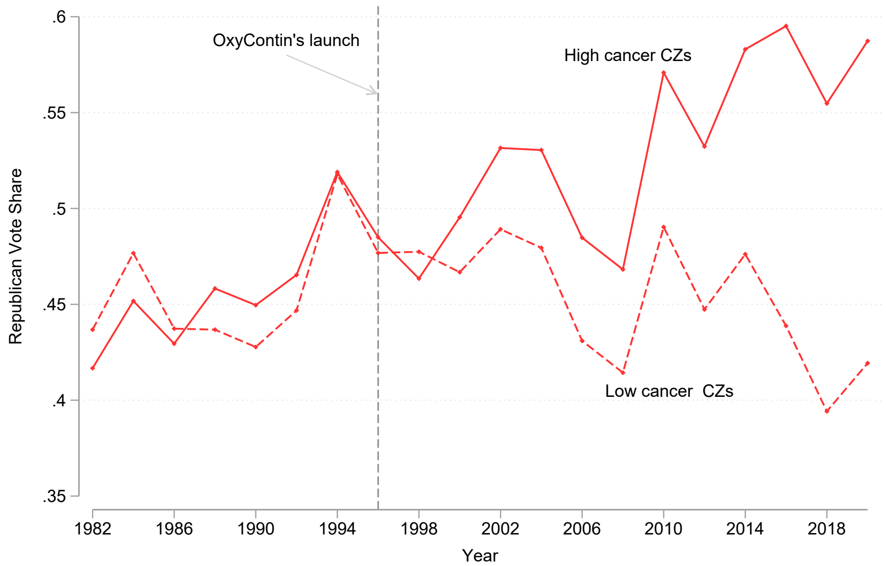
(d) Effects on Claims for SSI



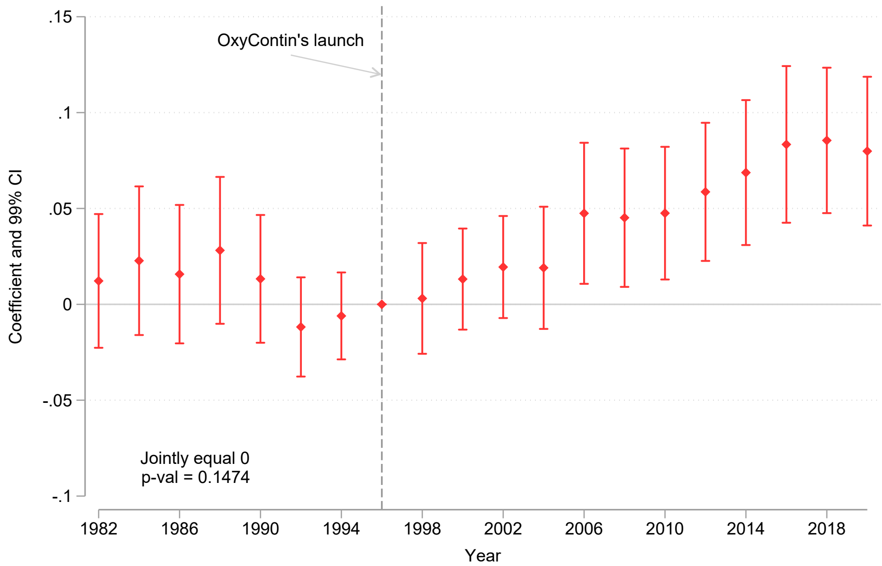
Notes: This figure shows the effects of exposure to opioid marketing on economic outcomes. We estimate the dynamic relationship between these outcomes and 1996 cancer mortality, our proxy for exposure to the opioid epidemic. Data for SSDI and SSI are available from 1999 and 1998, respectively; thus we cannot estimate pre-launch coefficients. This figure is referenced in Section V.c.

Figure 5: Effects of the Opioid Epidemic on the Republican Vote Share in House Elections

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



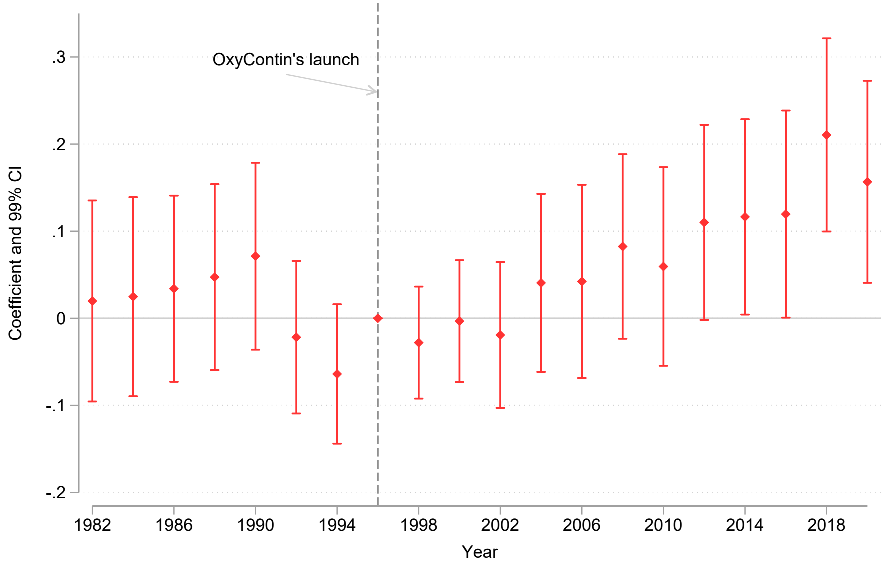
(b) Effects of Mid-1990s Cancer-Market Targeting



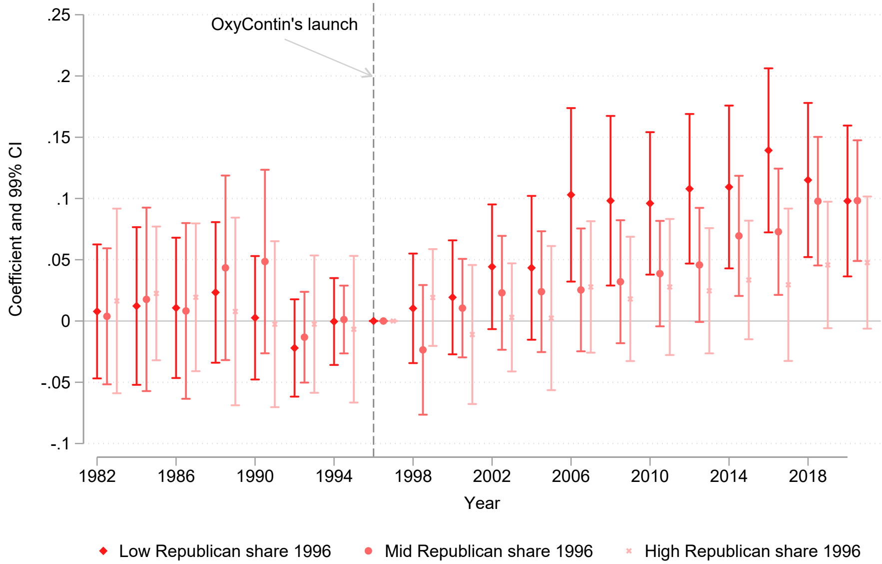
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in House elections for the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and mid-1990s cancer mortality, our proxy for exposure to the opioid epidemic. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1982}, \phi_{1984}, \ldots, \phi_{1994}$) are jointly equal to zero. The p value of this test is presented in the figure. This figure is referenced in Section VI.a.

Figure 6: Effects of the Opioid Epidemic on House Wins and Vote Share Heterogeneity

(a) Republican Candidate Wins a House Seat



(b) Effects on Republican Vote Share – by Tercile

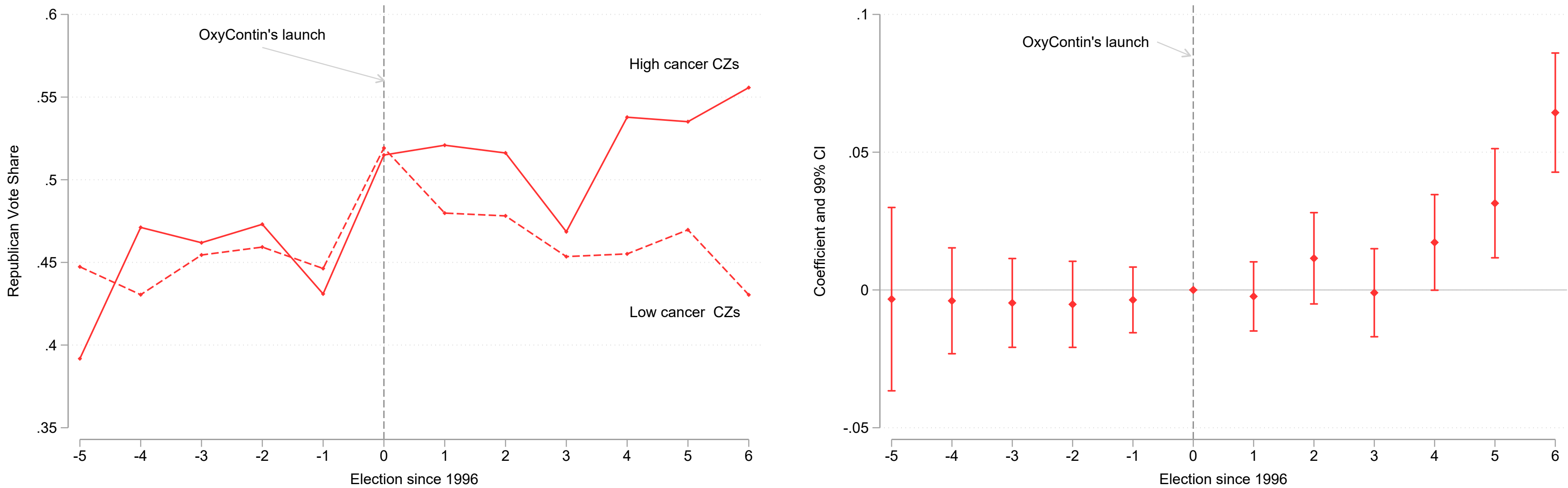


Notes: Panel (a) presents estimates of the dynamic relationship between the probability that a Republican candidate wins a seat in the House elections and mid-1990s cancer mortality, our proxy for exposure to the opioid epidemic. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality by the initial level of Republican support in the 1996 House election. Low, medium, and high Republican shares correspond to the terciles of this variable. The Republican vote share for CZs in the first tercile varies between 0 and 0.475, for the second tercile between 0.476 and 0.601, and for the third tercile between 0.602 and 1 in 1996. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1982}, \phi_{1984}, \ldots, \phi_{1994}$) are jointly equal to zero. The p value of this test is 0.0690. 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 VI.a.

Figure 7: Effects of the Opioid Epidemic on the Republican Vote Share in Gubernatorial Elections

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

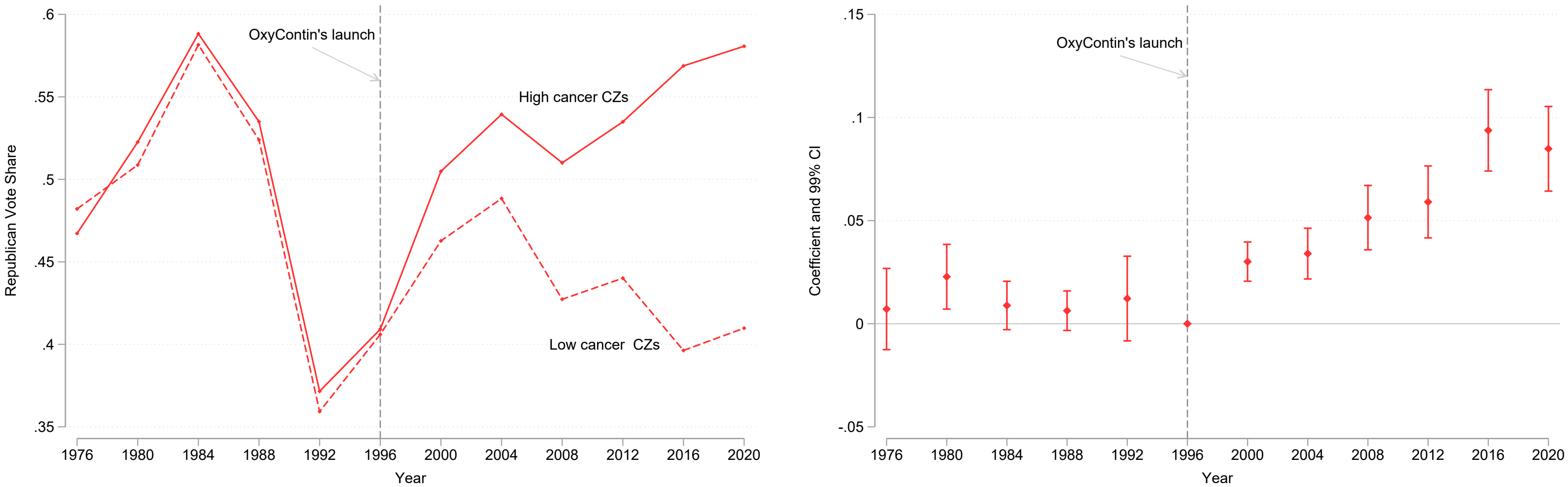
(b) Effects of Mid-1990s Cancer-Market Targeting



Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in gubernatorial elections for 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 for exposure to the opioid epidemic. Gubernatorial elections are held every four years. The horizontal axis counts elections relative to the last election before the launch of OxyContin. For example, Idaho's gubernatorial elections in 1994 and 1998 are assigned the values zero and one, respectively. New Hampshire and Vermont hold gubernatorial elections every two years; these states are excluded from the analysis. This figure is referenced in Section VI.b.

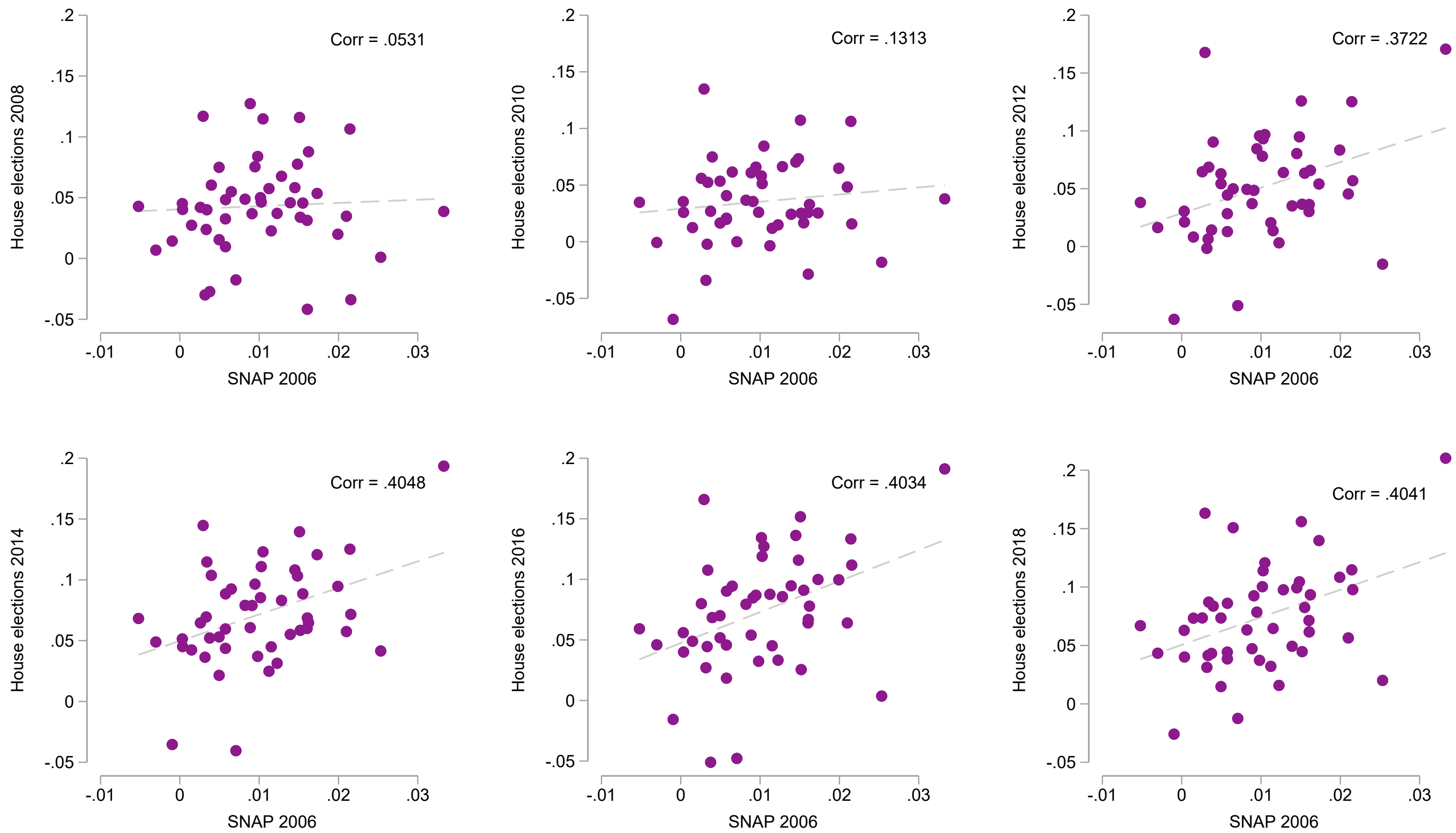
Figure 8: Effects of the Opioid Epidemic on the Republican Vote Share in Presidential Elections

(a) Trends in High- versus Low-Cancer-Mortality CZs (b) Effects of Mid-1990s Cancer-Market Targeting



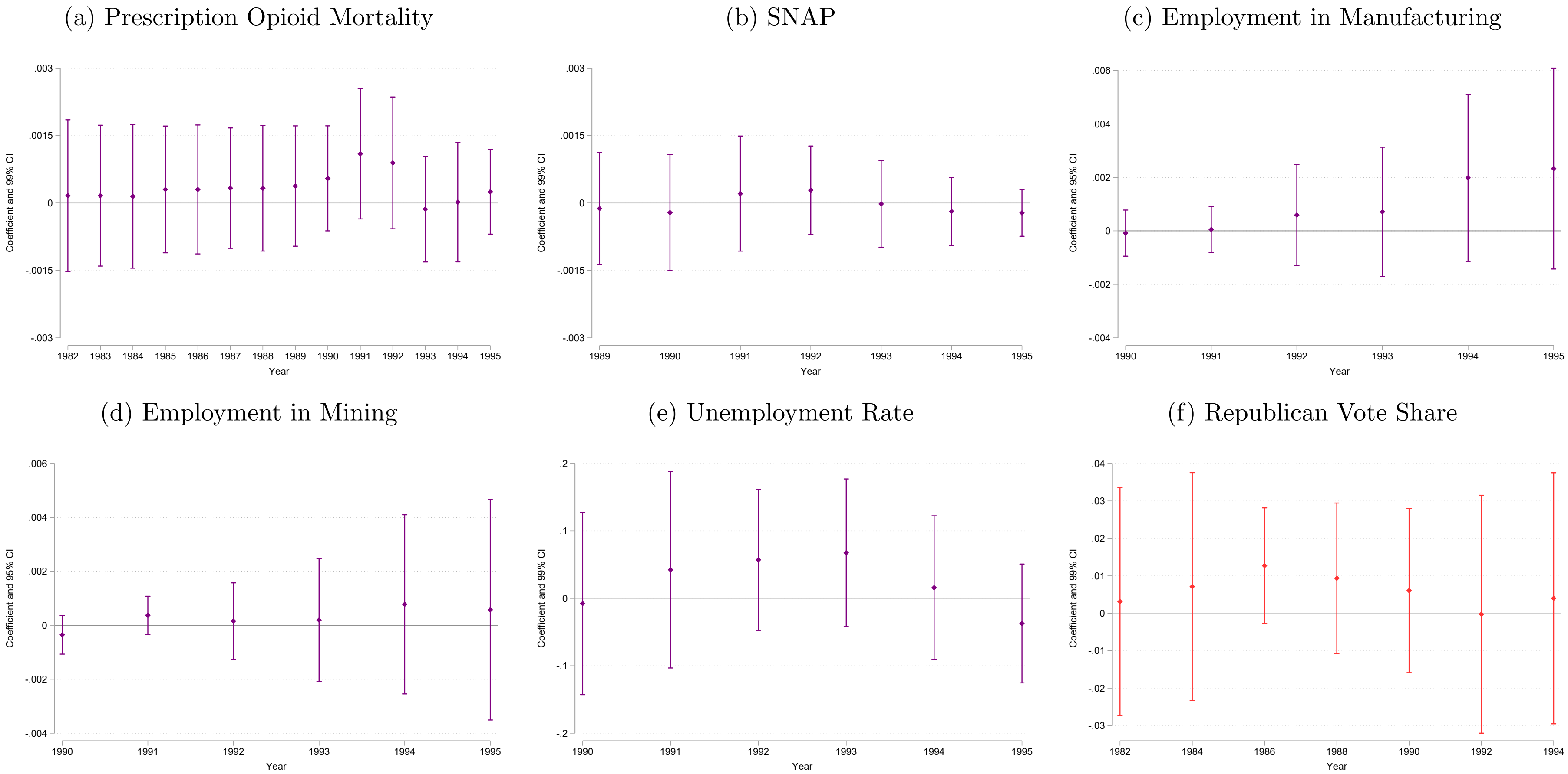
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections for the bottom (dashed line) and top (solid lines) quartiles of the cancer mortality distribution before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship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

Figure 9: Where Are Republican Gains Concentrated? SNAP and Vote Share Treatment Effects Correlation



Notes: This figure shows the correlation between the treatment effects for SNAP in 2006 and the treatment effects for Republican vote share in the House from 2008 to 2018—that is, the estimated $\phi_{s,t}$ coefficients from Equation (4). This figure is referenced in Section VII.a.

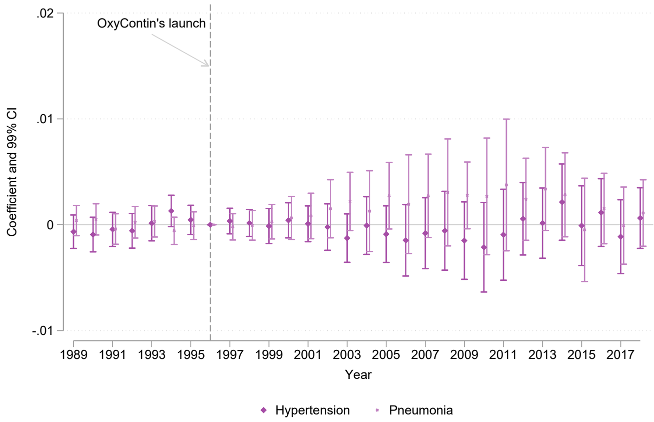
Figure 10: Out-of-Sample Analysis: 1976 Cancer Mortality and Future Outcomes



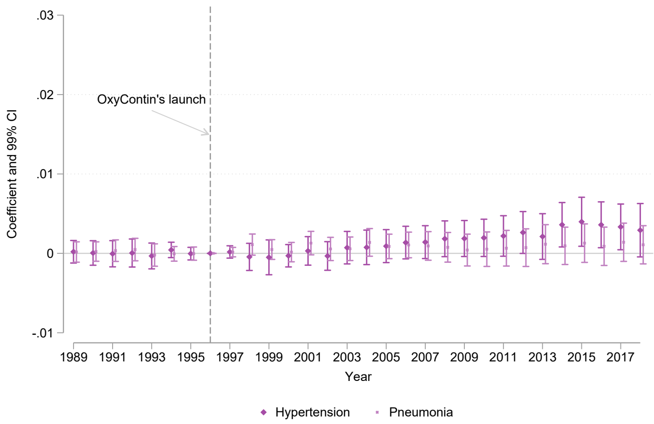
Notes: This figure presents estimates of an out-of-sample dynamic reduced-form analysis. In this exercise, we regress lagged cancer mortality, i.e., cancer in 1976 interacted with year dummies, on mortality, economic, and political outcomes. The figure shows that there is no relationship between lagged cancer mortality and either the outcomes of interest or the other economic outcomes. This figure is referenced in Section VIII.a.

Figure 11: Placebo Checks: Effects of Placebo Mortality Rates on Main Outcomes

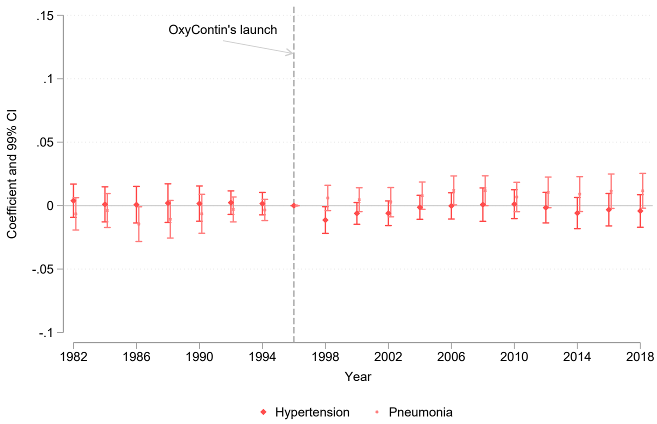
(a) Prescription Opioid Mortality



(b) SNAP Share



(c) Rep. Vote Share in House Elections

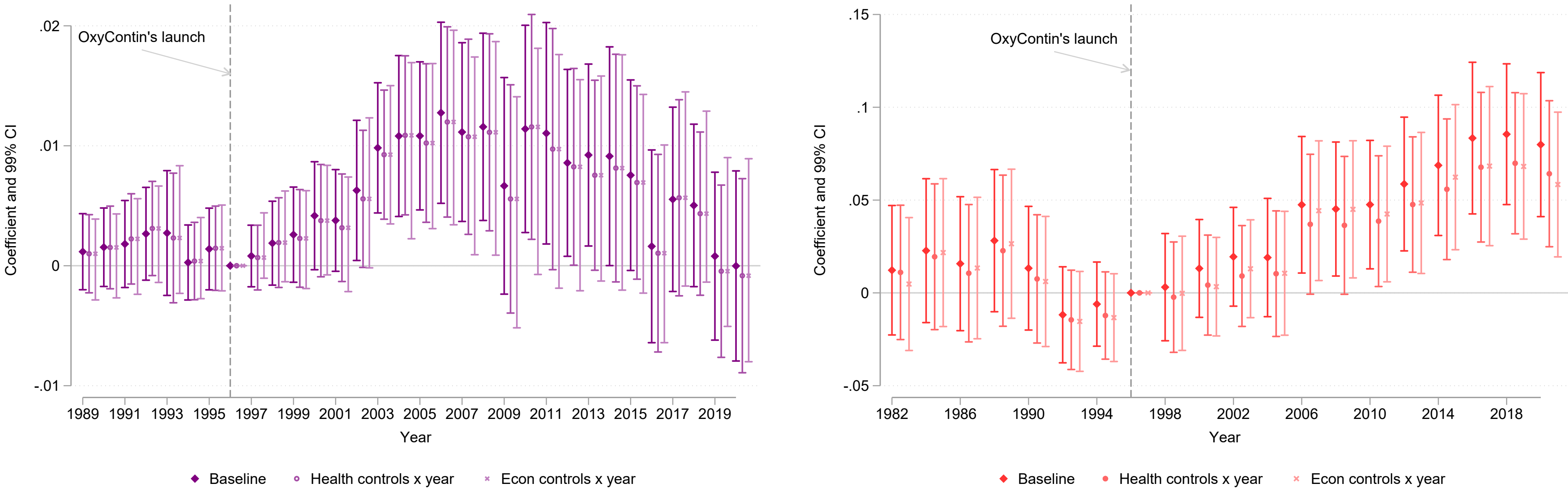


Notes: This figure presents estimates of the dynamic relationship between prescription opioid mortality (panel a), the share of SNAP recipients (panel b), and the Republican vote share (panel c) and our placebo mortality measures: hypertension and pneumonia for adults over 65 years old. All regressions include the same set of controls as the baseline specification. The scale in each graph is the same as its corresponding baseline graph, e.g., the scale of panel (a) coincides with that of panel (c) for Figure 3. This figure is referenced in Section VIII.a.

Figure 12: Robustness Checks – Additional Health & Economic Controls

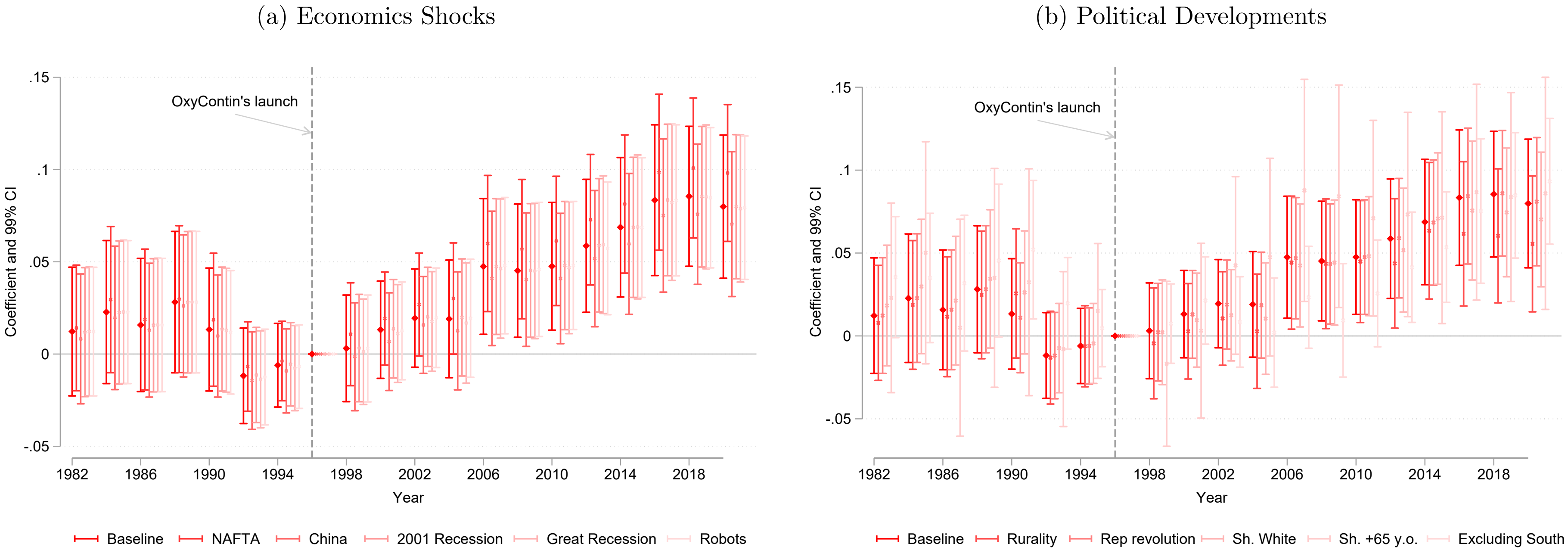
(a) Prescription Opioid Mortality

(b) Republican Vote Share in House Elections



Notes: This figure presents estimates of the baseline dynamic relationship between prescription opioid mortality (panel a) and the share of votes for Republican candidates (panel b) and mid-1990s cancer mortality, along with estimates where we add controls that capture the underlying health and economic characteristics at baseline. Health controls are share of smokers, share of overweight adults, infant mortality rate, and share of primary care physicians. Economic controls are unemployment rate, share of employment in manufacturing industries, income per capita, and share of population with some college education. Appendix B. provides details on the construction of these variables. This figure is referenced in Section VIII.a.

Figure 13: Republican Vote Share in House Elections and Exposure to Economic Shocks and Political Developments



Notes: This figure presents the baseline estimates of the relationship between the Republican vote share and cancer mortality along with estimates in which we flexibly control for economic shocks and political developments. Economic shocks (panel a) correspond to measures of exposure to NAFTA, PNTR with China—termed the "China shock" in the trade literature—the 2001 and 2007 economic recessions, and the adoption of robots. Political developments (panel b) correspond to measures of exposure to rurality, the Republican Revolution, the share of White and above 65 years old population. Each of these measures is interacted with year dummies. Panel (b) also includes an exercise where we exclude the CZs in the South (222 CZs). Appendix B. provides details on the construction and source of each measure. This figure is referenced in Sections VIII.b and VIII.c

XI. 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						
Doses of prescription opioids per capita$^{(a)}$				5.9293	4.9612	4.9227
Cancer mortality rate 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
Drug-induced mortality per 10,000$^{(b)}$	0.2591	0.2242	0.2532	1.0778	0.8655	0.9480
Economic Outcomes						
Unemployment rate (%)	6.7412	6.3120	2.9094	5.9548	5.4289	2.5276
SNAP	0.1061	0.0918	0.0617	0.1169	0.1070	0.0634
SSDI				0.0484	0.0440	0.0214
SSI				0.0389	0.0329	0.0245
Sh. of votes for Republican Party						
Gubernatorial elections	0.4836	0.4939	0.1383	0.5535	0.5514	0.1444
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

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 to avoid changes in the classification used to record deaths (ICD 9 to ICD 10). This table is referenced in Section III.

Table 2: Baseline Determinants of Opioid Distribution, 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 the CZ level. Republican vote corresponds to the Republican vote share in House elections. Standard errors are robust to heteroskedasticity. *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Section III..

Table 3: Demographic Heterogeneity and Effects on Republican Vote Share in House Elections

	Dependent Variable: Republican Vote Share in the House								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cancer 1996	0.0615***	0.0347*	0.0490***	0.0627***	0.0474**	0.0550***	0.0705***	0.0538***	0.0598***
	[0.0190]	[0.0202]	[0.0176]	[0.0208]	[0.0198]	[0.0185]	[0.0211]	[0.0198]	[0.0200]
Sample	Full sample	White	Not-white	Pop. Under 50	Pop. Over 50	Male	Female	Some college or less	College or more
Observations	265,500	144,873	120,627	104,668	160,832	129,481	136,019	156,231	109,269
CZs	615	614	614	615	614	615	615	615	611

Notes: We estimate the following equation in an individual-level repeated cross-section using data from the CCES for the years 2006-2020 : $y_{ict} = \alpha_1 + \beta\ CancerMR_{ct_0} + \alpha\ \Delta X_{ct} + \gamma_{st} + \varepsilon_{ict}$. The reported coefficient corresponds to the β parameter. *p<0.10, **p<0.05, *** p<0.01. This figure is referenced in Section VI.a.

Table 4: Cancer Mortality in 1996 and Political Views and Preferences

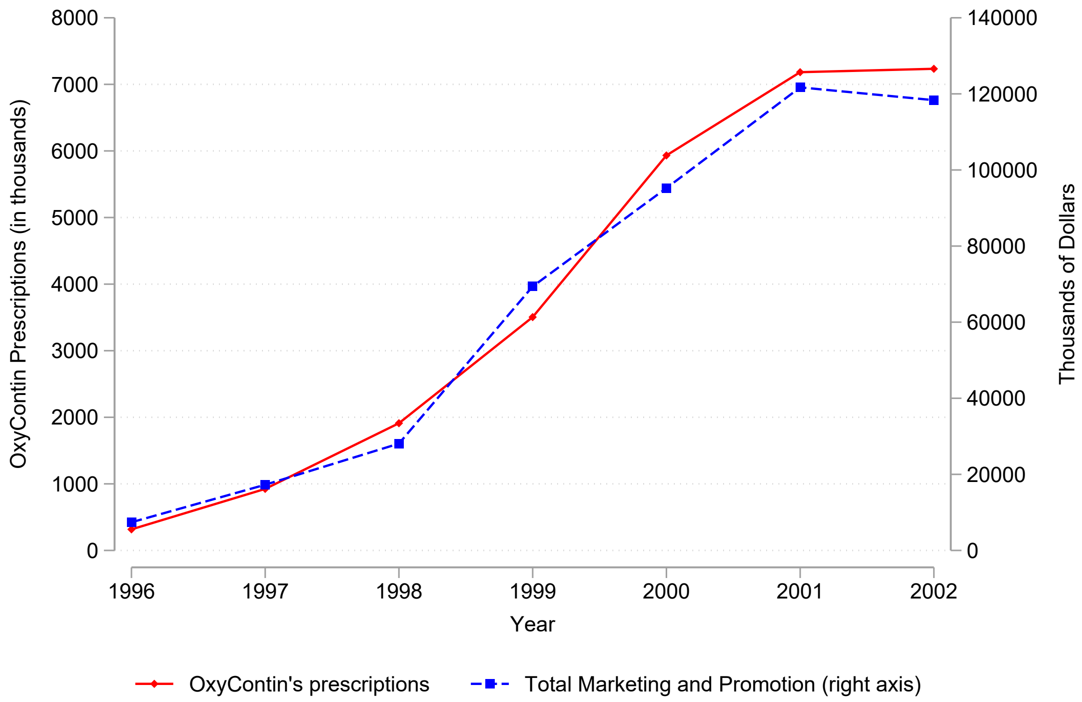
Panel A. Voter's views on	Increase Police Officers (1)	Feel Safe around Police (2)	Marijuana Ballots (3)	Fox News Viewership (4)
Cancer 1996	0.0313***	0.0778***	-0.0256***	0.0509***
	[0.0117]	[0.0287]	[0.00845]	[0.0194]
Observations	59,419	59,354	198	25,142
Dep. var mean	0.446	3.141	0.49	0.405
Dep. var SD	0.497	0.941	0.10	0.491
CZs	610	610	198	587
Period	2020	2020	2012-2023	2020
Source	CCES	CCES	States Sec. State	CCES

Panel B. Voter's views on	Abortion (5)	Gun Control (6)	Immigration (7)	Own Ideology (8)
Cancer 1996	-0.0475***	-0.0529***	-0.0619***	-0.175***
	[0.0169]	[0.0154]	[0.0137]	[0.0515]
Observations	59,420	59,424	59,390	54,777
Dep. var. mean	0.610	0.644	0.421	5.00
Dep. var. SD	0.488	0.479	0.490	1.206
CZs	610	610	610	607
Period	2020	2020	2020	2020
Source	CCES	CCES	CCES	CCES

Notes: Police-related questions are coded such that increases indicate support for police. We measure support for marijuana legalization as the share of "Yes" votes in state ballots. Fox News is a dummy variable equal to 1 when respondents report watching Fox News. Questions in panel (b) are coded such that lower values indicate more conservative views. For example, the question on own ideology is "Thinking about politics these days, how would you describe your own political viewpoint?", and answers are coded such that 1 = "Very conservative" and 5 = "Very liberal". Regressions in all but column (3) include state fixed effects; regressions in column (3) include state times year fixed effects. Similarly, all but column (3) include a set of control variables at the CZ level and the individual level. *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Sections VII.b and VII.c.

A. Additional Figures and Tables

Figure A1: OxyContin Marketing Budget and Total Prescription Sales



Notes: Authors' constructions based on OxyContin Budget Plans 1998-2002 and *United States General Accounting Office (GAO). Prescription Drugs: OxyContin Abuse and Diversion and Efforts to Address the Problem. Report to Congressional Requesters. 2003.* This figure is referenced in Section II.

Figure A2: Purdue Pharma Budget Plan 1997: Target Audiences

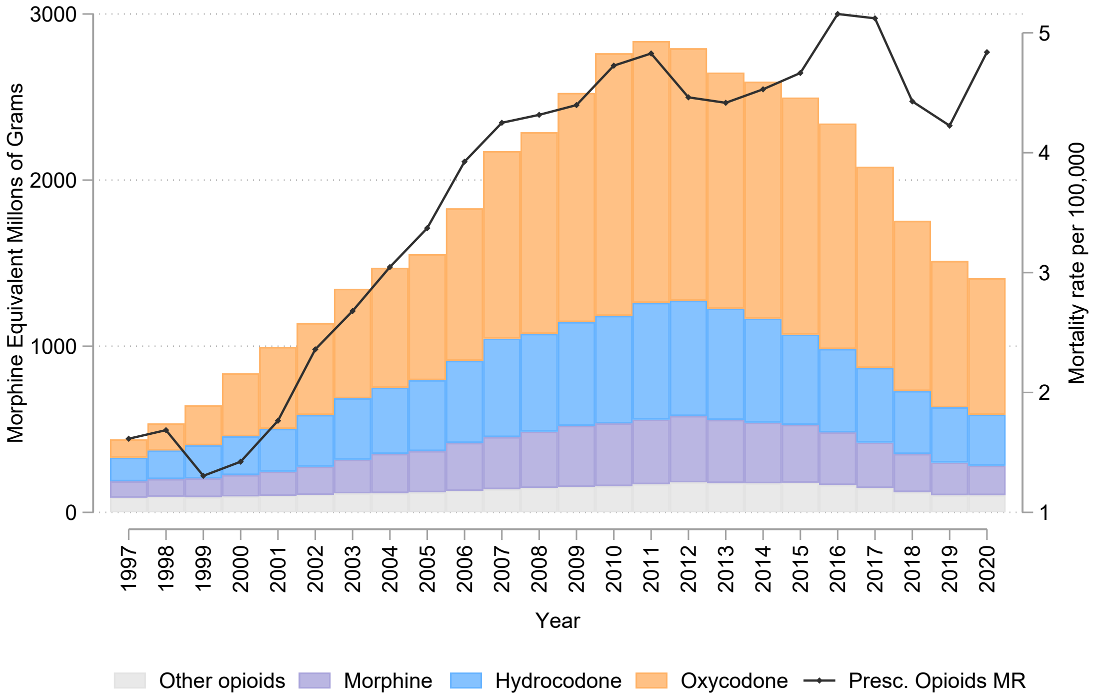
C. Target Audiences

1. Primary Audiences

Primary Audiences	Site	Targets	Comments
A. Physicians • ONCs Hem/Oncs Rad/Oncs • IMs • FP/GPs • DOs • ANS • Surg • Other	• Office and Hospital	13,000 7,600 33,000	Target List 1A Decile 8, 9, or 10 for "Strong" opioids who are also Decile 8, 9, or 10 for "Combo" opioids Target List 1B Decile 9 and 10 for "Strong" opioids only Target List #2 Decile 10 for combo only but not in Target List 1A; non-malignant market

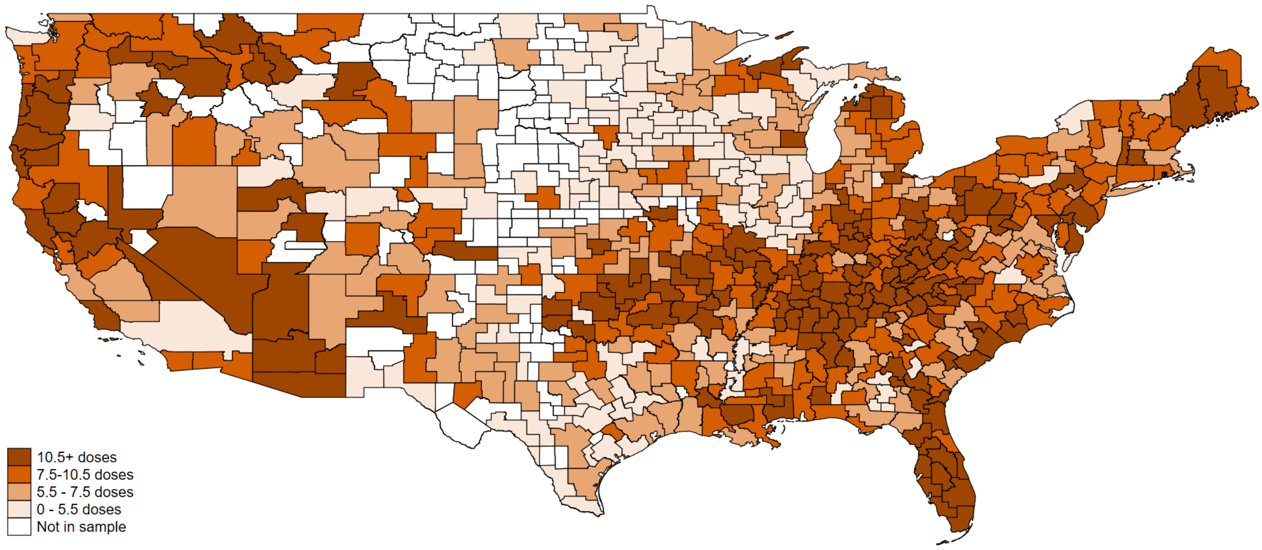
Notes: This figure is an extract of the Purdue Pharma marketing plan, which shows that Purdue marketing targeted top opioid prescribers. Purdue Pharma Budget Plan 1997, p.25. This figure is referenced in Section II., and details about the data are included in Appendix B.

Figure A3: Evolution of Prescription Opioid Distribution



Notes: This figure shows the evolution of shipments of all prescription opioids and of the three main components: oxycodone, hydrocodone and morphine. Oxycodone is the active ingredient of OxyContin. Shipments of prescription opioids are expressed in morphine-equivalent doses. The secondary y-axis corresponds to the mortality rate from prescription opioids. Details on the construction of this measure are included in Section B. This figure is referenced in Section III.

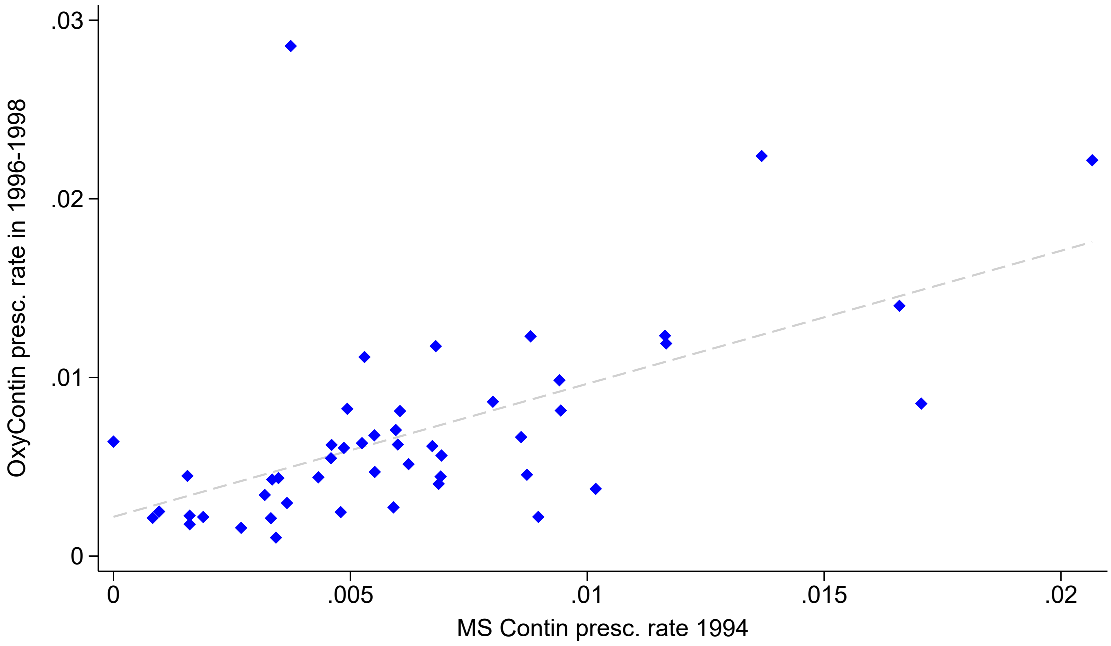
Figure A4: Prescription Opioid Distribution at the Peak of the Epidemic (2010)



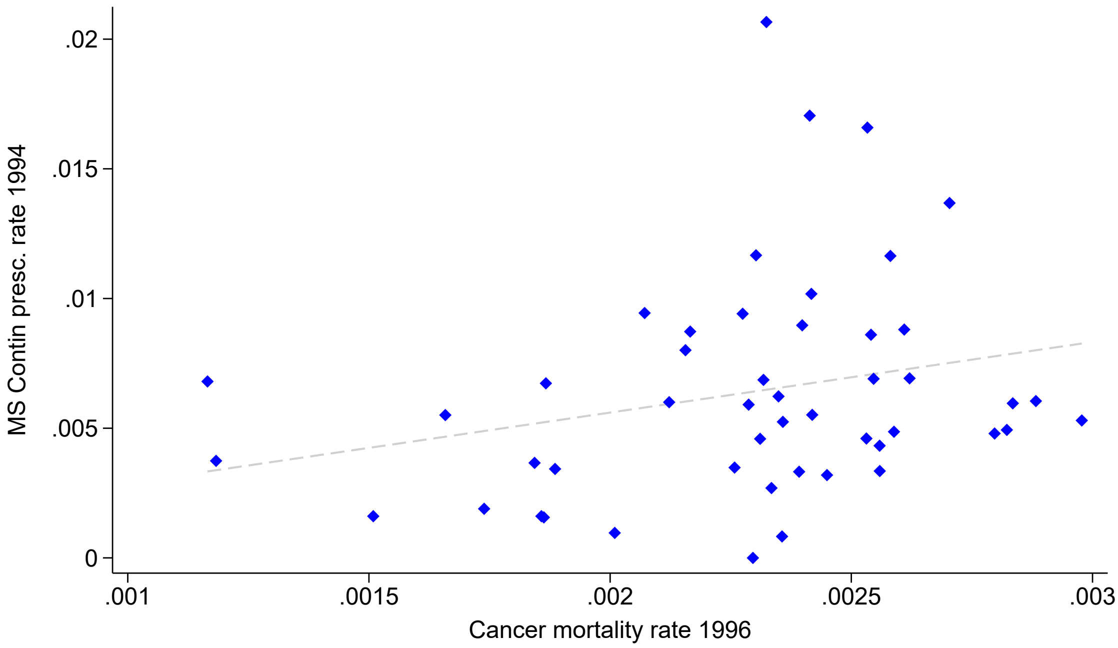
Notes: This map shows the distribution of prescription opioids at the CZ level in 2010, the year when the distribution of prescription opioids peaked. Lighter shades indicate CZs with a lower prescription-opioid distribution, and darker shades indicate CZs with a higher prescription-opioid distribution. Each group corresponds to one quartile of the prescription opioid distribution; i.e., each color represents 25% of the mass of this distribution. CZs not included in the sample, i.e., "Not in sample", are white in the figure. This figure is referenced in Section III.

Figure A5: MS Contin, OxyContin, and Cancer Mortality Rate (State Level)

(a) OxyContin and MS Contin Prescription Rates

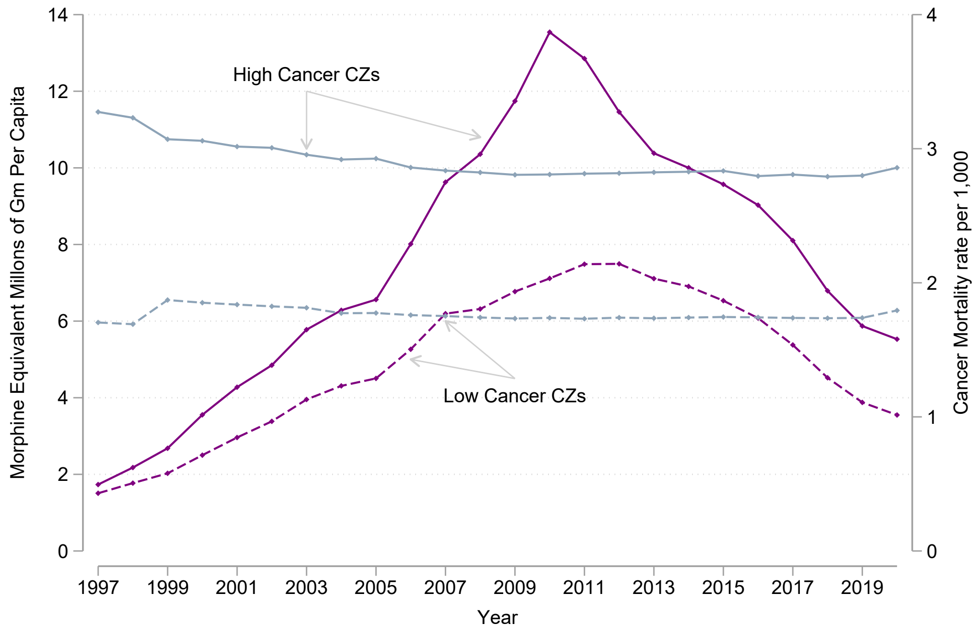


(b) MS Contin Prescription Rates and Cancer Mortality Rate



Notes: Panel (a) of this figure shows the correlation between OxyContin prescription rates in 1996-1998 and 1994 MS Contin prescription rates. We pool 1996 to 1998 data for OxyContin to capture the initial stage of its roll out. The population-weighted correlation coefficient is 0.70. Panel (b) shows the correlation between 1994 MS Contin prescription rates and the 1996 cancer mortality rate. The population-weighted correlation coefficient is 0.45. This figure is referenced in Section IV.b.

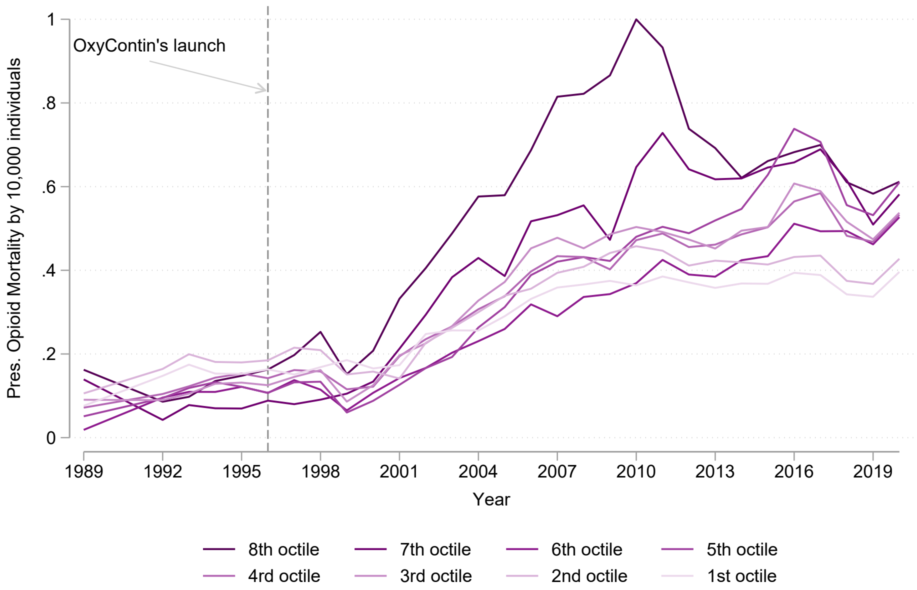
Figure A6: Evolution of Cancer Mortality and Prescription Opioid Distribution



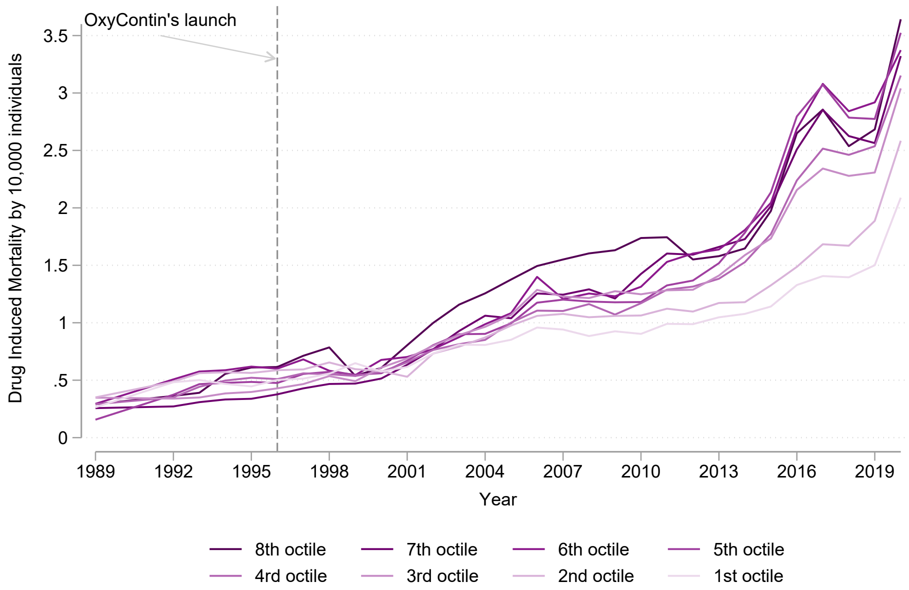
Notes: This figure shows the evolution of prescription opioids (left-hand axis) and cancer mortality rates (right-hand axis) over time for CZs in the top and bottom quartiles of the cancer mortality distribution. Areas in the top quartile of the cancer distribution experience an influx of opioids that is up to 3 times larger than that experienced by areas in the bottom quartile. Changes in cancer mortality do not explain this discrepancy; trends in cancer mortality rates in these groups of CZs suggest that mortality was quite stable during the period. Prescription opioids are measured in morphine-equivalent mg. This figure is referenced in Section IV.b

Figure A7: Opioid Mortality Rate by Octiles of the 1994-1996 Cancer Prevalence

(a) Prescription Opioids

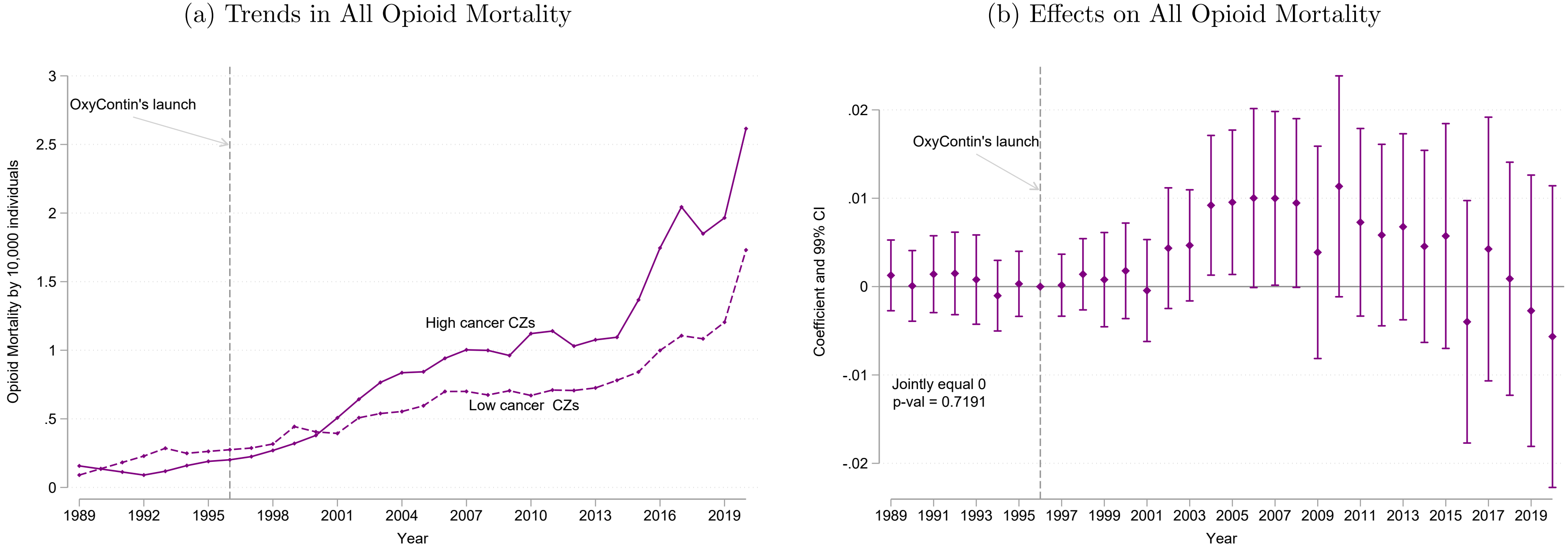


(b) Drug Induced Mortality



Notes: This figure shows the evolution of prescription opioid (panel a) and all opioid (panel b) mortality in eight groups of CZs. Each group is composed of those CZs in the *n-th* octile of the cancer mortality rate distribution before the launch of OxyContin. Darker colors indicate groups with higher cancer prevalence; lighter colors indicate groups with lower cancer prevalence. This figure is referenced in Section V.b

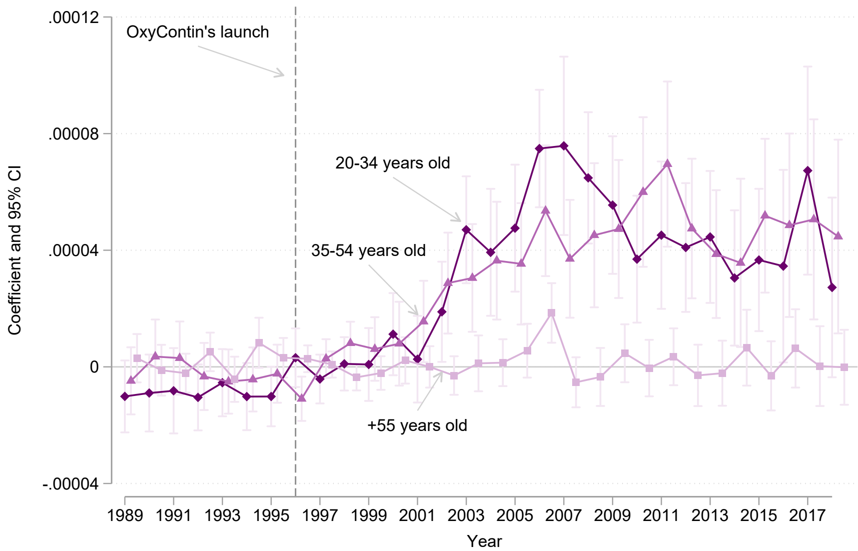
Figure A8: Effects of Cancer-Market Targeting on All Opioid Mortality



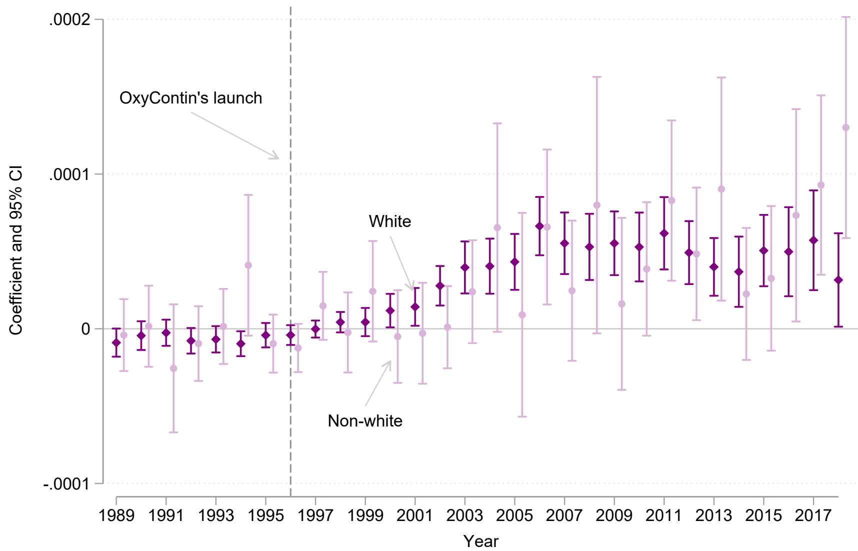
Notes: Panel (a) of this figure shows the evolution of all opioid mortality in CZs in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) shows estimates of the effects of cancer-market targeting on the distribution of prescription opioids and mortality. We do not reject the null hypothesis that the estimated coefficients before 1996 are jointly equal to zero. This figure is referenced in Section V.b.

Figure A9: Heterogeneous Effects of Cancer-Market Targeting on Drug Induced Mortality

(a) By Age



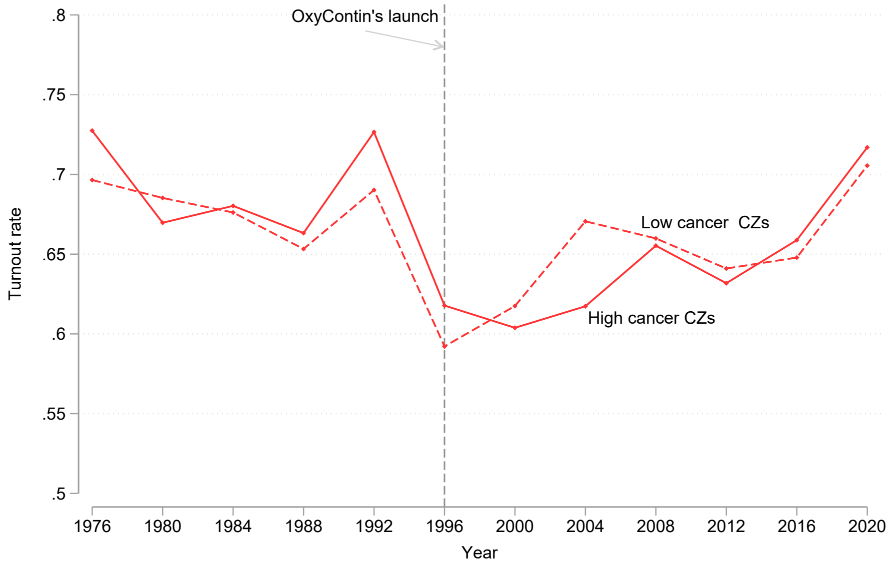
(b) By Race



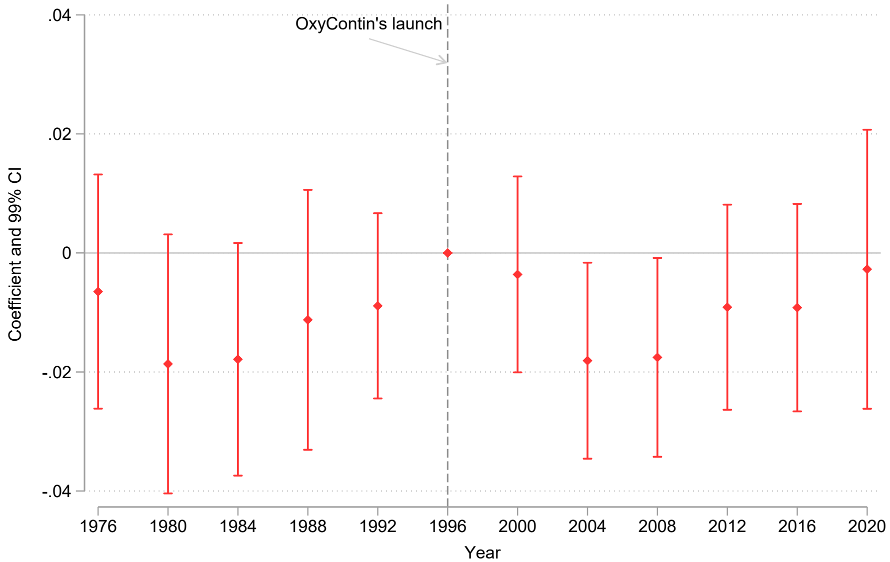
Notes: This figure presents heterogeneity by age and race and the effects on drug induced mortality. Race analysis is restricted to adults between 20 and 54 years old. This figure is referenced in Section V.b.

Figure A10: Effects of the Opioid Epidemic on Turnout Rates

(a) Trends in Turnout



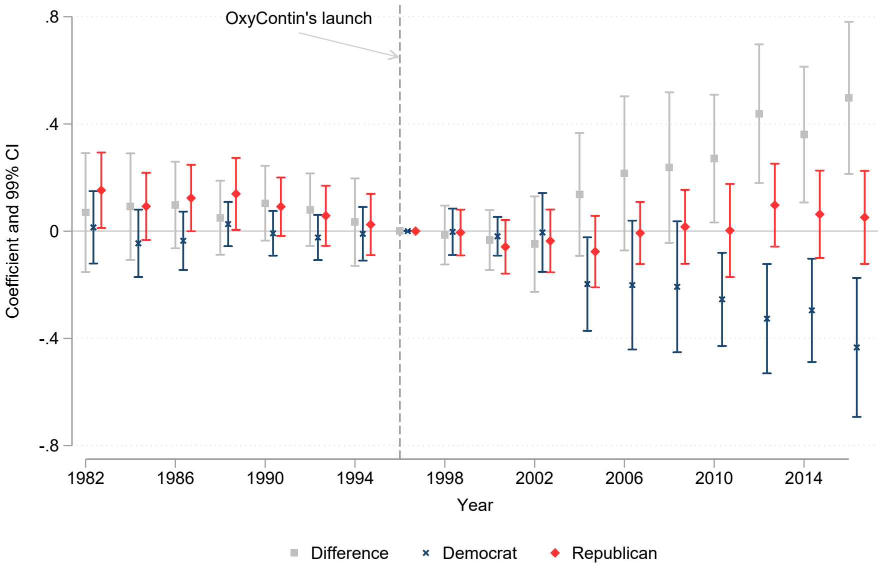
(b) Event-Study Approach



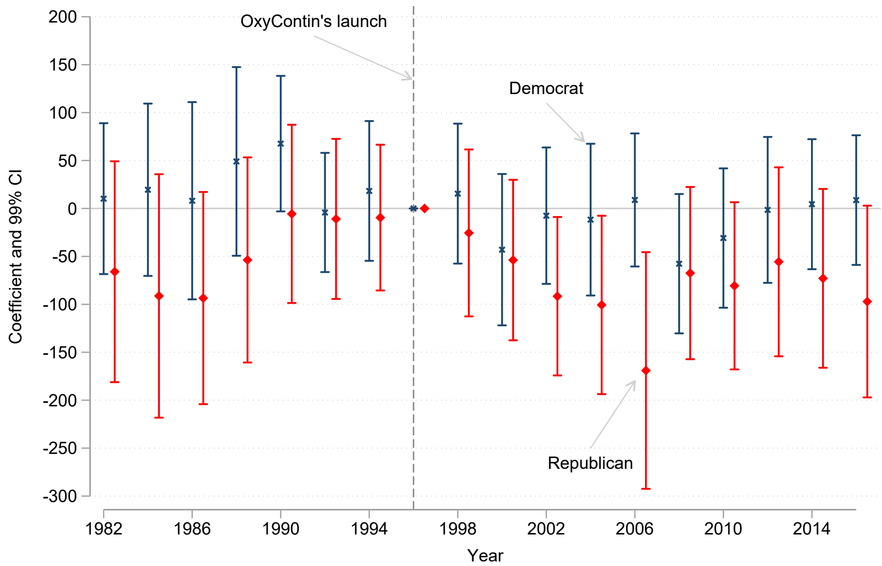
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turnout rates and mid-1990s cancer mortality, our proxy for exposure to the opioid epidemic. This figure is referenced in Section VI.a.

Figure A11: Effects of the Opioid Epidemic on Donations to House Candidates

(a) Per Capita Donations



(b) Median Donation Amounts by Party



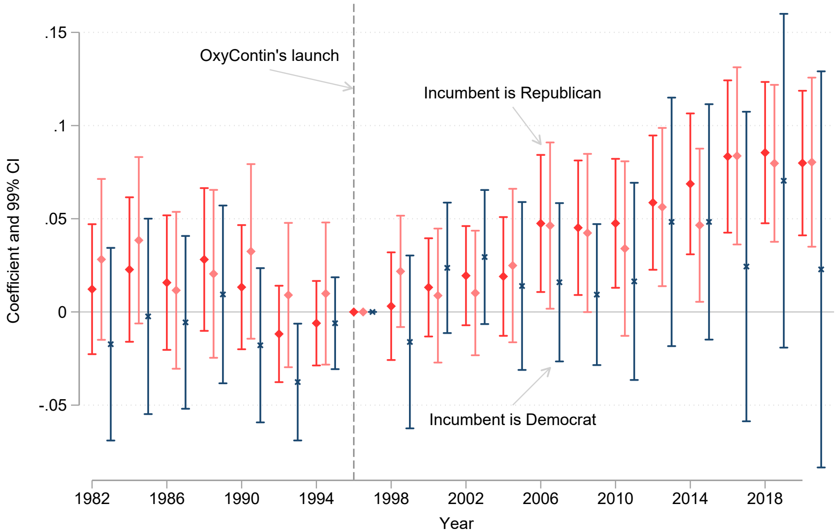
Notes: Panel (a) presents estimates of the dynamic relationship between the difference in the number of donors to Republican and Democratic candidates for House elections and 1996 cancer mortality, our proxy for exposure to the opioid epidemic. The difference is defined as donations to Republican minus donations to Democratic candidates. It also presents estimates of this relationship by party of the donation recipient. Panel (b) presents estimates of the effect of exposure to the opioid epidemic on median donation amounts by party. This figure is referenced in Section VI.a.

Figure A12: Effects of the Opioid Epidemic on Ideology of House Members

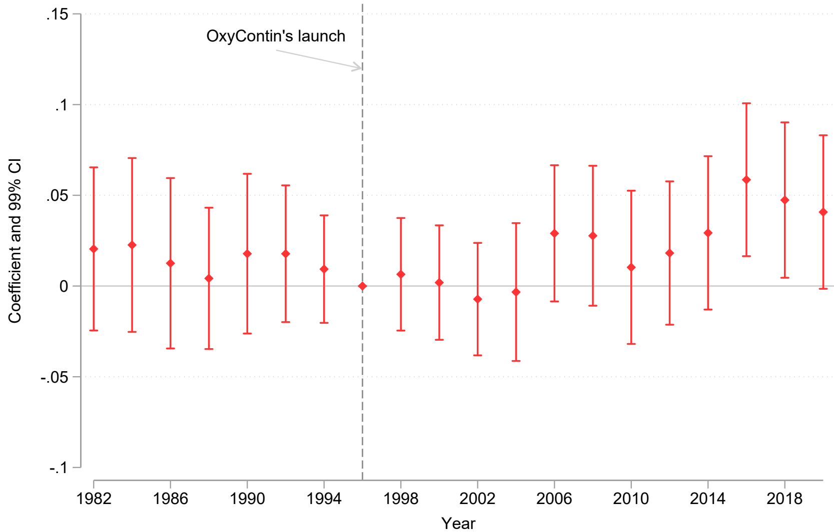
Notes: This figure presents estimates of the dynamic relationship between candidate ideology in roll-call votes and mid-1990s cancer mortality. Panel (a) shows the main effects, and panel (b) splits the sample by initial Republican vote share in House elections. Panels (c) and (d) show candidates' probability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

Figure A13: Effects of the Opioid Epidemic on Republican Vote Share and Anti-Incumbent Responses

(a) Baseline and Spliting Sample by Party

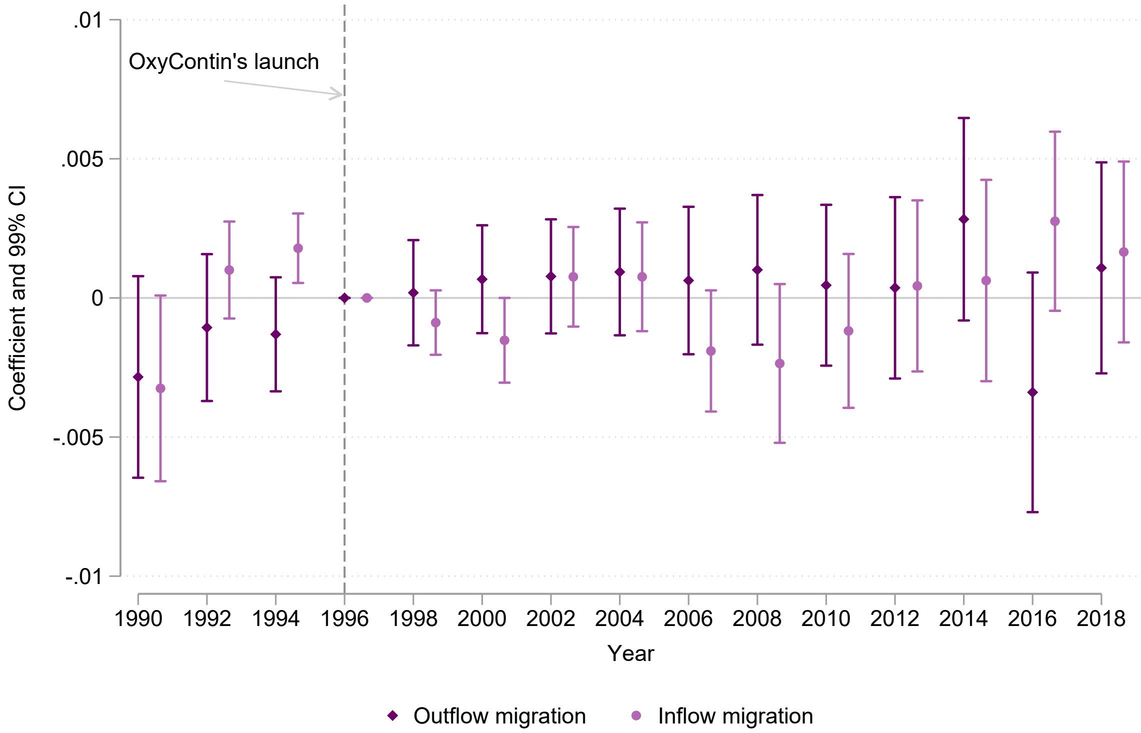


(b) Incumbent Vote Share



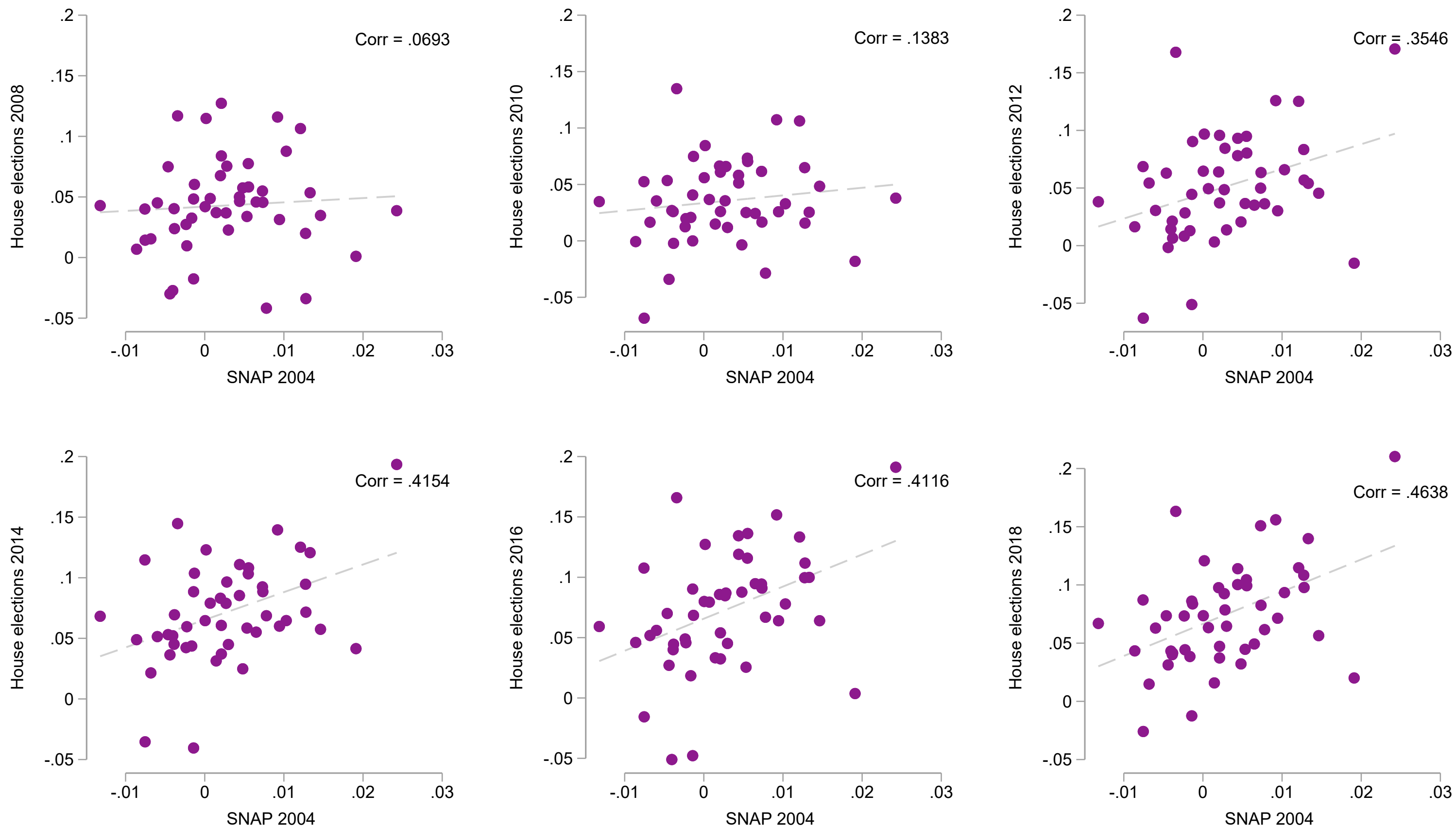
Notes: Panel (a) of this figure presents estimates of the effects of exposure to the opioid epidemic on the Republican vote share in House elections when we split the sample by whether a Republican or Democrat is the incumbent at the time of the election. It also includes the baseline estimates for reference. Panel (b) presents estimates of Equation (3) when the incumbent vote share is the dependent variable. This figure is referenced in Section VI.d.

Figure A14: Migration Flows and Opioid Epidemic Exposure



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

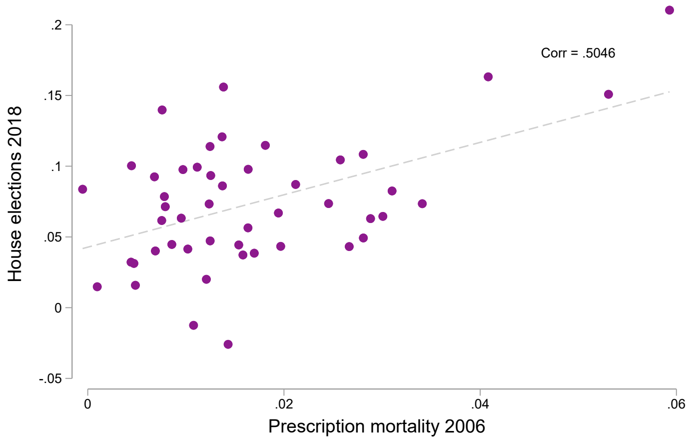
Figure A15: Where Are Republican Gains Concentrated? SNAP and Vote Share Treatment Effects Correlation



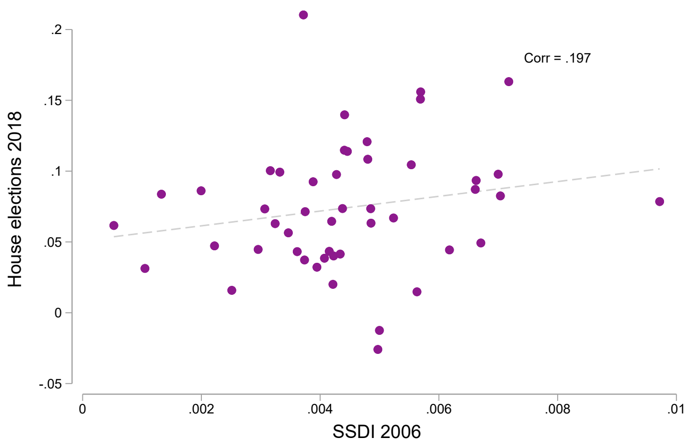
Notes: This figure shows the correlation between the treatment effects for SNAP in 2004 and the treatment effects for Republican vote share in the House from 2008 to 2018—that is, the estimated $\phi_{s,t}$ coefficients from Equation (4). This figure is referenced in Section VII.a.

Figure A16: Treatment Effects Correlation: House Elections, Mortality, SSDI, and SSI

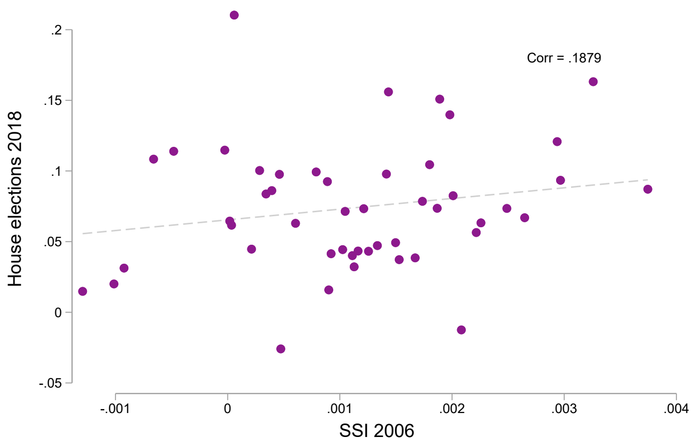
(a) Prescription Opioid Mortality



(b) SSDI



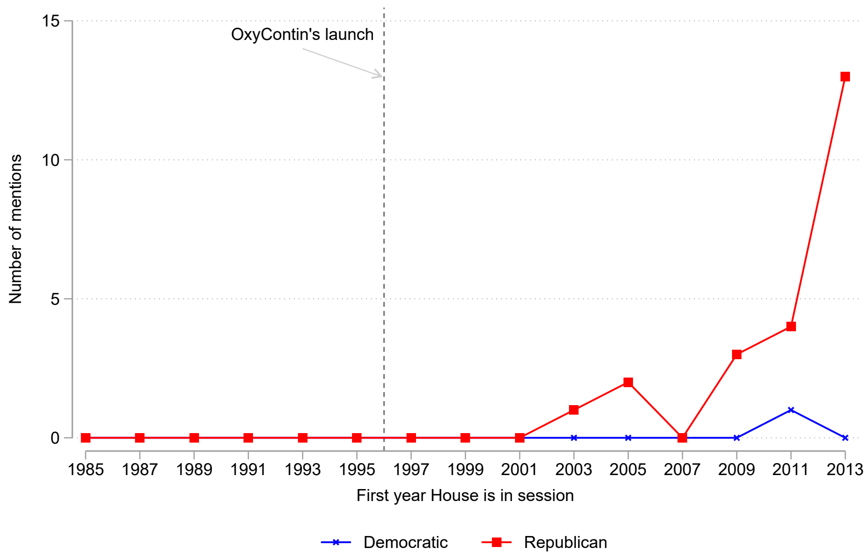
(c) SSI



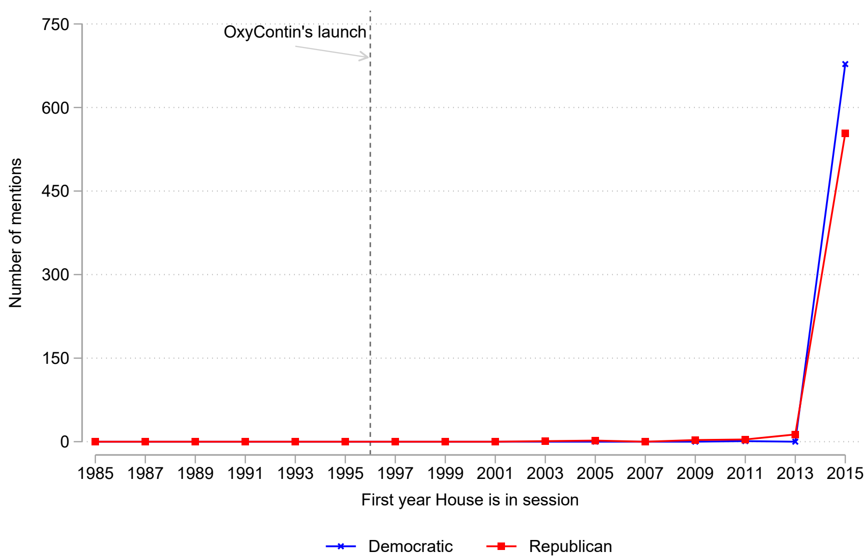
Notes: This figure shows the correlation between the treatment effects for the Republican vote share in the House elections in 2018 and 2006 prescription opioid mortality, SSDI, and SSI—that is, the estimated $\phi_{\tau,s}$ coefficients from Equation (4) for selected outcomes and years. This figure is referenced in Section VII.a.

Figure A17: Opioid Mentions in House Sessions by Party

(a) Period: 1985 to 2014

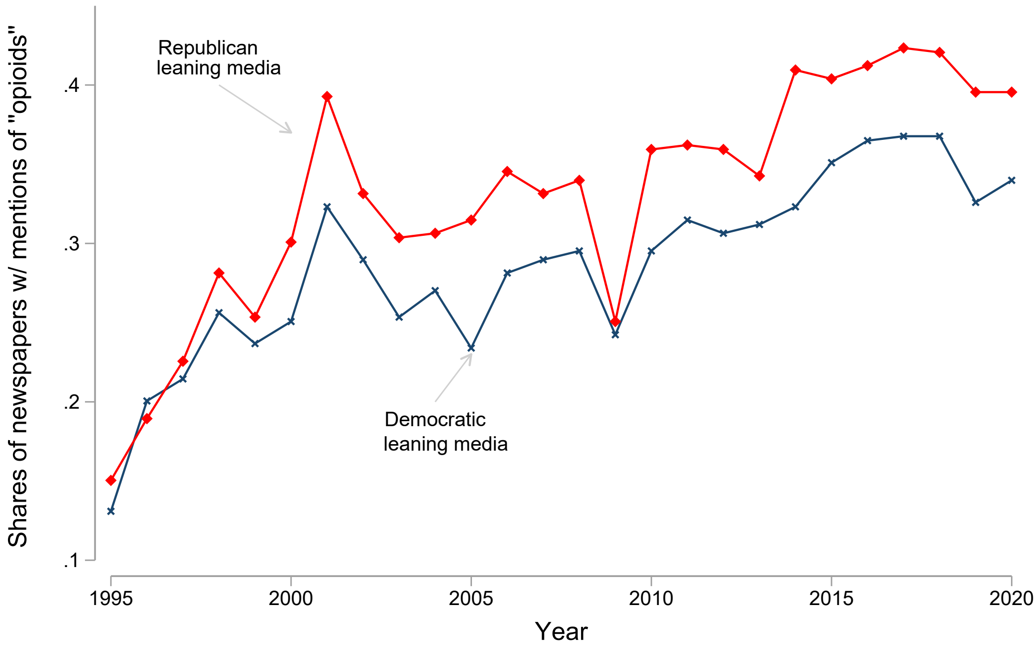


(b) Period: 1985 to 2016



Notes: This figure presents counts of mentions of the word *opioid* during House interventions by party of the representative. Years indicate the first year a House is in session, e.g., for House elections held in 1984, the first year of the new House is 1985, and the counts correspond to mentions in 1985 and 1986. Data come from Gentzkow et al. (2018). This figure is referenced in Section VII.b

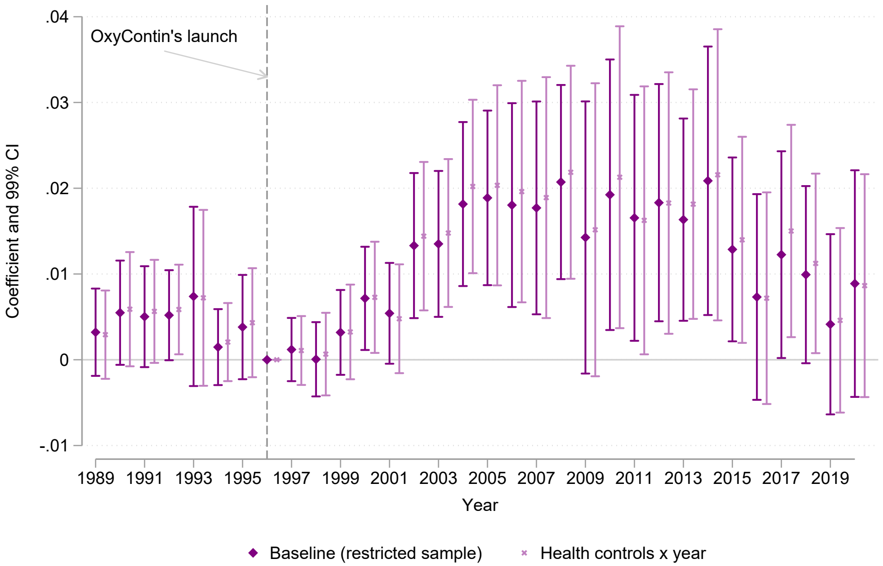
Figure A18: Share of “Opioid” Mentions by Partisan Newspapers



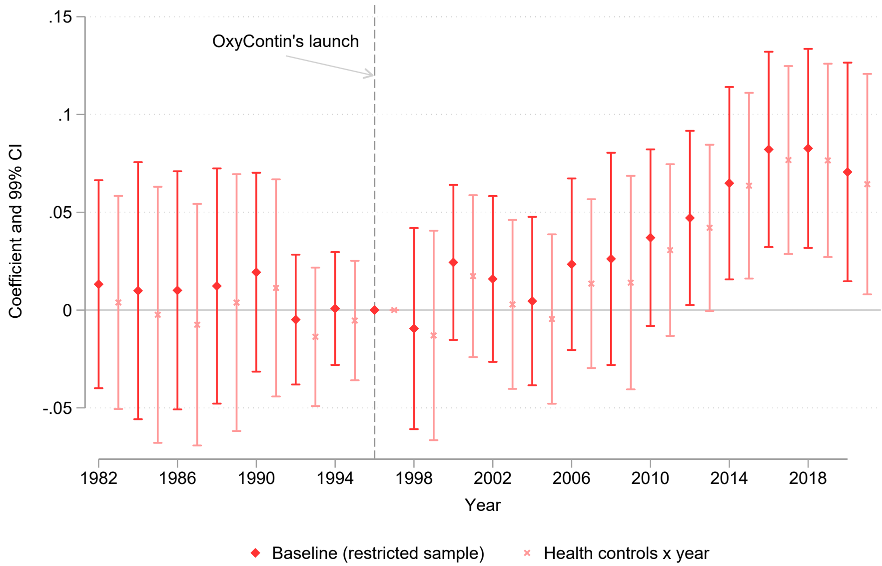
Notes: This figure presents the average share of Republican- (Democratic-) leaning newspapers with articles mentioning “opioids” in a given CZ. That is, the red line presents the evolution of the average ratio between the number of Republican-leaning newspapers with at least one article mentioning “opioids” and the number of Republican-leaning newspapers in the CZ. We collect the data from Newspapers.com by selecting all articles mentioning the word “opioids”. The assignment of party affiliation uses the classification developed by Gentzkow and Shapiro (2011) for 1994. This figure is referenced in Section VII.b.

Figure A19: Robustness Checks – Health Covariates with Pollution

(a) Prescription Opioid Mortality



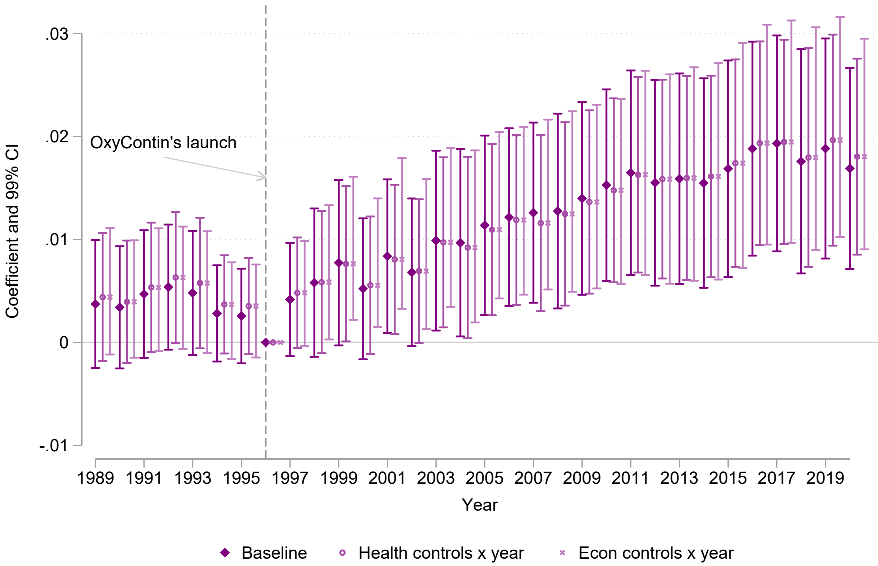
(b) Republican Vote Share in House Elections



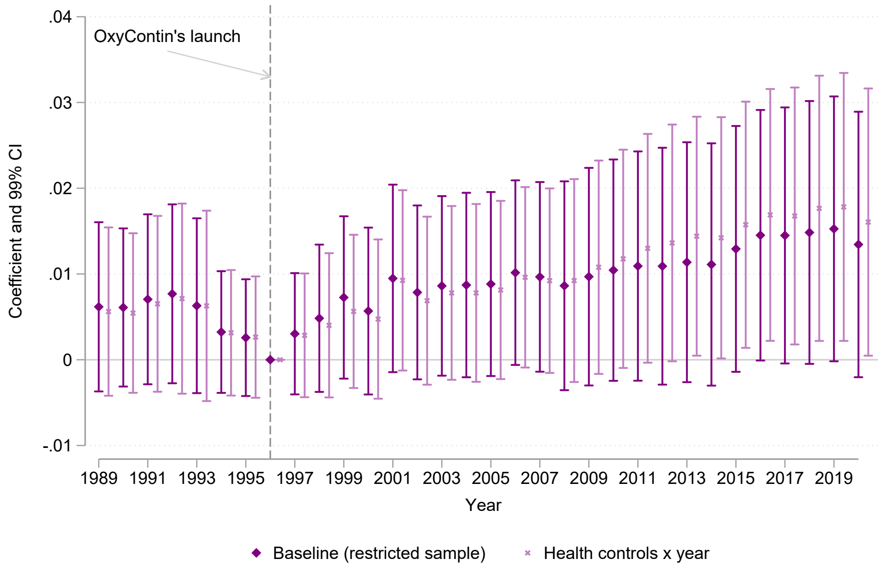
Notes: This figure presents estimates of the baseline dynamic relationship between prescription opioids mortality (panel a) and the share of votes for Republican candidates (panel b) and mid-1990s cancer mortality, along with estimates where we add controls that capture underlying health at baseline. These controls are the share of smokers in 1996, the share of overweight adults in 2004 (first year of data available), the infant mortality rate in 1996, the share of primary care physicians in 1996, and a measure of pollution in 2000 and 2001 (the first available year). That is, this figure reproduces Figure 12 and includes a measure of pollution. One limitation of this analysis is that the EPA's data coverage is limited. Thus, we present estimates of the baseline specification in a restricted sample. Appendix B. provides details on the construction of these variables. This figure is referenced in Section VIII.a.

Figure A20: SNAP with Additional Health & Economic Covariates

(a) Additional Health & Economic Covariates



(b) Additional Health Covariates with Pollution

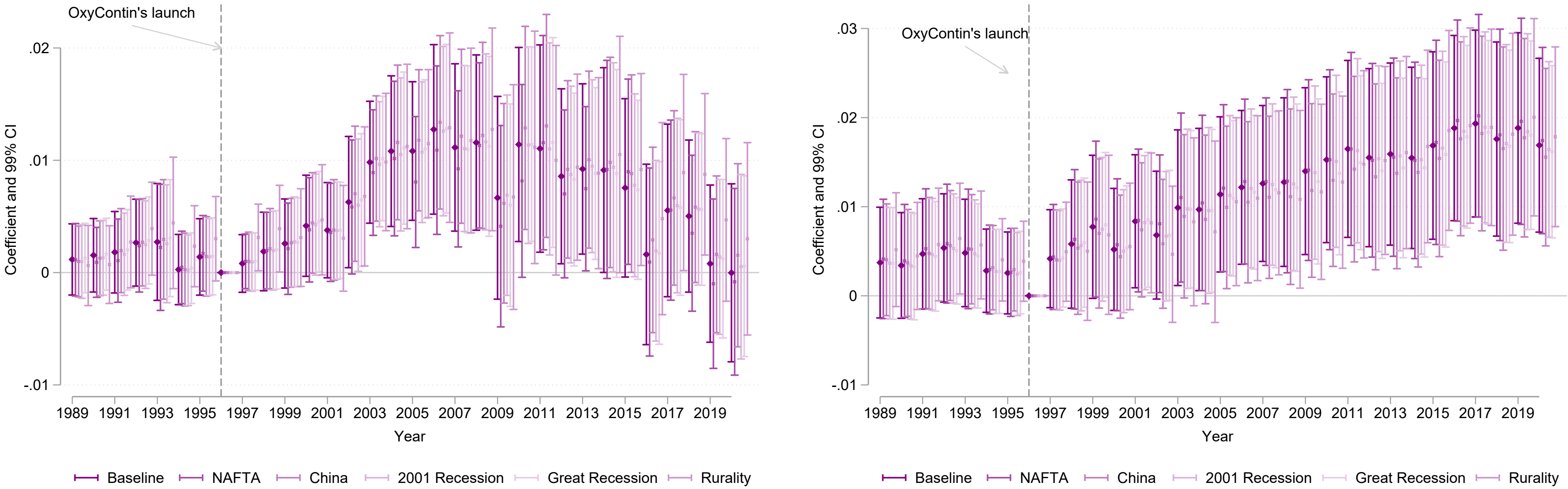


Notes: Panel (a) of this figure presents estimates of the baseline dynamic relationship between the SNAP share and mid-1990s cancer mortality, along with estimates where we add controls that capture the underlying health and economic characteristics at baseline. Health controls are share of smokers, share of overweight adults, infant mortality rate, and share of primary care physicians. Economic controls are unemployment rate, share of employment in manufacturing industries, income per capita, and share of population with some college education. In panel (b) we include a measure of pollution to our health covariates. One limitation of this analysis is that the EPA's data coverage is limited. Thus, we present estimates of the baseline specification in a restricted sample. Appendix B. provides details on the construction of these variables. This figure is referenced in Section VIII.a.

Figure A21: Robustness Checks – Economic Shocks & Rurality

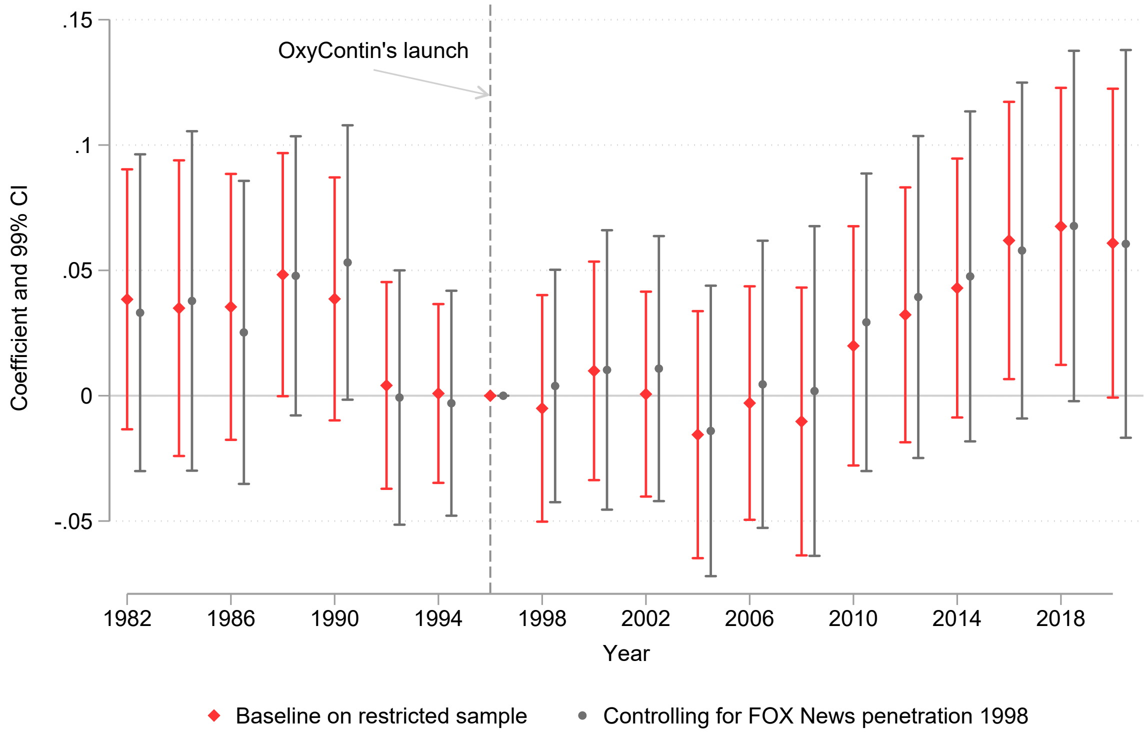
(a) Prescription Opioids

(b) SNAP



Notes: This figure presents the baseline estimates of the relationship between prescription opioid mortality (panel a) and SNAP (panel b) with 1996 cancer mortality along with estimates in which we flexibly control for economics shocks. The economic shocks correspond to measures of exposure to NAFTA, PNTR with China (termed the "China shock" in the trade literature), the 2001 and 2007 economic recessions. We also control for rurality. Each of these measures is interacted with year dummies. Appendix B. provides details on the construction and source of each measure. This figure is referenced in Sections VIII.b and VIII.c

Figure A22: Robustness Checks – House Elections and the Introduction of Fox News



Notes: This figure presents the baseline estimates along with estimates in which we control for early exposure to Fox News. We use data from Clinton and Enamorado (2014). These data cover only 60% of our CZs, so there is substantial shrinkage in sample size. Thus, we present estimates of the baseline equation restricting the sample to those CZs included in their data; we label this "Baseline of restricted sample". This figure is referenced in Section VIII.c.

Table A1: Opioid Mortality and Media Engagement with the Epidemic

Dependent var: Mentions of “opioids” in local newspapers						
	(1)	(2)	(3)	(4)	(5)	(6)
Opioids mortality rate	0.270	-0.939	0.550**	-0.138	0.917***	-0.532
	[0.503]	[0.695]	[0.214]	[0.231]	[0.346]	[0.470]
Mean dep. var	0.16	0.15	0.35	0.3	0.33	0.28
Observations	2,492	2,492	7,476	7,476	5,340	,5340
CZs	273	273	273	273	273	273
Newspaper sample	Rep.	Dem.	Rep.	Dem.	Rep.	Dem.
Period	Pre 1997		2000-2020		2000-2014	

Notes: We estimate the following regression on a CZ-year panel: $y_{ct} = \alpha_1 + \beta$ Opioid mortality$_{ct}$ + $X_{ct} + \varepsilon_{ct}$, where y_{ct} corresponds to an indicator variable that takes the value one if there is at least one news article referring to opioids in CZ c at time t by a newspaper with a given affiliation. We run this regression on a sample of CZs that have at least one newspaper with an identified political leaning. The vector X_{ct} includes the following demographic controls: the white and female population shares, total population, 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; total newspaper circulation and circulation of Republican outlets, all of these measured at the CZ level. Circulation data come from Gentzkow and Shapiro (2011). *p<0.10, **p<0.05, *** p<0.01. This table is referenced in Section VII.c

Table A2: Sentiment Analysis of Newspaper Coverage of the Opioid Epidemic

	Relative frequencies of words in each category				
	Illegality and Cartels (1)	Fear and Panic (2)	Economic Hardship (3)	Rehabilitation (4)	Policy (5)
Newspaper leaning:					
Republican	0.0048	0.0088	0.0007	0.0118	0.006733
Democrat	0.0041	0.0085	0.0006	0.0097	0.008362
% Difference in Coverage (R-D)	18.6%	4.0%	22.8%	21.9%	-19.5%

Notes: We collect all newspaper articles that mention the word "opioid" from 1995 to 2020 that are part of the archive at *newspapers.com* (118,210 articles). From these data, we draw a random sample of 9,044 and hand annotate the title of the article. We then define a set of keywords related to each of the categories in columns 1 to 5 and count the word frequencies in each category for those newspapers that are classified as Democratic or Republican leaning according to the assignment in Gentzkow and Shapiro (2011). This table is referenced in Section VII.c

B. Data

We collect data from multiple sources to construct a panel at the CZ level from 1982 to 2020. This appendix provides additional details on sources and variable definitions.

B.1 ARCOS Data

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. The digitized ARCOS system data are available here. For periods before 2000, we use the WayBack Machine application to access reports from 1997 to 1999. We construct a crosswalk from 3-digit ZIP codes to commuting zones (CZs) using the geographic correspondence engine powered by the Missouri Centers for Disease Control. The group of drugs included in the ARCOS changes over time—e.g., to account for changes in the classification of an ingredient. Nonetheless, we focus on a set of prescription opioids that can be tracked consistently over the period of analysis. Our main measure of prescription opioids per capita corresponds to the sum of oxycodone, codeine, morphine, fentanyl, hydrocodone, hydromorphone, and meperidine in morphine-equivalent mg.

B.2 Mortality Data

We compute mortality rates as the ratio between the number of deaths for a particular cause (and age group) over the relevant population. Data on the number of deaths come from the restricted-access version of the Detailed Multiple Cause of Death (MCOD) data. These files record every death in the United States along with the county of residence, the underlying cause of death, and up to 20 additional causes and thus represent a census of deaths in the US. The 1989-1998 data use ICD-9 codes to categorize the cause of death, and the 1999-2020 data use ICD-10 codes.

Cancer deaths. Our main measure of cancer mortality defines cancer deaths as those from malignant neoplasms (codes 140-208 in ICD-9 data and C00-C97 in ICD-10 data) and in situ neoplasms, benign neoplasms and neoplasms of uncertain or unknown behavior (codes 210-239 in ICD-9 data and D00-D48 in ICD-10 data). We also construct cancer mortality excluding lung cancer; these correspond to codes 162 in ICD-9 and C33–C34 in ICD-10 data.

Opioid-related mortality. We follow CDC (2013), Ruhm (2018), Venkataramani and Chatterjee (2019), and Alpert et al. (2022) to define alternative measures of opioid-related mortality. The prescription opioids category captures deaths for which the underlying cause is substances usually found in prescription painkillers such as hydrocodone, methadone, morphine, and oxycodone. We use identification codes X40–X44, X60–64, X85, or Y10–Y14 with contributing causes T40.2 and T40.3 to specify prescription-opioid-related overdoses in the ICD-10 data and codes 965.00, 965.02, 965.09, E850.1, and E850.2 for the ICD-9 data. We exclude deaths with contributing cause T40.4 from this definition, since these deaths include synthetic opioid involvement, e.g., fentanyl (Ruhm, 2018). The any-opioid category is a broader measure of opioid-related deaths, in which we include deaths from heroin and synthetic opioids, e.g., fentanyl. We use identification codes X40–X44, X60–64, X85, or Y10–Y14 with contributing causes T40.0-T40.4 to count deaths from any opioid in the ICD10-data and codes 965.00, 965.01, 965.02, 965.09, E850.0, E850.1, and E850.2 for the ICD-9 data. An even more comprehensive category is drug-induced mortality, which includes deaths from poisoning and medical conditions caused by the use of legal or illegal drugs, as well as deaths from poisoning due to medically prescribed and other drugs. We use identification codes D521, D590, D592, D611, D642, E064, E231, E242, E273, E661, F11-19, G211, G240, G251, G254, G256, G444, G620, G720, I952, J702, J703, J704, K853, L105, L270, L271, M102, M320, M804, M814, M835, M871, M102, R502, R781, R782, R783, R784, R785, X40–X44, X85, or Y10–Y14.

Deaths of despair. Case and Deaton (2015) define deaths of despair as deaths by drug and alcohol poisoning, suicide, and chronic liver diseases and cirrhosis. Our measure of deaths of despair does not include drug poisonings, as these are counted in prescription- and any-opioids deaths separately in our analysis. That is, our measure is limited to deaths from suicide, chronic liver disease, cirrhosis, and poisonings that are attributable to alcohol—these deaths amount to, on average, 79% of the deaths studied by Case and Deaton (2017). We use identification codes K70 and K73-74 to count deaths from alcoholic liver diseases and cirrhosis in the ICD10-data and codes 571.0 – 571.4 and 57109 for the ICD-9 data. We count deaths from suicide using codes X60-84 and Y87.0 for the ICD10-data and codes E950-E959 for the ICD-9 data. Deaths from alcohol poising are counted using codes X45 and Y15 for the ICD10-data and codes E850-E858, E860, and E980.1 for the ICD-9 data.

Placebo mortality. For our robustness checks, we construct alternative measures of mortality. We construct over-65 *essential hypertension and hypertensive renal disease*, i.e., hypertension, and *influenza and pneumonia* mortality measures. We count deaths from hypertension using ICD-9 codes 401 and 403 and ICD-10 codes I10 and I12. Deaths from influenza and pneumonia are identified using codes J10-J18 for the ICD-10 and codes 480-487 for the ICD-9 classifications. We follow Anderson et al. (2001) to construct these death categories across ICD classifications.

B.3 Population Counts

Data on population counts come from the Survey of Epidemiology and End Results (SEER), which reports population at the county level and by age, race, gender, and Hispanic origin. The SEER population estimates are a modification of the US Census Bureau's intercensal population estimates designed to provide more accurate population estimates for intercensal years. We use these data for two main purposes: (i) to construct the denominators for adult mortality rate measures, e.g., opioid and aggregate mortality; and (ii) to construct the share of the population of a particular age or demographic group for control variables. One limitation of these data is that Hispanic origin is only available starting in 1990.

B.4 Voting Data

House Elections. Data on the number of votes received by Democratic, Republican, and other candidates for the House of Representatives at the county level come from Dave Leip's Atlas of US Elections (Leip, 2022). These data are available from 1992 to 2020. We complement these data using the United States Historical Election Returns Series developed by the ICPSR (ICPSR 0013) from 1982 to 1990. In cases where House elections are uncontested, the candidate's party receives 100% of the vote share.[1]

Gubernatorial Elections. Data on the number of votes received by Democratic, Republican, and other candidates running for governor at the county level come from Dave Leip's Atlas of US Elections (Leip, 2022). These data are available from 1990 to 2020. For elections that occurred between 1976 and 1989, we use the United States Historical Election Returns Series developed by the ICPSR (ICPSR 0013). Some gubernatorial elections are not included in this collection; for these cases, we conduct state-specific data collection. Data for elections held in Virginia in 1977 and 1989 come from the Virginia Department of Elections.[2] We use the Election Results Archive for the state of New Jersey to collect data for the 1977 and 1989 elections and digitize the official election results.[3] Similarly, the states of Kentucky, Louisiana, and Mississippi held gubernatorial elections in 1975 and 1979, and their results are not included in ICPSR 0013. For the state of Kentucky, we use the Commonwealth of Kentucky State Board of Elections site to retrieve data for these elections.[4] For the state of Mississippi, we were unable to find official data sources and thus collect information from ourcampains.com and uselectionatlas.org.[5] For the 1979 Louisiana elections, we hand digitize the results using the Department of

[1] No presidential election since the early 1800s has gone uncontested.

[2] Virginia Historical Election Database: https://historical.elections.virginia.gov/

[3] These files are stored here: https://nj.gov/state/elections/election-information-results.shtml

[4] See https://elect.ky.gov/results/1973-1979/Pages/default.aspx

[5] The following are the websites we exploit: https://www.ourcampaigns.com and https://uselectionatlas.org

State Primary and General Election Results. The state of New Hampshire and Vermont hold elections every two years; we exclude them from the main analysis. The Book of the States (The Council of State Goverments, 2024) provides detailed information about gubernatorial term limits and dates of service.

Presidential Elections. Data on the number of votes received by Democratic, Republican, and other candidates for presidential elections at the county level come from Dave Leip's Atlas of US Elections (Leip, 2022). These data are available from 1976 to 2020.

For every election, we define the Republican vote share as the ratio between the number of votes for a Republican candidate and the total number of votes cast in the election.

Turnout. Turnout and voter registration data at the county level come from Dave Leip's Atlas of US Elections (Leip, 2022). We calculate turnout rates for presidential elections as the ratio between total votes and total registered voters.[6]

B.5 Campaign Donations

We use the Database on Ideology, Money in Politics, and Elections (DIME) from Bonica (2023) to construct counts on the number of campaign donations made to candidates running in House races by party spanning the years 1982 to 2016. We exclude data for 2018 and 2020 from our analysis because donation patterns underwent significant changes during these election cycles, rendering the data incomparable. These data provide unique individual identifiers, with geolocated addresses and details on the contribution amount, campaign, and candidate supported. We focus on donations made by individual contributors. We aggregate the count of individual campaign contributions directed toward Republican or Democrat candidates in House races.

B.6 House Member's Ideology

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

[6] We refrain from using the CCES to study turnout, as studies have raised issues with using these data for this purpose (Agadjanian, 2018). Grimmer et al. (2018) show that the percentage of respondents who fail to match to the voter registration database increased from approximately 10% in 2010 to 30% in 2014. Additionally, the criteria used to link survey respondents to registration records have changed over time and vary across states. The inconsistency in the CCES vote validation process can generate time-correlated measurement error in turnout estimates.

is well suited for measuring how members of the House's ideological positions may have changed over time, since the scores are generated while allowing members to hold different positions in each congress (Nokken and Poole, 2004). That is, the Nokken-Poole estimates assume that each congress is completely separate for the purposes of estimating a member's ideology. For further discussion of the NOMINATE model, see Poole and Rosenthal (1985) and Poole (2005).

B.7 Survey Data

The variables constructed using data from the Cooperative Congressional Election Study (CCES) exploit answers from the following questions:

- Abortion question takes the following values: 1="Always allow a woman to obtain an abortion as a matter of choice" and 0 otherwise.

- Gun control question corresponds to "Ban assault rifles" and takes the following values: 1="Support" and 0="Against."

- Immigration question is "Increase the number of border patrols on the US–Mexican Border," where 1="Against" and 0="Support."

- Own ideology question is "Thinking about politics these days, how would you describe your own political viewpoint," where 1="Very conservative" and 5="Very liberal"

- Support for "Increase police officers on the street by 10 percent" takes values 1="Support", 0="Oppose".

- Safety around police question is "The police make me feel safe" where 4="Mostly safe", 3="Somewhat safe, 2="Somewhat unsafe", and 1="Mostly unsafe"

- Fox Viewership is a dummy variable equal to 1 when respondents report watching Fox News.

B.8 Marijuana Ballots

We collected data for 18 out of the 19 states that put forward a ballot initiative between 2012 and 2023. The list of states in chronological order from most recent to first is Ohio, Oklahoma, South Dakota, Arkansas, Maryland, Missouri, North Dakota, New Jersey, Arizona, Montana, Michigan, California, Nevada, Maine, Massachusetts, Oregon, Alaska, Colorado and Washington. We could not obtain county-level data for Alaska. For each state, we collect county-level data on the number of ballots cast and the number of "yes" and "no" answers for each ballot. In each case, the vote "yes" implies support for marijuana legalization, though there is heterogeneity in how the legalization is defined in different states. A list of all ballots and results can be found here: Marijuana ballots.

B.9 Speeches of House Members

We use the Congressional Record for the 43rd-114th Congresses: Parsed Speeches and Phrase Counts dataset (Gentzkow et al., 2018) to create counts of mentions of the word "opioid" during speeches on the floor of the House from 1985 to 2016. The data are collected by Congress; thus, year indicates the first year a Congress is in session. For example, for the House elected in 1984, counts correspond to speeches given in 1985 and 1986. The data are parsed in a way that controls for plurals, i.e., searches for the word "opioid" will include speeches where the word "opioids" was used as well.

B.10 Data for Composition of the Electorate and Alternative Explanations

We consider a host of alternative explanations for our results. Testing these hypotheses requires pulling data from multiple sources. When possible, we follow the literature to construct measures of various shocks that occurred during our period of study. If available, we prioritize using replication packages and extracting variables directly from them.

IRS statistics of income tax. The IRS Statistics of Income tax (SOI) is based on the universe of Forms 1040 that were filed and processed by the IRS during a calendar year. The data are available for filing years 1991 through 2021 and include the number of personal exemptions claimed, which approximates the number of individuals in a given county. We use the migration data, which are based on year-to-year address changes reported on individual income tax returns. They present migration patterns by county for the entire United States and are available for inflows—the number of new residents who moved to a county and where they migrated from—and outflows—the number of residents leaving a county and where they went. These data can be downloaded here: https://www.irs.gov/statistics/soi-tax-stats-migration-data

NAFTA. We use the replication data files from Hakobyan and McLaren (2016) and use the change in average local tariffs as the measure of the induced local competition from Mexican imports created by NAFTA.

China shock. We use Pierce and Schott (2020)'s replication package to obtain a measure of exposure to trade liberalization. Specifically, they define this measure as the difference between the non-NTR rates to which tariffs could have risen prior to PNTR and the NTR rates that were locked in by the change in policy. A higher NTR gap indicates greater trade liberalization after the passage of PNTR.

Economic recessions. We construct a measure of exposure to the 2001 economic recession as the change in the unemployment rate from 2001 to 2000 at the CZ level.

We use data on unemployment from the Local Area Unemployment Statistics from the Bureau of Labor Statistics (BLS). We use Yagan (2019)'s replication package to measure exposure to the Great Recession. This measure is a function of the percentage-point change in a CZ's unemployment rate between 2007 and 2009. In its construction, the author computes the annual CZ unemployment rate 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.

Robot adoption. We obtain a measure of exposure to robotic technology directly from the replication package in Acemoglu and Restrepo (2020). We use the measure defined in Equation (18) and plotted in Figure 4; this measure exploits variation in industry-level adoption of robots weighted by 1970 employment shares to focus on historical, persistent differences in the industrial specialization of CZs that predate robotics technology.

Rurality. We use the decennial county Rural-Urban Continuum Codes from the Economic Research Service US Department of Agriculture for 1993. This index takes values from zero to nine; it classifies counties by the population size of their metro area, and nonmetropolitan counties by their degree of urbanization and adjacency to a metro area. A higher value represents a higher level of rurality.

Census of religion. We collect data from the US Religion Census, which reports the number of churches, members, and adherents from Judeo-Christian church bodies in the United States. In particular, we exploit the Churches and Church Membership in the United States, 1990, collected by the Association of Statisticians of American Religious Bodies (ASARB). This publication can be downloaded from the ARDA data archive: https://www.thearda.com/data-archive?fid=CMS90CNT. The RCMS collection reports a measure of members and adherents. Members include only those designated as "full members" by the congregation. Congregational "adherents" include all full members, their children, and others who regularly attend services or participate in the congregation. Some religious groups differ in whether they count children as members or not. When religious groups reported only adult membership, the ARDA provides estimates of adherents using Census data.

Unionization rates. We take the 2000 CZ-level measure constructed by Connolly et al. (2019). The authors combine data from the Current Population Survey (Outgoing Rotation Groups) and from the Quarterly Workforce Indicators (QWI).

Fox News launch. We leverage the replication data from Clinton and Enamorado (2014). These authors build upon the impressive data collected by (DellaVigna and Kaplan, 2007) and collect data on the presence of Fox News for additional locations. Their final dataset spans to 14,748 towns in 35 states for the years 1998 and 2000.

B.11 Additional Health Outcomes

Share of smokers. We construct the share of smokers using data from the Behavioral Risk Factor Surveillance System (BRFSS). In 2011, BRFSS changed its data collection, structure, and weighting methodology. In 2011, there is an increase in the proportion of people being surveyed on cell phones, and this increase also coincides with a rise in the percentage of respondents with unknown smoking status as documented by DeCicca et al. (2022).

Share of overweight adults. We use data provided by the United States Diabetes Surveillance System (USDSS) to measure the share of the adult population that reports height and weight that would put them in the overweight category for BMI. The first available year of these data is 2004; thus, we use this year as the baseline year.

Share of primary care physicians. We use data from the Hospital and Physician Capacity Measures collected by the Dartmouth Atlas to construct a measure of the number of primary care physicians in a CZ in 1996. These data provide population counts for a given service area, which we use as the denominator to preserve consistency. Data are available here: https://doi.org/10.21989/D9/QRWSDG.

Infant mortality rate. Data on birth outcomes come from the Linked Birth and Infant Death Data of the National Vitals Statistic System (NVSS). We construct infant mortality as the ratio of infant deaths to live births in a given calendar year. The denominators for the infant mortality rate come from the "Denominator File" provided by the NVSS.

Pollution. We obtain data on air pollution from the EPA's Air Quality System (AQS) database (available at https://www.epa.gov/aqs). Following Notowidigdo et al. (2024), we average pollution monitor readings within a monitoring site to the site-year level, weighting these by the number of daily pollution readings for each monitor if there are multiple monitors at the same site. We then average these data to the county-year level, weighting sites by the number of daily pollution readings from the monitors within those sites. We focus on the levels of fine particulate matter (PM2.5), which is measured in micrograms per cubic meter (μg/m3). We combine data for 2000 and 2001 as the baseline year.

B.12 Newspapers

We collect news article titles, dates, locations, and paper names for all articles mentioning the term "opioids" between 1995 and 2020 from *newspapers.com*. This site is the largest online newspaper archive, consisting of over 969 million pages of historical newspapers from 26,100+ newspapers from around the United States and other countries.

To conduct our text analysis, we calculate the relative frequencies of different word categories. The keywords used for this analysis are as follows:

Economic Hardship: economic, poverty, unemployment, job loss, financial, debt, bankruptcy, hardship, homelessness, cost, burden, welfare, struggle, income loss, economic impact, recession, downturn, housing crisis, eviction, foreclosure, financial strain, low-income, underemployment, economic burden, economic instability.

Crime/Illegal Activities/Immigration: crime, illegal, trafficking, smuggling, arrest, police, violence, gang, immigration, cartel, drug lord, criminal, drug dealer, cartel, law enforcement, border, undocumented, migrant, Mexico, drug bust, criminal activity, illegal drugs, border control, immigration policy, human trafficking, criminal justice, drug-related crime, violent crime.

Fear/Panic/Alarm: fear, panic, alarm, crisis, outbreak, danger, risk, threat, scare, warning, urgent, public health crisis, emergency, severe, deadly, fatal, critical, hazardous, epidemic proportions, widespread, alarming.

Rehabilitation/treatment: rehabilitation, rehab, treatment, recovery, therapy, support, care, detox, counseling, intervention, medication-assisted treatment, methadone, buprenorphine, naltrexone, naloxone, suboxone, inpatient, outpatient, intervention program, support services, treating

Policy solutions such as medical and regulatory changes and legislation: policy, solution, reform, legislation, regulation, law, mandate, bill, act, statute, ordinance, medical policy, prescribing guidelines, monitoring, drug regulation, prescription policy, public health policy, overdose prevention, addiction policy, treatment act, recovery act, substance abuse legislation, controlled substances act, drug abuse prevention, mental health legislation, initiative, task force, government response, funding, budget allocation, research funding, prevention program, intervention program, support services lawmakers, board.

B.13 Geographic Harmonization

The electoral outcomes 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. The contribution database provides the latitude and longitude of individual contributions, allowing us to geo reference these donations to a CZ. Some 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. Data on House ideology is collected at the electoral district level, and we use the crosswalks developed by Ferrara et al. (2021) to compute the outcomes of interest at the CZ level. This second step serves two purposes: i) to harmonize to a common geographic unit and ii) to account for the redistricting of congressional districts, since Ferrara et al. (2021) provide year-specific crosswalks.[7]

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

C. Pharmaceutical Marketing and Mid-Nineties Cancer

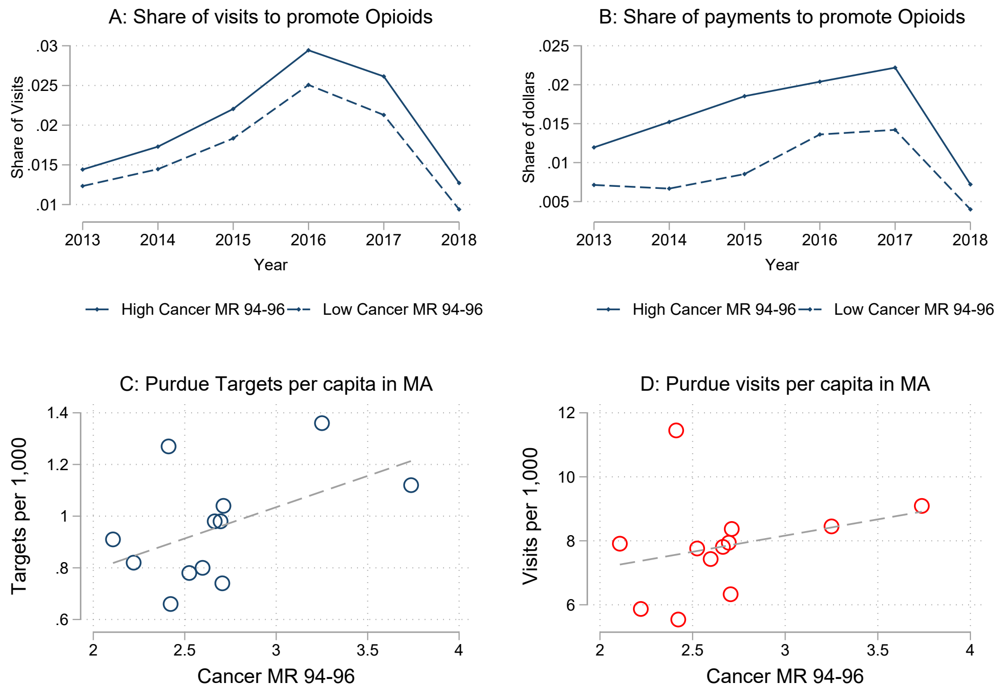
Our hypothesis is that the connection between pre-OxyContin cancer rates and future opioid inflows is generated by the marketing efforts of Purdue and other pharmaceutical companies. That is, in the absence of the targeting to the cancer and end-of-life pain markets, measures of cancer mortality would not predict opioid mortality. Unfortunately, most of the data that could test this hypothesis is still confidential. We perform two exercises that provide evidence in this direction: one using public data and the second using new unsealed records we digitized.

First, we examine pharmaceutical marketing in 2013–2018 using the CMS Open Payments database. These data report visits and payments from pharmaceutical manufacturers to physicians related to promoting specific drugs, including payments for meals, travel, and gifts. Panels (a) and (b) of Figure C1 show that, even 17 years after the introduction of OxyContin, the share of visits and the share of payments to promote opioids relative to all other drugs was higher in high-cancer CZs. CZs at the top quartile of the cancer distribution in the mid-nineties, relative to CZs in the bottom quartile, received on average 22% more opioid-related visits, and the share of payments was 83% higher. We interpret this as a measure of the persistent effect of the initial targeting of cancer areas by pharmaceutical companies.

Second, records from May 2007 to December 2018 on all sales representatives' visits to promote OxyContin in Massachusetts have been released as part of recent litigation (Figure C2). We digitized these data for 2007 to 2011 and created aggregate measures at the county level of the number of visits per 1,000, and the number of targets, either physicians or pharmacists, per 1,000. Panels (c) and (d) of Figure C1 show scatter plots of these variables on the y-axis and mid-nineties cancer mortality on the x-axis. Both of these measures show a positive relationship between cancer mortality at the time of launch and persistent future marketing in those areas. This persistence of the initial targeting is consistent with the marketing strategy discussed in the internal documents and supports our identification strategy.

congressional districts.

Figure C1: Opioids Marketing and Mid-Nineties Cancer Mortality



Notes: Panels A and B use data from CMS Open Payments. High cancer corresponds to the top quartile of cancer incidence in 1994-1996, and low cancer corresponds to the bottom quartile. Panels C and D use digitized data from "Exhibit 1 - Sales Visits By Purdue In Massachusetts. Commonwealth of Massachusetts v. Purdue Pharma c.a. No. 1884-cv-01808"(Figure C2) to construct county-level averages. This figure is referenced in Section C.

Figure C2: Extract Exhibit 1 - Sales Visits By Purdue In Massachusetts

Commonwealth of Massachusetts v. Purdue Pharma et al.
Exhibit 1 - Sales Visits By Purdue In Massachusetts

Date	Purdue Sales Rep	Target	Address	City
5/16/2007	Raczkowski, Paula J	Belezos, Elias	164 South Street Harrington Hospital Medical Arts Bld	Southbridge
5/16/2007	Raczkowski, Paula J	Jeznach, Gary	118 Main St Rte 131	Sturbridge
5/16/2007	Raczkowski, Paula J	Welch, Heidi	118 Main Street	Sturbridge
5/16/2007	Raczkowski, Paula J	Keaney, Stephanie	100 South Street Medical Arts Bldg Suite#201	Southbridge
5/16/2007	Raczkowski, Paula J	Kereshi, Stjepan	100 South St Harrington Hospital	Southbridge
5/16/2007	Raczkowski, Paula J	Litani, Vladas	100 South St Harrington Mem Hos	Southbridge
5/16/2007	Raczkowski, Paula J	CVS Pharmacy Southbridge	380 Main St	Southbridge
5/16/2007	Mulcahy, Maurice	Boyd, Kenneth	23 Whites Path	South Yarmouth
5/16/2007	Mulcahy, Maurice	Hartley, Marie	23 Whites Path	South Yarmouth
5/16/2007	Mulcahy, Maurice	Terrill, Donna	269 Chatham Rd	Harwich
5/16/2007	Mulcahy, Maurice	Fair, Dianne	269 Chatham Rd	Harwich
5/16/2007	Mulcahy, Maurice	CVS Patriot Square-So. Dennis	Paqtriot Square/Route 134	S Dennis
5/16/2007	Mulcahy, Maurice	CVS Rt 28 S.Yarm.	976 Route 28 Yarmouth Shopping Plaza	S Yarmouth
5/16/2007	Arias, Alexander	Huang, Wynne	1 Roosevelt	Peabody
5/16/2007	Arias, Alexander	CVS - Main St [Woburn]	415 Main St	Woburn
5/16/2007	Ritter, Andrew	Kehlman, Glenn	637 Washington St	Brookline

Notes: Extract of Exhibit 1 - Sales Visits By Purdue In Massachusetts. COMMONWEALTH OF MASSACHUSETTS v.PURDUE PHARMA C.A. No. 1884-cv-01808. This figure is referenced in Section C.

D. Additional Robustness Checks

In this appendix, we present additional robustness checks. In addition to the exercises presented in the main text, we further test for the role of health trends and behaviors and the decline in unionization rates and the rise of evangelicals support to the Republican party. We also present a set of exercises where we reproduce the main analysis at the county level, drop individual states, modify the population sample restrictions, and use alternative measures of cancer mortality. Across all these tests, we estimate results that are quantitatively and qualitatively similar to our baseline estimates.

D.1 Health Trends and Health Behaviors

We complement our analysis on the potential threats of health behaviors and health trends by providing direct evidence that there is no systemic relationship between mid-nineties cancer mortality and overall health trends or despair. In Figure D1, we study the relationship between 1996 cancer mortality and both suicides and overall mortality excluding cancer (for 75-years-old and 20-years-old and older adults). We find no evidence of pre-trends or effects after the introduction of OxyContin. In Figure D2, we document that high cancer areas were not on a differential trend along health behaviors such as smoking. Additionally, as shown before, young adults entirely drive the estimated excess opioid mortality, while opioid mortality does not increase for adults over 55 years old (see Figure A9). This finding supports the argument that our results are not driven by underlying health conditions, as the population over 55 is the closest in health profile to the population that drives the variation in cancer mortality. Instead, what we observe is a spillover effect from the cancer population to the younger and healthier population, facilitated by the introduction of opioids in those markets.

D.2 Additional Political Developments and Group Realignments

Republican Party and evangelical churches. In recent elections, white evangelicals have supported the Republican Party.[8] We ask whether the support of evangelical voters for the Republican Party drives our results. To answer this question, we collect data from the US Religion Census.[9] Using these data, we construct the number of churches with such denomination per 10,000 individuals in a CZ. We re-estimate our main results, including interactions of this variable with year dummies. We find that our results remain unchanged after including this control (see Figure D3).

The Republican Party and union membership. Considering the partisan nature of union membership, the decline in unionization rates and its subsequent effects on income

[8] See, for example, Nortey (2021).

[9] See Churches and Church Membership in the United States, 1990, collected by the Association of Statisticians of American Religious Bodies (ASARB) and Appendix B. for details.

inequality and working conditions (Farber and Western, 2016; Farber et al., 2021; Frandsen, 2021) could potentially act as a confounder for the results presented in this paper. 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 could be attributed to a correlation between our measure of opioid epidemic exposure and broader dynamics related to the political and economic effects of the decline in unionization. Figure D3 also incorporates a specification where union membership rates are added as an additional control; our results remain unaffected.

D.3 Geographic Unit of Analysis

We replicate our results using counties as the unit of observation for our analysis, rather than CZs. This exercise allow us to test whether our results are robust to the geographic harmonization needed to compute outcomes at the commuting zone level. In Figure D4, we find that the patterns and sizes of the coefficients for the prescription rate of opioids, mortality from opioids, SNAP shares, and Republican vote share are all very similar to the baseline results.

D.4 Alternative Definitions of Cancer Mortality

We reproduce the main analysis using two alternative definitions of cancer mortality. To alleviate concerns related to behavioral and environmental factors that could correlate with our outcome variables, we exclude deaths from lung cancer in our definition of the cancer mortality rate. Additionally, we provide estimates using age-adjusted cancer mortality rates as a measure of exposure to account for the age composition of a CZ. Figure D5 shows the estimated effect sizes for each specification. That is, we report the effect of a one-standard-deviation increase in each measure of cancer mortality. The effect sizes follow the same temporal pattern and have very similar magnitudes across specifications.

Since mortality is a lagged measure of the cancer patient market, our baseline specification exploits cancer mortality in 1996 as a measure of exposure to the epidemic. To address potential concerns around the timing of this shock we replicate the analysis using cancer mortality in 1994 and 1990 as alternative measures of exposure to the epidemic and find similar results to those in the baseline specification (see Figure D6).

D.5 Alternative Samples and Specifications

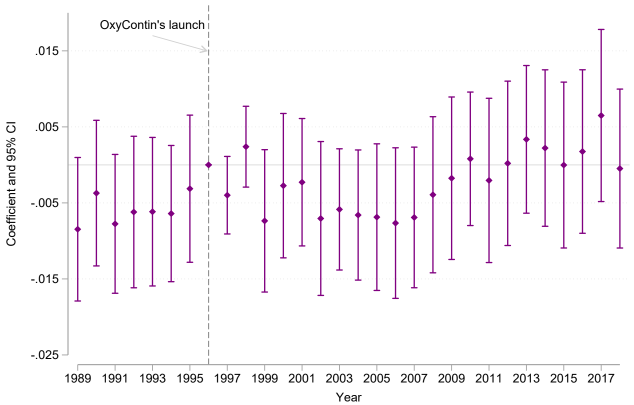
In our main specification, we restrict our sample to areas with more than 20,000 residents; these represent 99.5% of the total population. We reproduce our analysis using samples with alternative restrictions on the size of CZs and arrive at conclusions analogous to those from the main analysis. We find that a strong and positive relation exists between mid-1990s cancer and post-1996 mortality and opioid deaths, SNAP rates and Republican vote share (see panel (a) of Figures D7, D8, and D9). We replicate our main specification using population weights or number of votes as weights, and we find that both the pre-trends and our effect estimations remain unaffected (see panel (b) of Figures D7, D8, and D9). Additionally, we examine whether our results are contingent on any particular state. In Figure D10, we present coefficient estimates corresponding to 2018 and 2020 and demonstrate that our findings remain robust when we exclude any individual state. Finally, we consider an alternative specification where we include the control variables in levels. We present these results in Figure D11, along with the baseline estimates, and find similar results.

D.6 Alternative Definition of Republican Vote Share

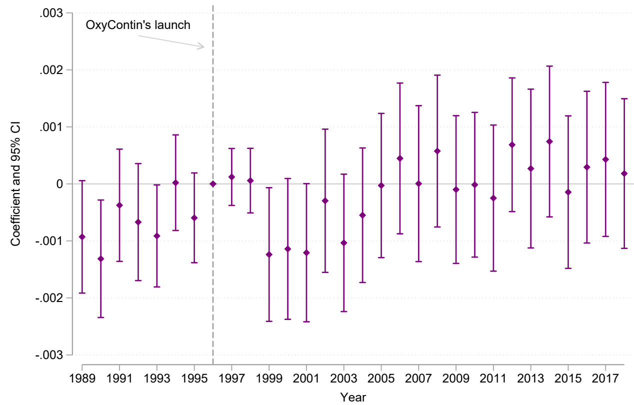
In this paper, we define the Republican vote share as the ration between votes to the Republican party and total votes cast in a given election. In Figure D12 we show that our results are robust to using two-party vote shares as the main outcome. That is, we replicate our analysis defining the Republican vote share as the ration between votes to Republican candidates and the sum of votes to Republican and Democratic candidates.

Figure D1: Trends in Despair Mortality and Overall Health

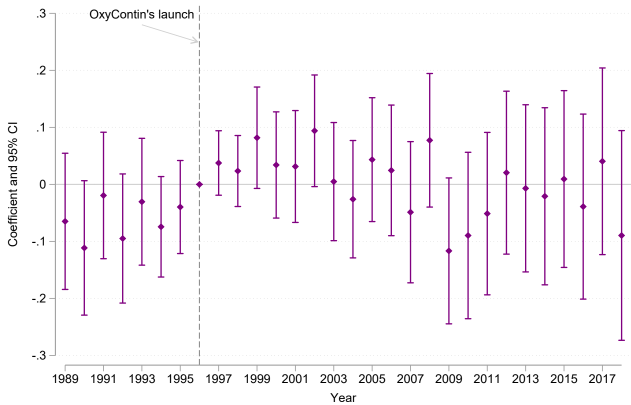
(a) Suicide Mortality Rate



(b) Noncancer Mortality. Adults +75 Years Old.

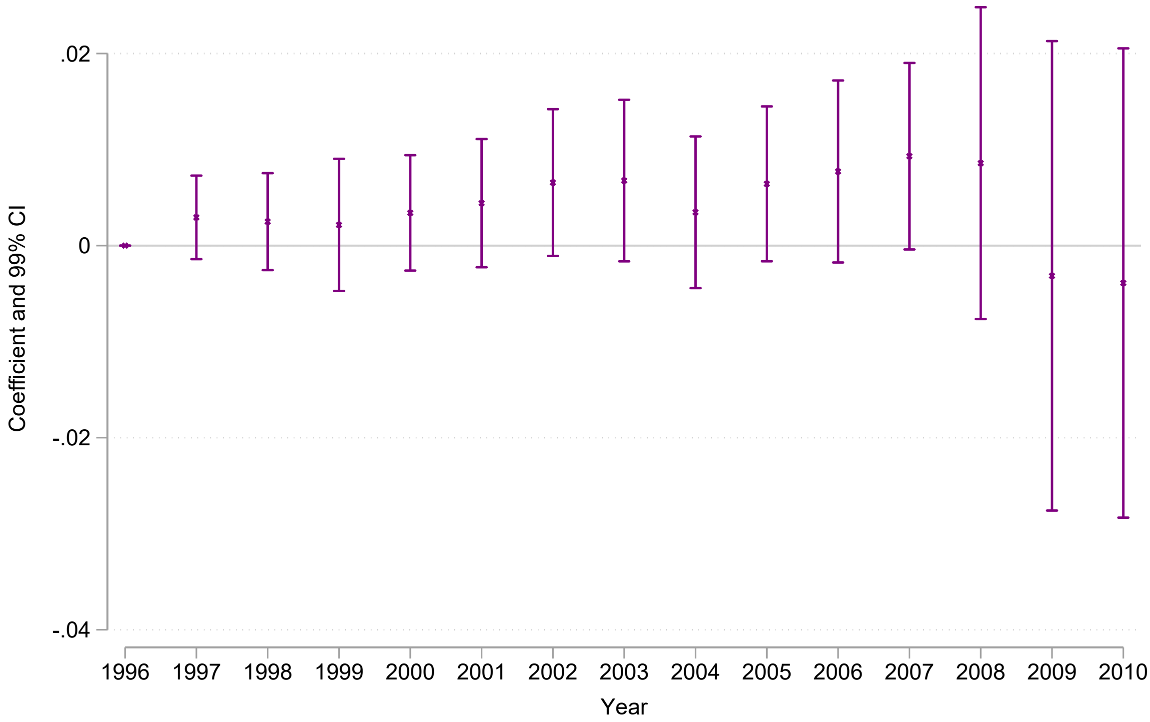


(c) Noncancer Mortality. Adults +20 Years Old.



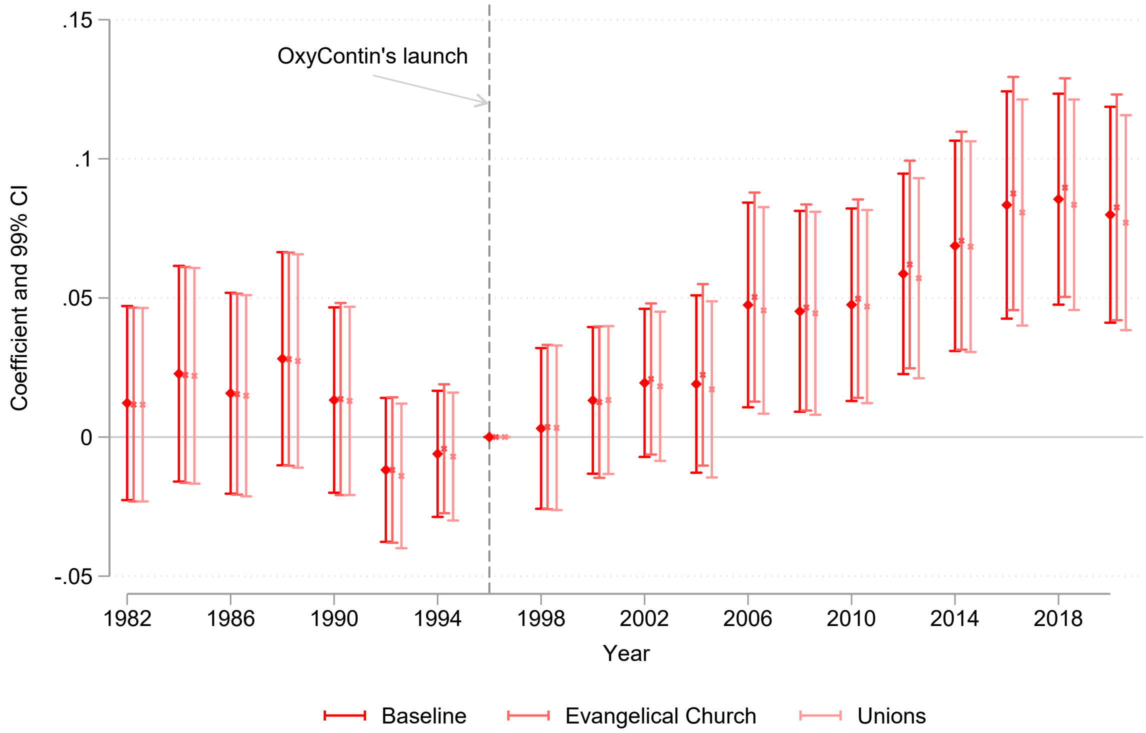
Notes: This figure shows the dynamic reduced-form relationship between despair mortality (panel a), noncancer mortality of 75-year-old and older adults (panel b), and noncancer mortality for adults aged 20 years and older (panel c) and our measure of exposure to the epidemic. This figure is referenced in Section V.b and Section D.1

Figure D2: Effects of Mid-Nineties Cancer-Market Targeting on Share of Smokers



Notes: This figure shows the effects of cancer marketing targeting on the share of smokers. We present the results of a dynamic reduced-form estimation where we regress the outcome on a set of year-dummy variables interacted with 1996 cancer mortality. We construct the share of smokers using data from the Behavioral Risk Factor Surveillance System (BRFSS). We perform the analysis up to 2010, since starting in 2011, the BRFSS changed its data collection, structure, and weighting methodology. In 2011, there is an increase in the proportion of people being surveyed on cell phones, and this also coincides with a rise in the percentage of respondents with unknown smoking status as documented by DeCicca et al. (2022). This figure is referenced in Section D.1.

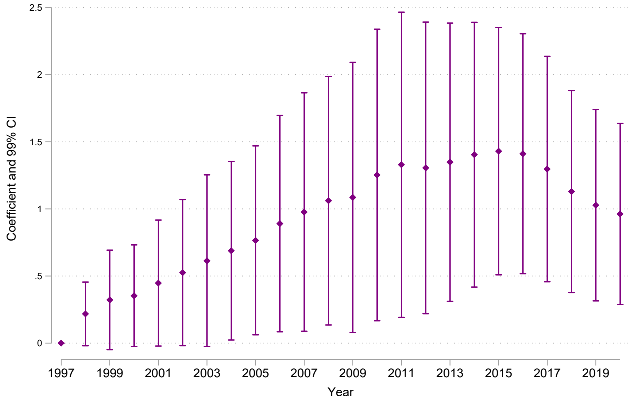
Figure D3: House Elections and Evangelicals and Unionization Political Trends



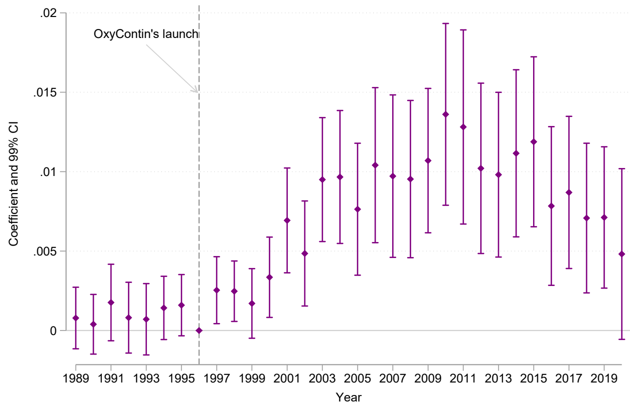
Notes: This figure presents the baseline estimates of the relationship between the Republican vote share and cancer mortality along with estimates in which we flexibly control for political developments. In particular, we control for the number of Evangelical churches in a commuting zone and the unionization rate. The correlation between these and cancer mortality are: 0.16 and 0.13 respectively. This figure is referenced in Section D.2.

Figure D4: County-Level Analysis: Reduced Form Estimates

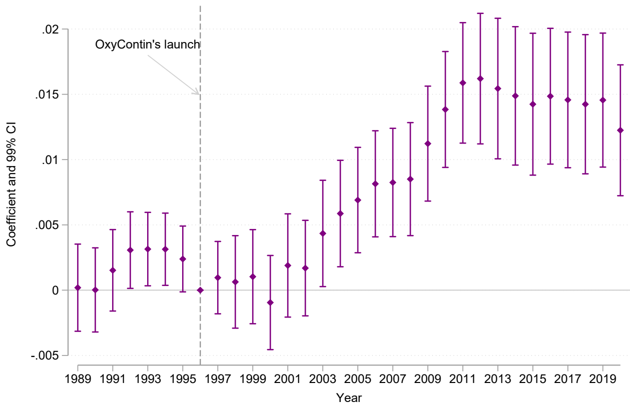
(a) Prescription Opioids



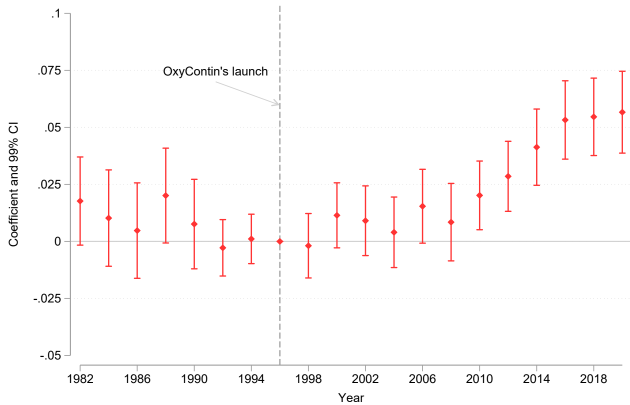
(b) Prescription Opioid Mortality



(c) SNAP



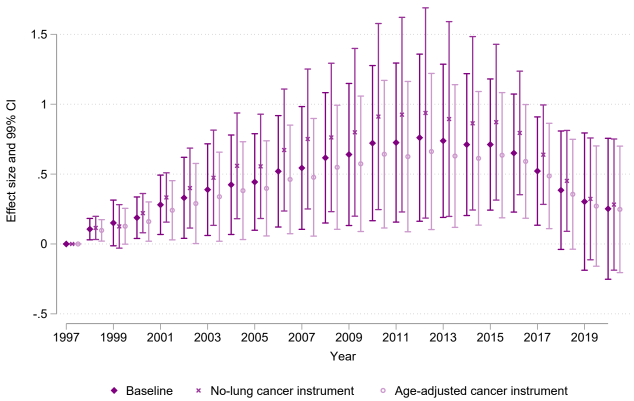
(d) Republican Vote Share



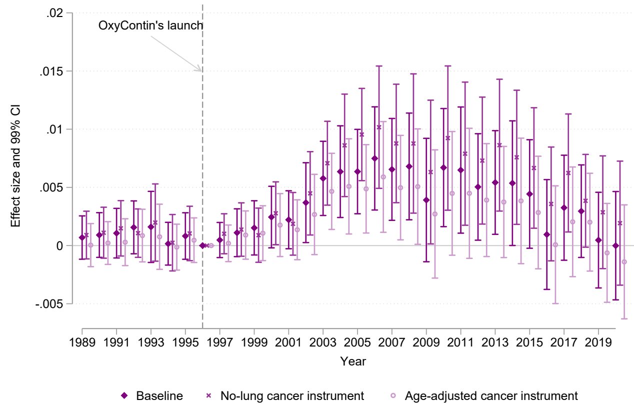
Notes: This figure replicates our baseline estimation, changing the unit of observation from the CZ to the county. The sample includes counties with populations of more than 15,000 in 1996. This figure is referenced in Section D.3.

Figure D5: Baseline, Non-Lung, and Age-Adjusted Cancer Mortality

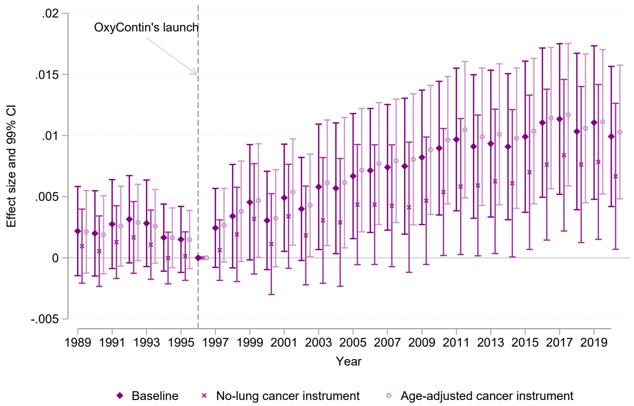
(a) Prescription Opioids



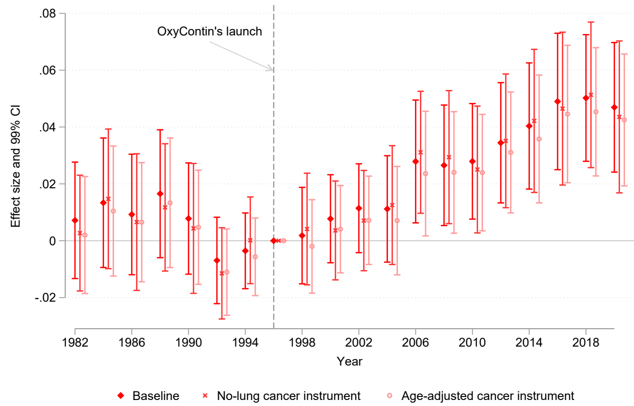
(b) Prescription Opioid Mortality



(c) SNAP



(d) Republican Vote Share



Notes: This figure presents the effects of the opioid epidemic on the four main outcomes of this paper using our baseline measure—i.e., 1996 cancer mortality—and alternative measures of exposure to the crisis. The 1996 cancer mortality rate has a mean of 2.53 deaths per 1,000 and a standard deviation of 0.59. Non-lung cancer mortality has a mean of 0.68 deaths per 1,000 and a standard deviation of 0.21. The age-adjusted cancer mortality rate has a mean of 2.49 per 1,000 and a standard deviation of 0.59. This figure is referenced in Section D.4.

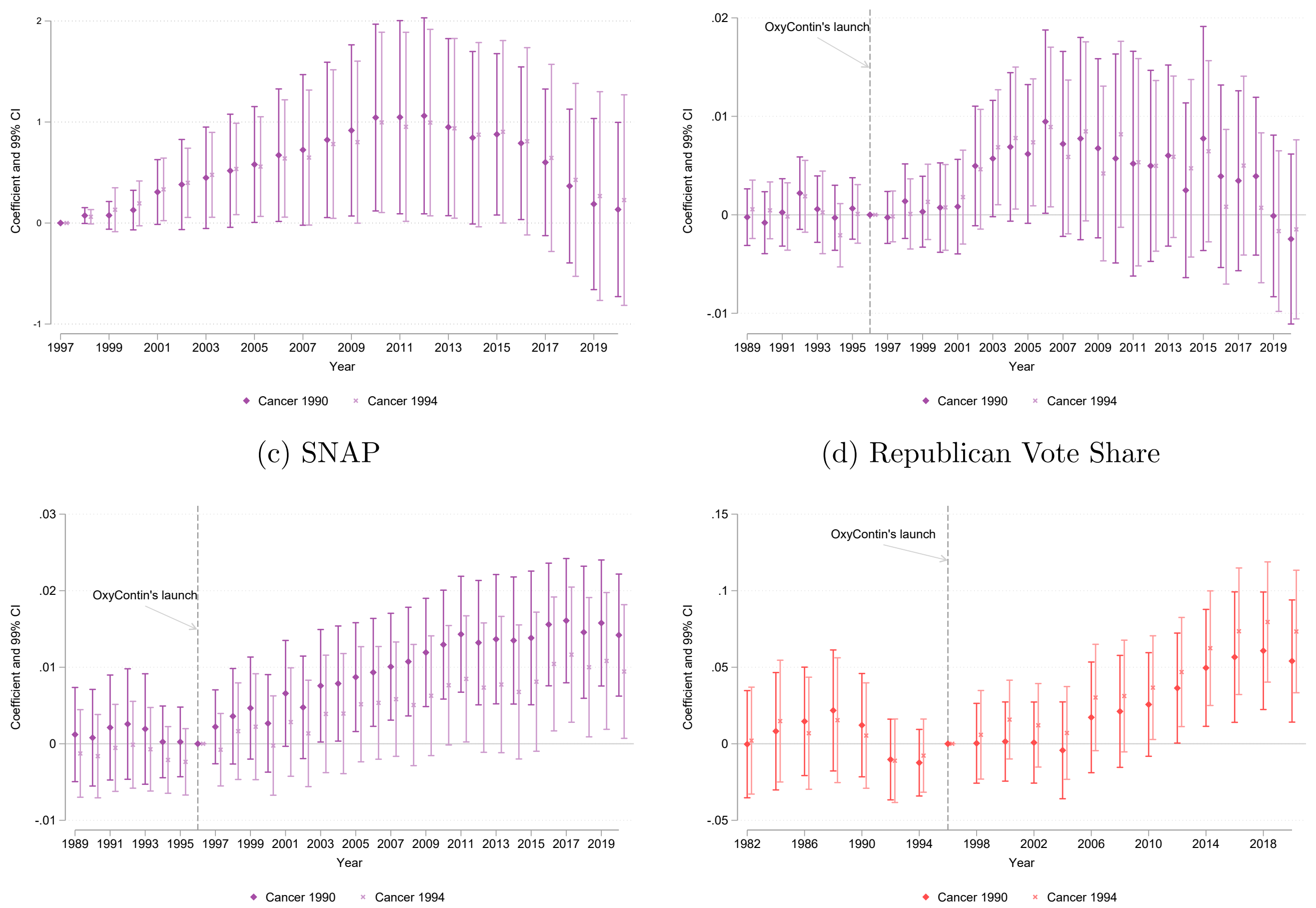
Figure D6: Alternative Measure of Exposure: 1990 and 1994 Cancer Mortality

(a) Prescription Opioids

(b) Prescription Opioid Mortality

(c) SNAP

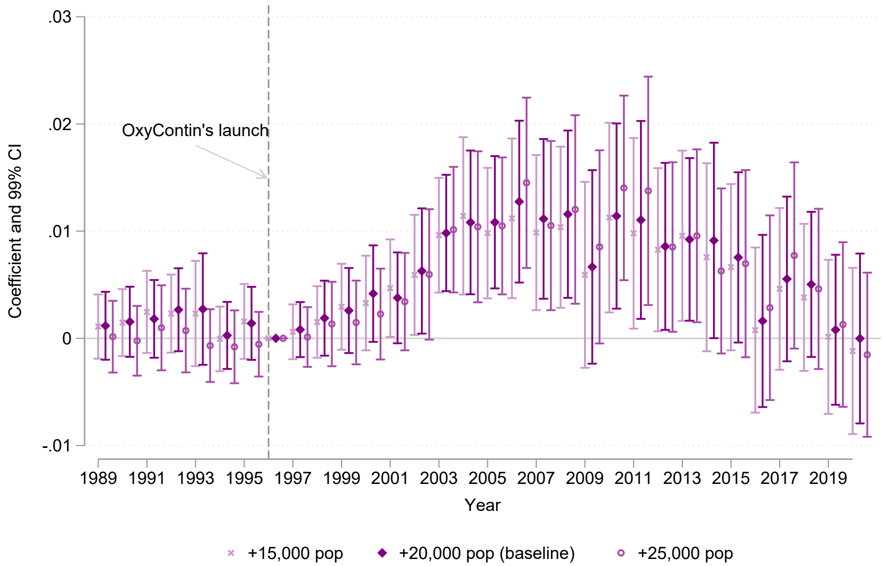
(d) Republican Vote Share



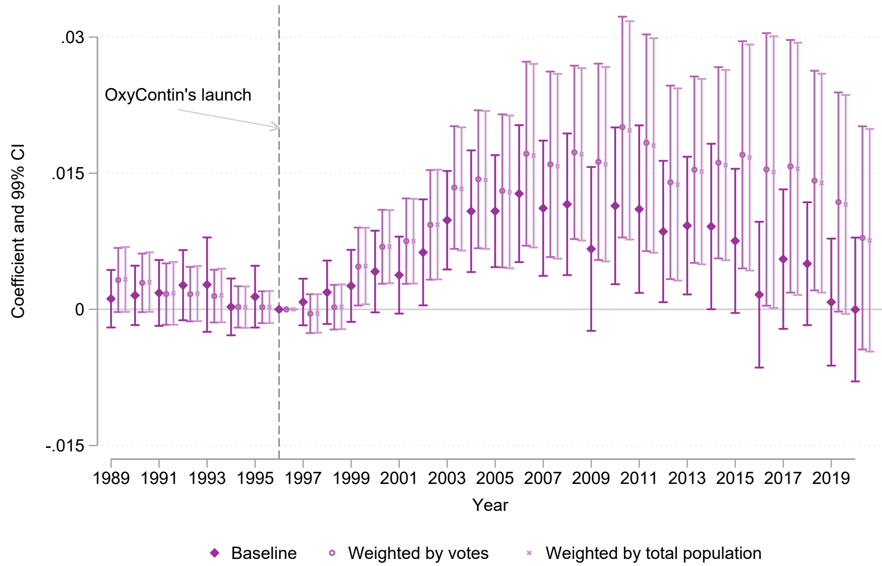
Notes: This figure replicates our baseline estimation, exploiting cancer mortality rates in 1990 and 1994 as measures of exposure to the opioid epidemic. This figure is referenced in Section D.4.

Figure D7: Prescription Opioid Mortality: Alternative Sample Restrictions & Weighted Estimations

(a) Alternative Sample Restrictions



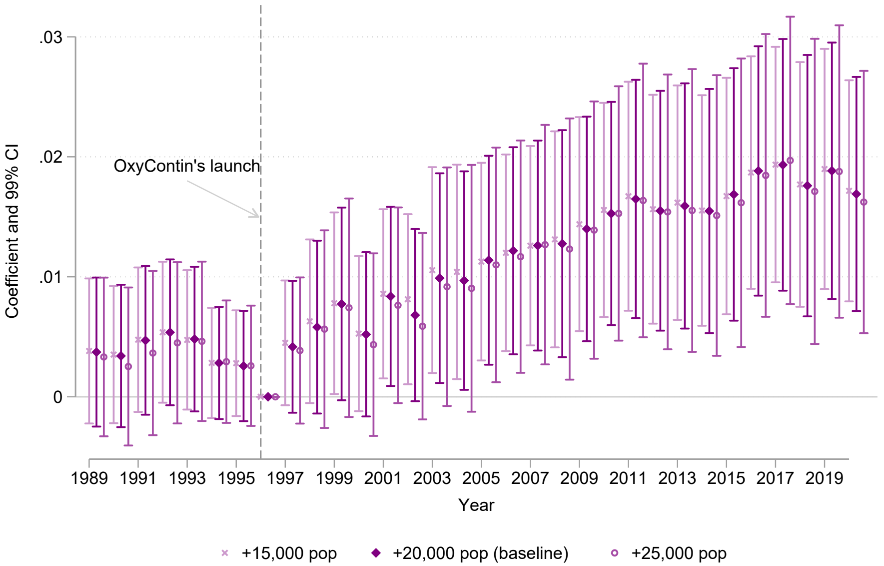
(b) Population-Weighted Estimations



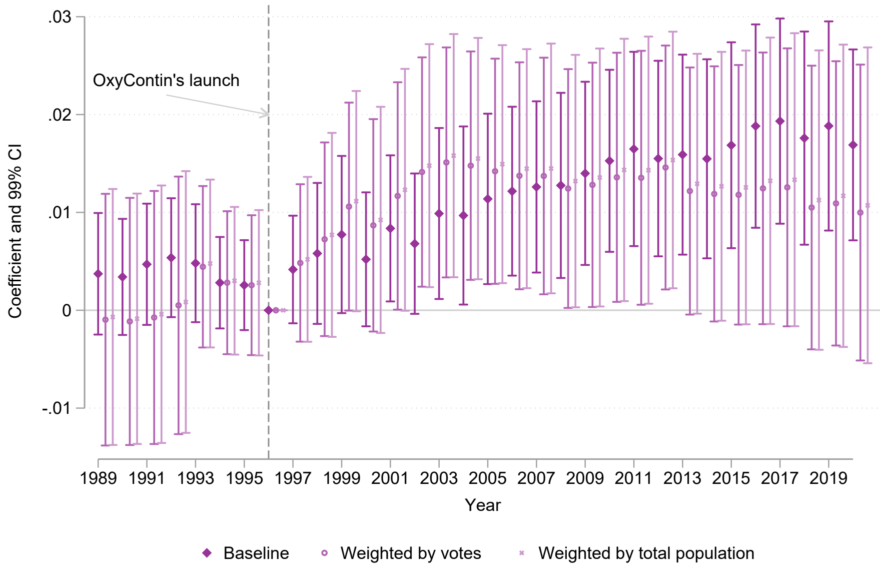
Notes: Panel (a) of this figure replicates our estimates from Figure 5 and adds weighted versions, where the weights correspond to the number of votes and total population over 18 years old. Panel (b) shows the results of our baseline specification without controls, the baseline specification adding 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 D.5.

Figure D8: SNAP: Alternative Sample Restrictions & Weighted Estimations

(a) Alternative Sample Restrictions



(b) Population-Weighted Estimations

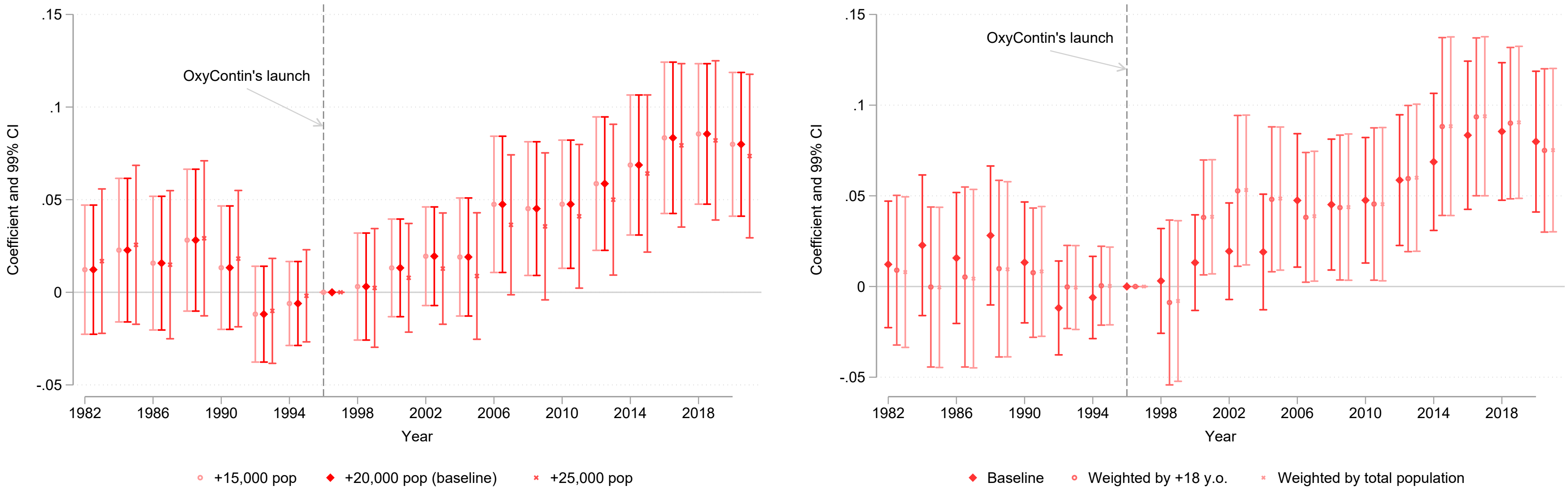


Notes: Panel (a) of this figure replicates our estimates from Figure 5 and adds weighted versions, where the weights correspond to the number of votes and total population over 18 years old. Panel (b) shows the results of our baseline specification without controls, the baseline specification adding 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 D.5.

Figure D9: Republican Vote Share: Alternative Sample Restrictions & Weighted Estimations

(a) Alternative Sample Restrictions

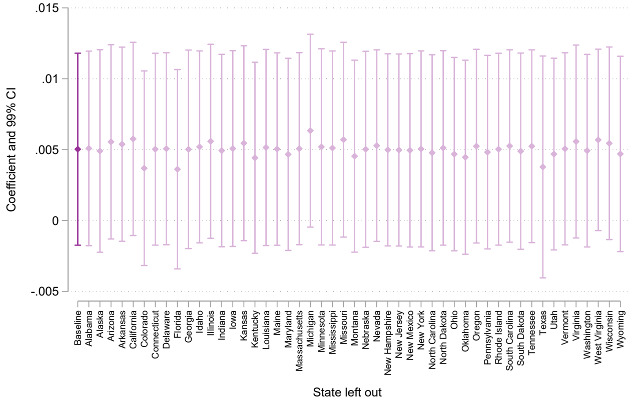
(b) Population-Weighted Estimations



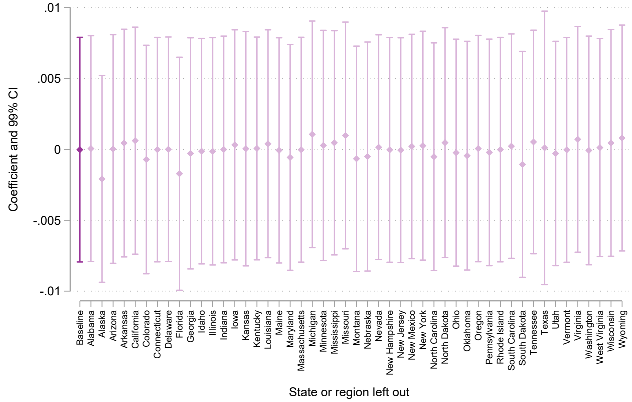
Notes: Panel (a) of this figure replicates our estimates from Figure 5 and adds weighted versions, where the weights correspond to the number of votes and total population over 18 years old. Panel (b) shows the results of our baseline specification without controls, the baseline specification adding 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 D.5.

Figure D10: Estimates of 1996 Cancer-Market Targeting Leaving One State Out for 2018 and 2020

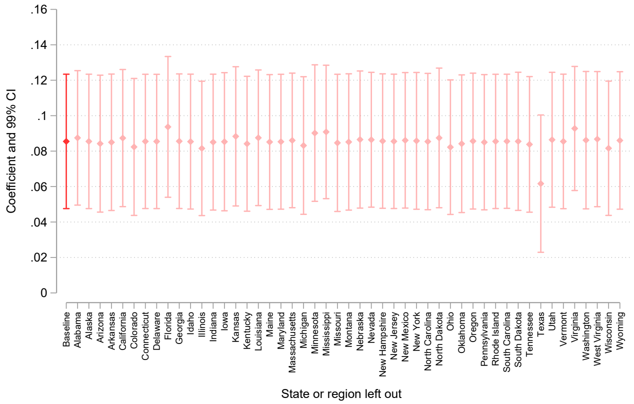
(a) Prescription Opioid Distribution - 2018



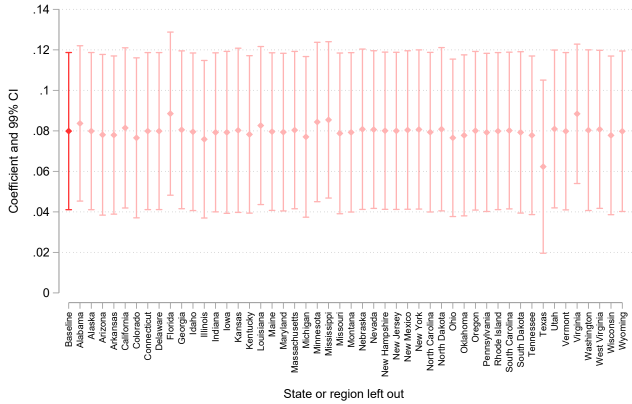
(b) Prescription Opioid Distribution - 2020



(c) House Elections - 2018



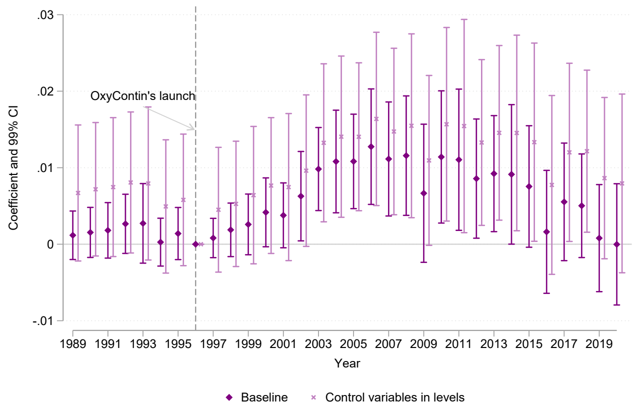
(d) House Elections - 2020



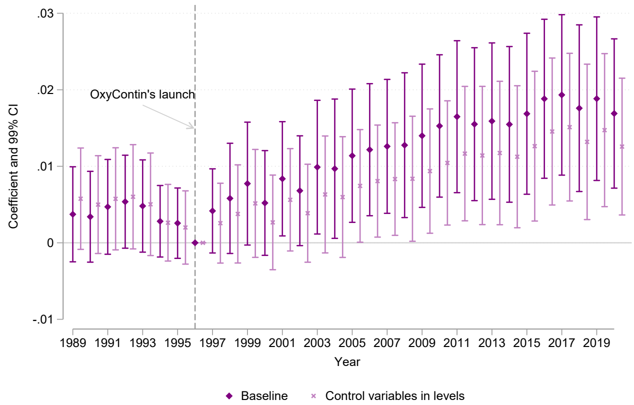
Notes: This figure presents estimates of the 2018 and 2020 coefficients from an event study similar to that in Equations (2) and (3) run on a sample that excludes all CZs in the state indicated on the horizontal axis. Texas has the highest number of CZs, totaling 52. This figure is referenced in Section D.5

Figure D11: Estimates with Control Variables in Levels

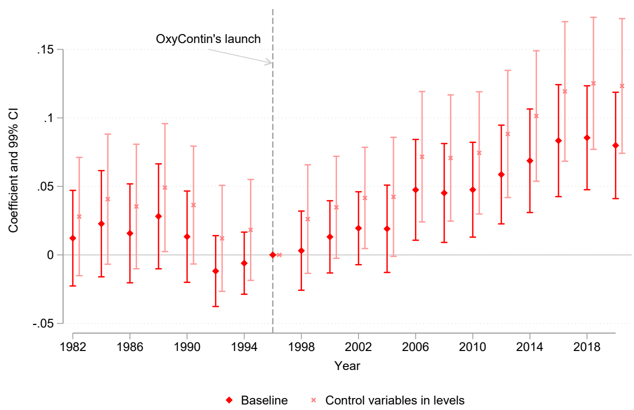
(a) Prescription Opioids Mortality



(b) SNAP share



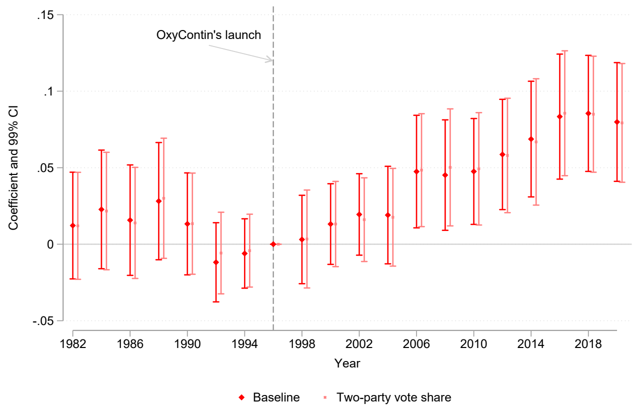
(c) Republican Vote Share in House Elections



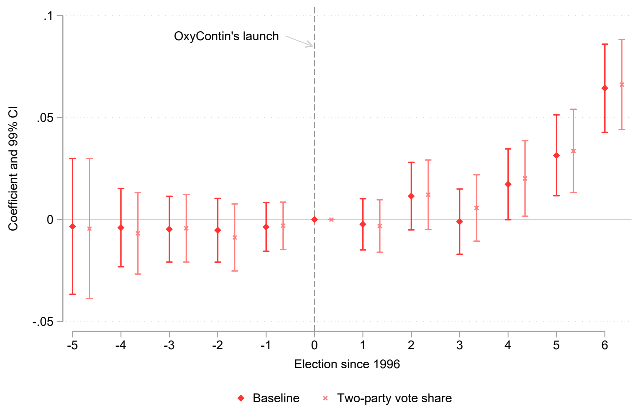
Notes: This figure presents estimates of the dynamic relationship between exposure to the opioid epidemic and prescription opioids mortality, SNAP share, and the Republican vote share in House elections. The control variables in levels are: the white and female population shares, the shares of the population aged 18–29, 30–49, 50–64, and above 65 years, and the share of the population aged under 1 year. The baseline specification control for these same variables expressed in long-changes. Both specifications control for the contemporaneous level of cancer mortality and all variables are expressed at the CZ level. This figure is referenced in Section D.5

Figure D12: Two-Party Vote Share Analysis: Sh. Republican Votes

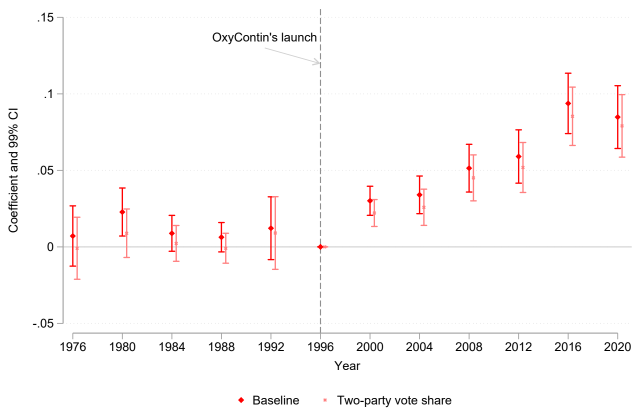
(a) House Elections



(b) Gubernatorial Elections



(c) Presidential Elections



Notes: This figure presents estimates of the dynamic relationship between exposure to the opioid epidemic and the Republican vote share in House, gubernatorial, and presidential elections. In the baseline estimation we compute the Republican vote share as the ratio between votes for Republican candidates and the sum of votes for any candidate. The denominator for the two-party vote share is the sum of votes for Republican and Democratic candidates. This figure is referenced in Section D.6