Democracy and the Opioid Epidemic

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July 24, 2023

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Abstract

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

JEL No. D72, I12, I18, J13.

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Comments are welcomed. We thank seminar participants at the University of Toronto. Gabriela Ramirez and Yanzun Yang provided excellent research assistance.

I. Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

II. The Opioid Epidemic and the Rise in Polarization

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

to increase prescriptions and with weak monitoring, created the perfect platform for the crisis to unfold.

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

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

That is, Purdue exploited its previously established network of cancer patients and their physicians to introduce its newest product to the broader pain market. Purdue Pharma's and its competitors' aggressive marketing of new prescription opioids successfully changed physicians' attitudes around prescribing opioids. Prescribing highly addictive opioids became the standard practice in treating moderate and chronic pain.[3] At

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

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

their peak, opioid prescriptions reached 81.3 prescriptions per 100 persons in 2012 (CDC, 2020). Rates of substance use disorder grew by a factor of six between 1999 and 2009 (Paulozzi et al., 2011), and prescription opioid mortality grew by a factor of five (Maclean et al., 2020).

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

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

In short, over the course of the past 27 years, the opioid epidemic has caused widespread disruption of health and economic outlooks at both the individual and the community levels. Recent work documents that exposure to the epidemic increased the share of the population in SNAP and disability programs, fertility, and the fraction of children living away from a parent and raised the rates of child removals (Gihleb et al., 2022; Buckles et al., 2022; Arteaga and Barone, 2023, Park and Powell, 2021). These changes are likely to have impacted the absolute and relative socioeconomic standing of individuals and communities affected by the epidemic. In turn, this could have translated into divergent political and policy preferences. Contemporaneously, political polarization and party tribalism in the United States have increased dramatically, creating divisions in society and stifling policy progress (Boxell et al., 2020; Afrouzi et al., 2022). The share of Americans consistently expressing conservative or liberal views doubled between 1994 and 2017 (Doherty et al., 2017). Political elites, particularly members of Congress across parties, increasingly disagree on policy issues (McCarty et al., 2016), and the content of political speech is more polarized (Gentzkow et al., 2019; Card et al., 2022). Support for partisan leaders is increasingly divided along party lines; the differences in presidential approval ratings across parties were 85 and 75 points for presidents Donald Trump and Barack Obama, respectively, relative to approximately 38 points for president George H.W. Bush in the early 1990s (Jones, 2021).

These trends stem from multiple factors, including the rise of social media and the

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

segmentation of media exposure, which has reduced the overlap of information viewed by partisans (Di Tella et al., 2021; Levy, 2021; Allcott et al., 2020; Jo, 2017; Barberá et al., 2015), the introduction of widely available decentralized propaganda or "fake news" (Azzimonti and Fernandes, 2018), new internet platforms for leaders to share their ideas, and the emergence of new media platforms (DellaVigna and Kaplan, 2007). This paper explores an additional explanation: the drifting trends in the health and socioeconomic outlooks of communities differentially affected by the opioid epidemic.

III. Data and Descriptive Statistics

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

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

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

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

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

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

of support for the Republican party in the mid-1990s. Panel (d) shows changes in the Republican vote share in 2020 relative to that in 1996.

We construct measures of political views and preferences using survey data from the American National Election Study (ANES) and the Cooperative Congressional Election Study (CCES). Additionally, we use the data constructed by Card et al. (2022) to measure the ideological positioning and views of elected politicians. These and the ANES data are collected at the electoral district level. We use the crosswalks developed by Ferrara et al. (2021) to compute the outcomes of interest at the commuting zone level.

In sum, our final dataset consists of a panel of 625 commuting zones from 1982 to 2020.[7] We restrict our sample to areas with more than 20,000 residents, which account for more than 99% of all opioid deaths and 99% of the total population.

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

IV. Empirical Strategy

IV.a. Causal Effects

To identify the effect of the opioid epidemic on political outcomes, we exploit rich quasi-exogenous geographic variation in opioid epidemic exposure driven by the marketing practices of prescription opioid manufacturers. We proxy the exposure to the epidemic using cancer mortality in the mid-1990s. For each outcome variable, we consider the following specification, which is run over our sample of commuting zones:

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

where c indexes commuting zones, s indexes states, t indexes years, and t_0 corresponds to 1996, the year of OxyContin's launch. We define Δ as the long-change operator: for any

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

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, and 50–64, and the share of population aged under 1 year.

$CancerMR_{ct_0}$ is the cancer mortality rate in commuting zone c in 1996 (t_0) and is interacted with a full set of year dummies indexed by τ. In this specification, the coefficients for the pre-OxyContin period, i.e., ϕ_{1982}, ϕ_{1983}, to ϕ_{1994}, test whether the outcome of interest y_{ct} followed similar trends in areas with higher and lower cancer mortality before the launch of OxyContin.

The term γ_{st} represents state-by-year fixed effects. These fixed effects control for state-specific trends and the state-level policy changes that were common during this period that directly affected the supply of opioids—e.g., the implementation of prescription drug monitoring programs (PDMPs), the regulation of "pill mill" clinics, and policies on the availability of naloxone[8]—as well as the evolution of our outcome variables.

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

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

We start by showing the evolution of prescription opioids per capita by cancer mortality in 1996 in Figure 2. Commuting zones in the top quartile of cancer mortality in 1996 saw an increase of 2,900% in oxycodone gm per capita, while areas in the lowest quartile experienced growth that was one-third of that magnitude, even though the two groups started the period with a comparable prevalence of oxycodone. Panel (b) of Figure 2 shows that there is a positive and statistically significant relationship between mid-1990s cancer mortality and shipments of prescription opioids per capita.

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

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

from zero. In contrast, for the years after 1996, strong patterns appear, and mid-1990s cancer mortality starts to predict opioid-related mortality.

V. Results

V.a. Republican Vote Share in House Elections

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

Election wins and heterogeneity. Whether increases in the Republican vote share translate into election wins depends on how contested districts are and how much the vote increases. We show that even though the Republican vote share started to increase in 2006, it is only for years from 2012 that we start to observe evidence of an increase in the probability of a Republican win (Panel (a) of Figure 4). The main reason behind this pattern is that the initial increases in vote share were concentrated in communities with a low baseline Republican vote share (Panel (b) of Figure 4). Starting in 2014, there began to be vote share increases in communities with a median level of initial vote share, and these increases are more likely to flip election results.

V.b. Additional Results

Presidential elections and turnout. The epidemic's effects on House elections are also present in presidential election results. From the raw data, the Republican party vote share in communities in the top and bottom quartiles of the 1996 cancer incidence distribution trended similarly until the mid-1990s (Figure A1). By the 2000 election, there is a wedge in Republican support that widens as time goes on, and by 2020, the gap in GOP vote shares in areas with high relative to low cancer mortality is greater than 0.15 points. We estimate that an increase of one standard deviation in cancer mortality in the baseline period increased the share of votes for a Republican candidate in presidential elections by 12 percentage points.

These increases in vote share are not driven by differential changes in the extensive margins measured by turnout. We document no notable changes along this margin in Figure A2.

V.c. Mechanisms

These changes in voting patterns are driven not by differential migration across commuting zones but by changes in political views in the incumbent population. We collect data on county-to-county migration flows from the IRS Statistics of Income (SOI) Tax Stats and compute total out-migration flows at the commuting zone level. Figure 5 estimates equation 1 and shows that opioid epidemic exposure is unrelated to differential migration trends.

Next, we use survey data from the ANES and CCES to document changes in political views and preferences as a function of geographic exposure to the opioid epidemic. To maximize power given the small samples in the ANES, in Table 3, we pool data from the pre-period, from 1982 to 1994, and look at the relationship between 1996 cancer mortality and views on immigration and abortion. We do not find any economically or statistically significant correlation between these variables for the period before the onset of the opioid epidemic. On the other hand, when looking at the post-period, either pooling years from the ANES (1996 to 2020) or using the much larger and richer CCES data for 2020, we find that 1996 cancer mortality predicts more conservative views in terms of immigration, abortion, and gun control and more conservative self-reported ideology.[9] This suggests that the wedge between communities that we document in terms of Republican vote share, which arose as a function of their exposure to the opioid epidemic, was also accompanied by a broader polarization in political views.

Finally, we test whether these changes in preferences affected the ideological positioning and views of elected local politicians. We use the data constructed by Card et al. (2022). These data measure the tone of all speeches on immigration given in Congress by House members. The *tone* of the speech is computed in terms of how anti- or pro-immigrant the speech was. We match House members' speeches to commuting zones between 1982 and 2018, the last year available, and estimate equation 1. The goal is to assess whether 1996 cancer mortality is related to differential trends in the anti-immigrant tone of speeches made by House members and to evaluate whether the drifting views on immigration across the general public can be mapped to the views and preferences of elected officials. In Figure A3, we show no pattern between mid-1990s cancer mortality and the pre-period outcomes but also no change in tone when the opioid epidemic began and developed.

[9] We cannot report views on gun control and own ideology in the pre-period, as these questions are not available for those years. The CCES started in 2006, but the questions over the years are not comparable.

VI. Robustness Checks

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

VI.a. Placebo Checks

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

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

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

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

higher NTR gap indicates larger trade liberalization after the passage of PNTR. Our findings are unaffected by the inclusion of this variable in our specification (see Panel (a) of Figure 7). Additionally, we assess whether the 2001 economic recession mediates some of our effects. To do so, we construct a measure of exposure to the recession as the change in the unemployment rate from 2001 to 2000 in the commuting zone. Similarly to our results on the China shock, we find that our instrument and this exposure measure have a very low correlation (ρ=0.03) and that our estimates do not change (see Panel (a) of Figure 7).

The timing of the opioid epidemic coincides with the introduction of Fox News to cable programming in selected locations in October 1996. DellaVigna and Kaplan (2007) show that a higher initial level of exposure to Fox News increases the Republican vote share in the 2000 presidential elections. If Fox News's initial coverage is correlated with cancer incidence, it is possible that some of the effects that we estimate reflect the Fox News effect and not the effects of the opioid epidemic. To investigate this threat, we control for initial Fox News coverage using the data in DellaVigna and Kaplan (2007) and replicate our estimates. The data in DellaVigna and Kaplan (2007) cover only 60% of commuting zones, so there is a substantial loss of sample size, making the results noisy. However, the point estimates are very similar to those from our baseline specification (see Panel (b) of Figure 7).

VI.c. Alternative Samples

In our main specification, we restrict our sample to areas with more than 20,000 residents, which represent 99.5% of the total population. We reproduce our analysis using alternative restrictions on the size of commuting zones. We arrive at conclusions analogous to those from the main analysis: a strong and positive relation exists between mid-1990s cancer mortality and the post-1996 Republican vote share. Finally, we also test whether any given state drives the relationship that we document. In Figure A4, we present estimates of the coefficient corresponding to 2020 and show that our results are stable to the exclusion of any state.

VII. Discussion

This paper provides the first evidence of the political effects of the opioid epidemic. We exploit rich quasi-exogenous geographic variation in opioid epidemic exposure to estimate its effect on the Republican vote share and polarization. We find that the opioid epidemic substantially increased Republican vote shares and started to flip elections by 2012. A one standard deviation higher level of 1996 cancer mortality increased Republican vote share by 13.8 percentage points in the 2020 congressional elections. This rise in Republican support was accompanied by an increase in polarization on immigration,

abortion, gun control and own ideology. This paper documents complex and long-lasting effects of a public health crisis that has touched communities on health, economic and social dimensions and indicates how it will continue to shape these communities through its effects on political outcomes.

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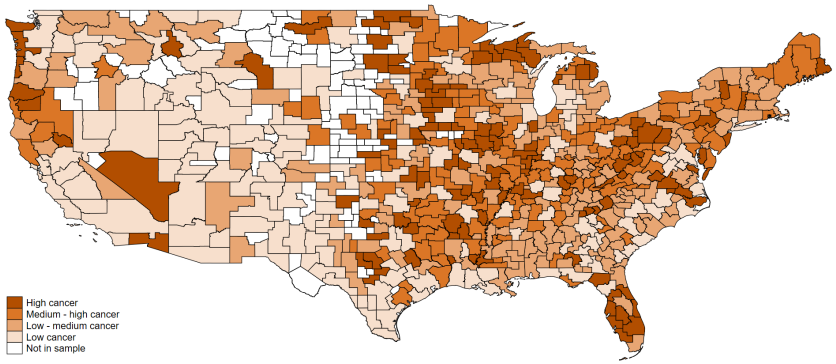
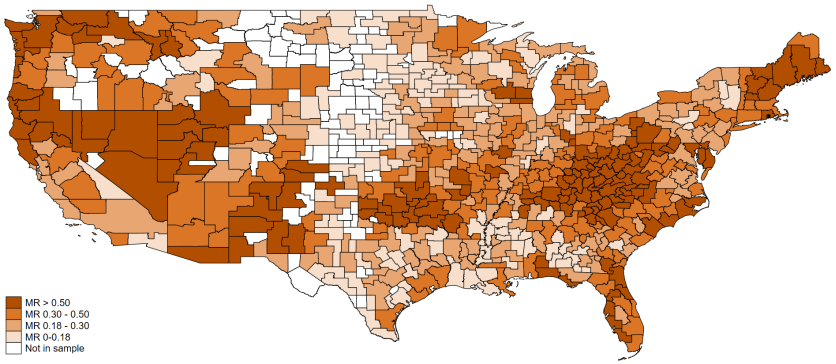
VIII. Figures

Figure 1: Geographical Variation

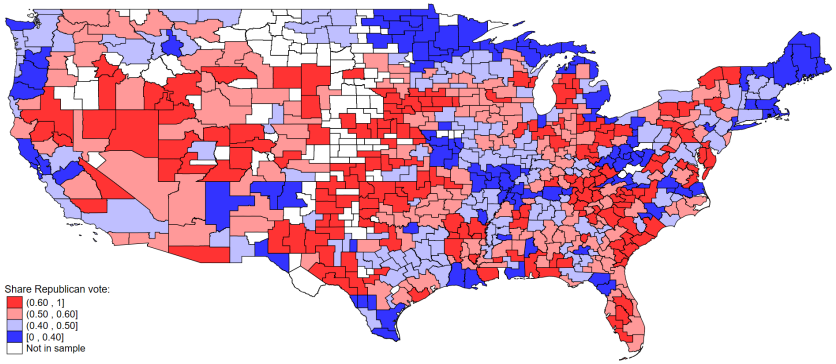
(a) Cancer Mortality Rates, 1996



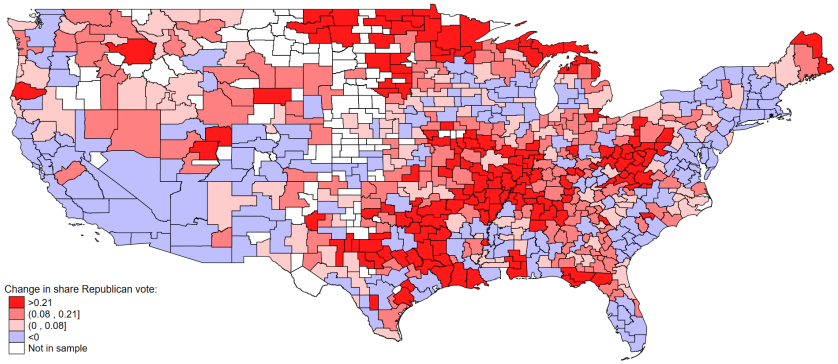
(b) Prescription Opioid Mortality Rate, 1999–2020



(c) Republican Vote Share - Congressional Elections, 1996



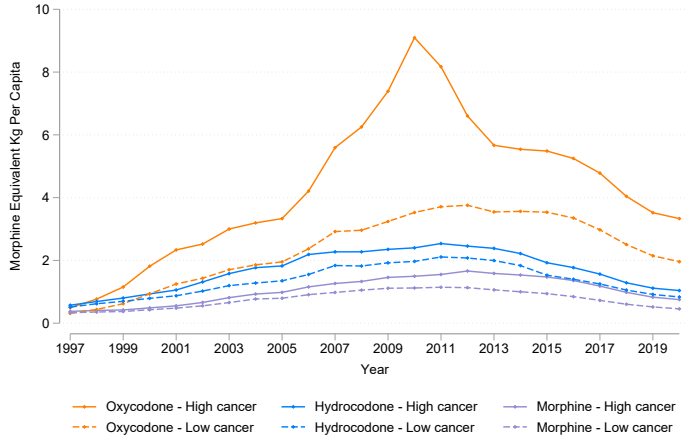
(d) Change in Republican Vote Sh. - Congressional Elections, 2020 – 1996



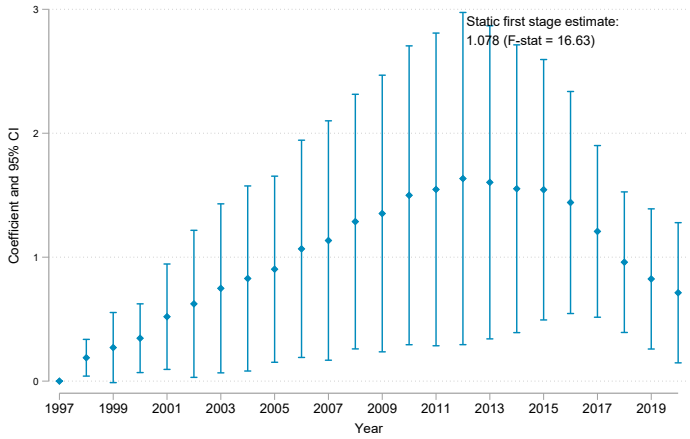
Notes: This figure shows the geographic distribution of our measure of exposure to the opioid epidemic—cancer mortality in 1996—in Panel (a) and the distribution of prescription opioid mortality in Panel (b). Panel (c) shows the geographic distribution of the Republican vote share in congressional elections,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

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

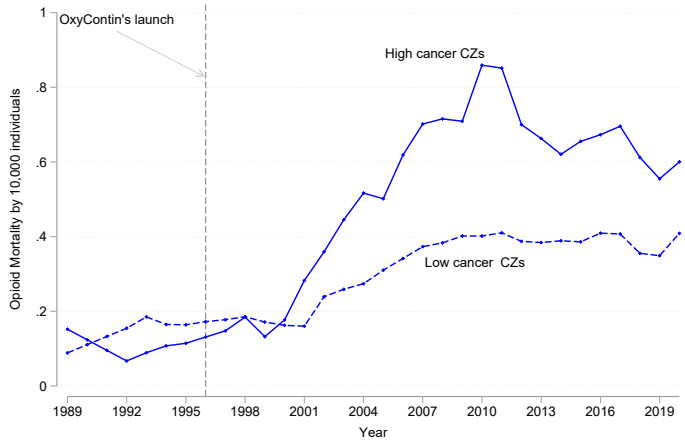
(a) Trends in High- versus Low-Cancer-Mortality CZs



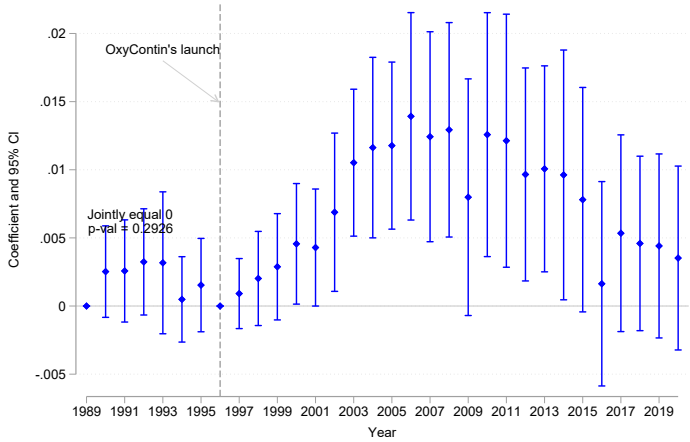
(b) Effects on Prescription Opioid Supply



(c) Trends in Prescription Opioid Mortality



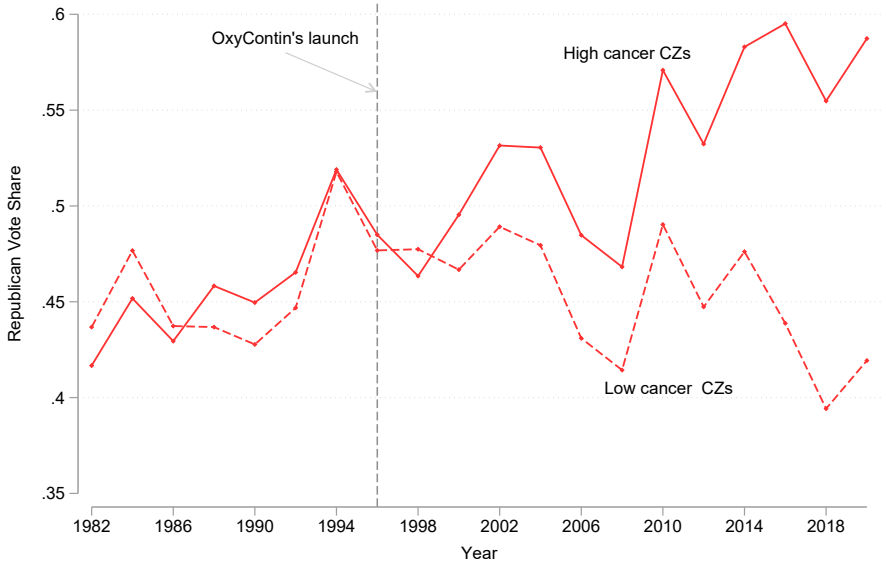
(d) Effects on Prescription Opioid Mortality



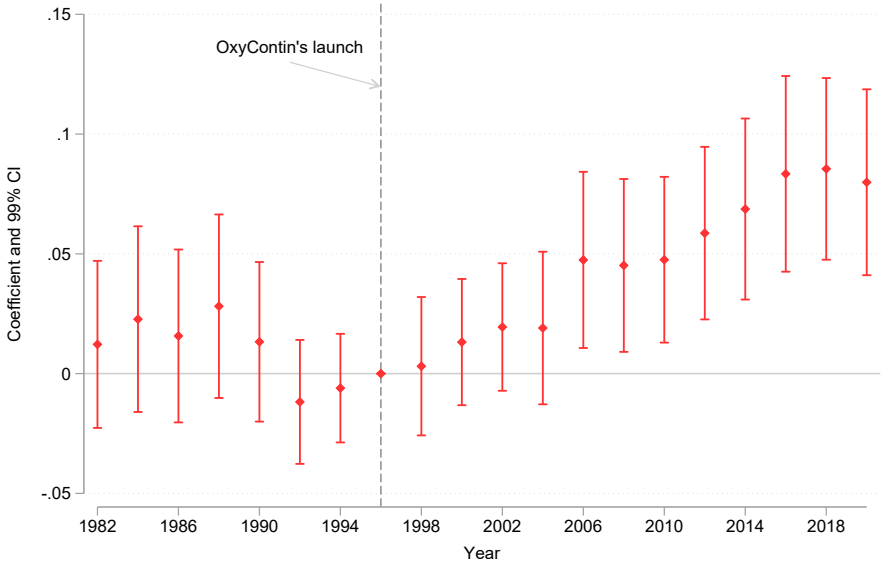
Notes: Panels (a) and (c) show the evolution of the distribution of prescription opioids and mortality in commuting zones (CZs) in the bottom (dashed lines) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Oxycodone is OxyContin's active ingredient. Panels (b) and (d) show estimates of the effects of mid-1990s cancer-market targeting on the distribution of prescription opioids and mortality. ARCOS data are available from 1997. We do not reject the null hypothesis that the estimated coefficients before 1996 $(\phi_{1982}, \phi_{1984}, \ldots, \phi_{1994})$ are jointly equal to zero. The p value of these tests is presented in the figure. This figure is referenced in Section IV.b.

Figure 3: Republican Vote Share: Congressional Elections

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



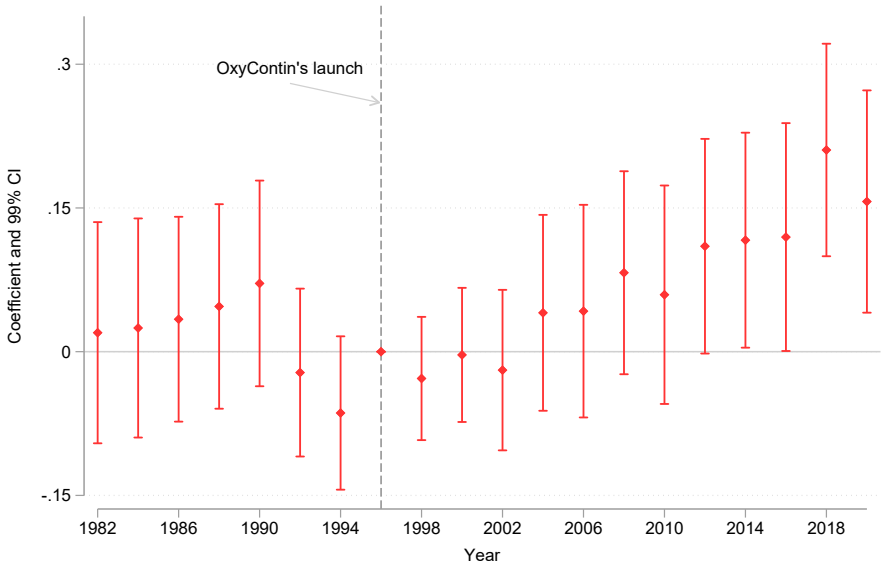
(b) Effects of Mid-1990s Cancer-Market Targeting



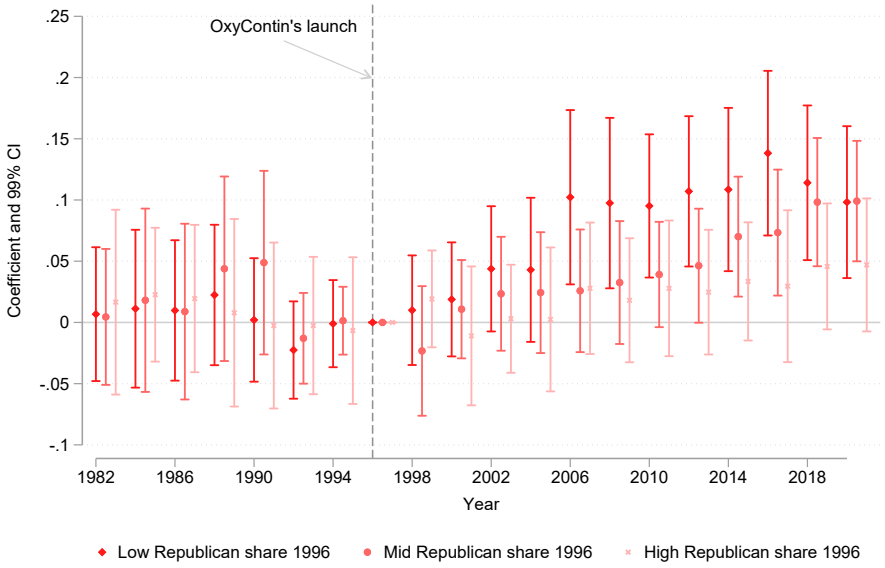
Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in congressional elections in the bottom (dashed line) and top (solid lines) quartiles of cancer mortality before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between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

Figure 4: Congressional Elections: Mechanisms

(a) Republican Candidate Wins a House Seat

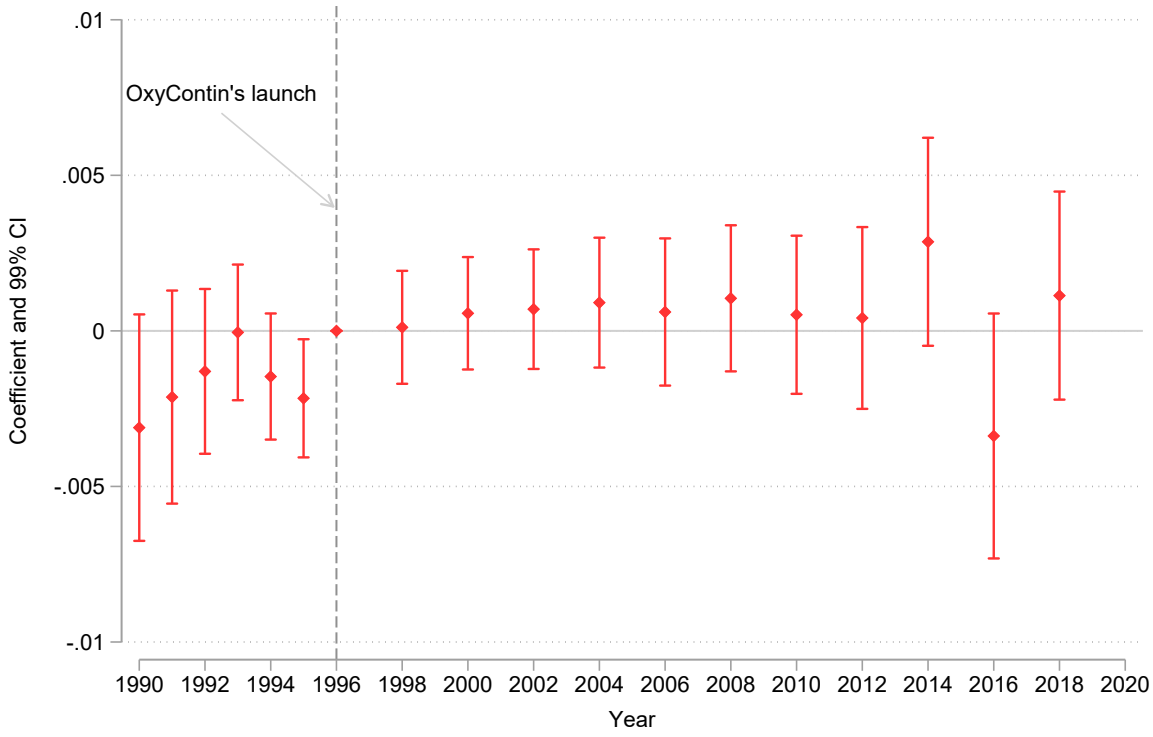


(b) Effects by Tercile of 1996 Republican Vote Share



Notes: Panel (a) presents estimates of the dynamic relationship between the probability that a Republican candidate wins a seat in House elections and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality by the initial level of Republican support in the 1996 House elections. This figure is referenced in Section V.

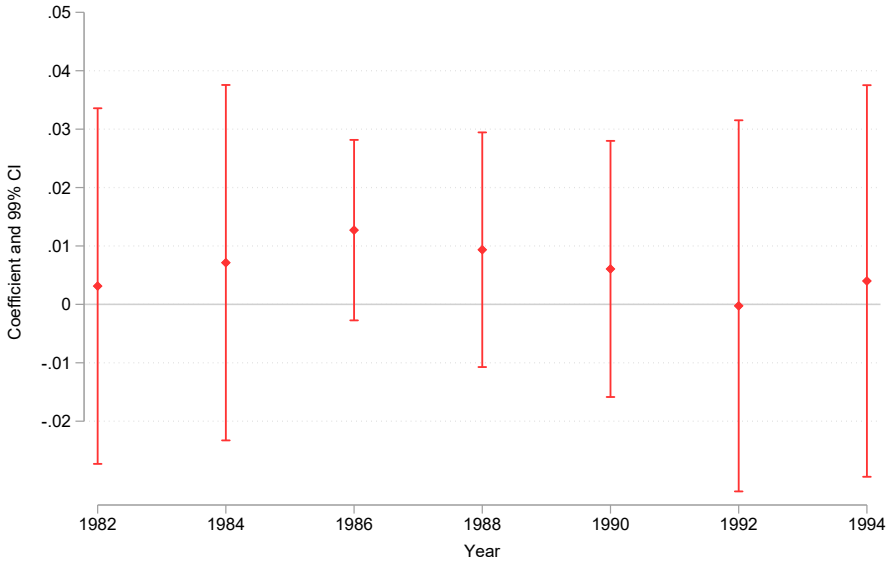
Figure 5: Commuting Zone Out-Migration Flows



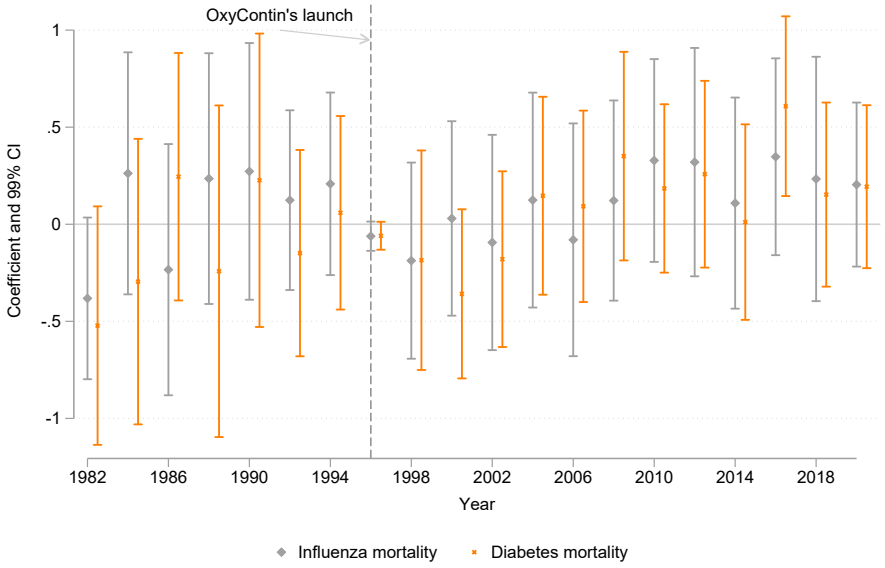
Notes: This figure presents estimates of the dynamic relationship between out-migration and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.

Figure 6: Placebo Checks: Out-of-Sample and Placebo Mortality Rates

(a) Out-of-Sample Analysis



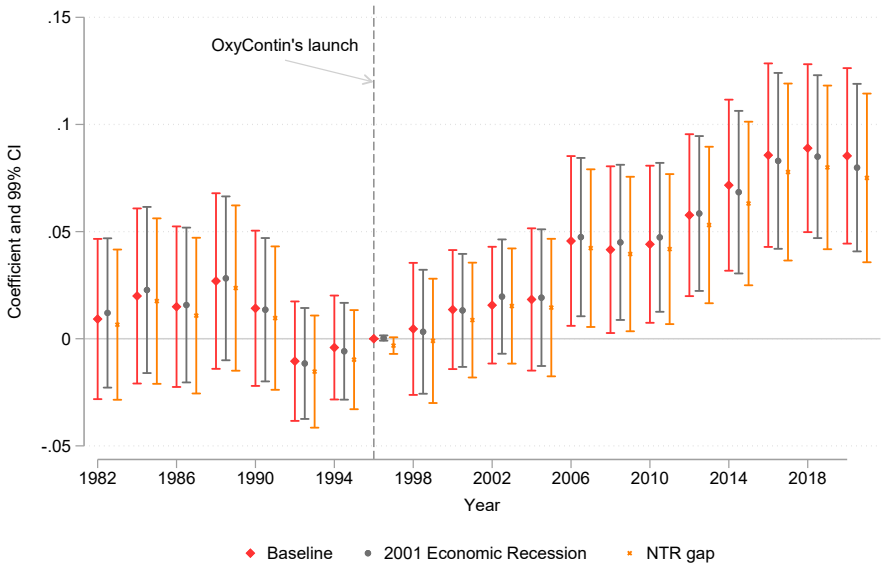
(b) Influenza and Diabetes Mortality



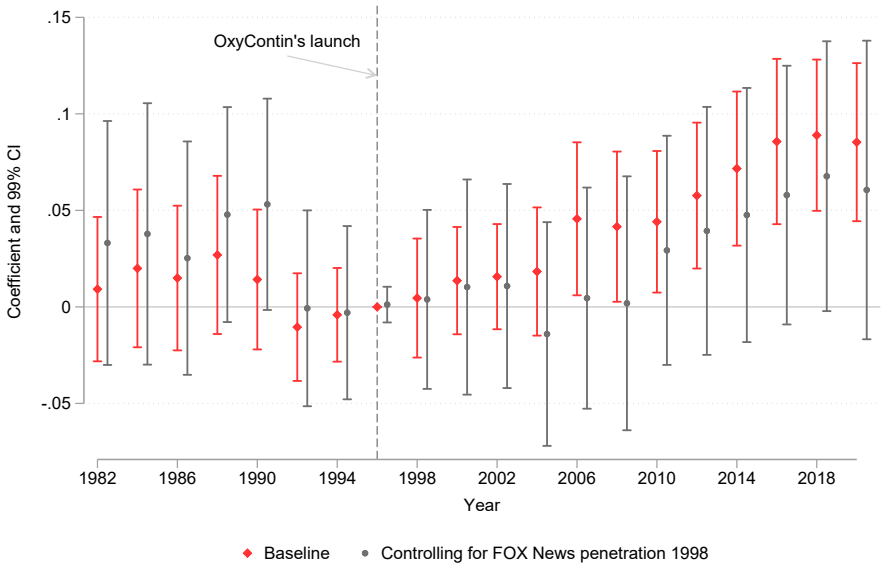
Notes: This figure presents two placebo checks. Panel (a) presents estimates of an out-of-sample dynamic reduced-form analysis for our pre-period. It provides evidence that lagged cancer mortality is not a predictor of future Republican vote share. Panel (b) presents estimates of the dynamic relationship between the Republican vote share and under-50 influenza or diabetes mortality. This figure is referenced in Section VI.

Figure 7: Robustness Checks – Congressional Elections: Economics Shocks and the Introduction of Fox News

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



(b) Introduction of Fox News



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

IX. Tables

Table 1: Summary Statistics

	1982–1995			1996–2020		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
Doses of prescription opioids per capita[(a)]				5.9293	4.9612	4.9227
Cancer mortality per 1,000 (1996)				2.5466	2.5369	0.7606
Cancer mortality per 1,000	2.4185	2.4100	0.5834	2.4907	2.4994	0.5840
Prescription opioids mortality per 10,000[(b)]	0.0652	0.0000	0.1320	0.3537	0.2410	0.4424
Sh. Republican votes	0.4522	0.4665	0.2131	0.5659	0.5782	0.1798

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. This table is referenced in Section III.

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

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

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

Table 3: Mid-1990s Cancer Mortality and Preferences

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

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

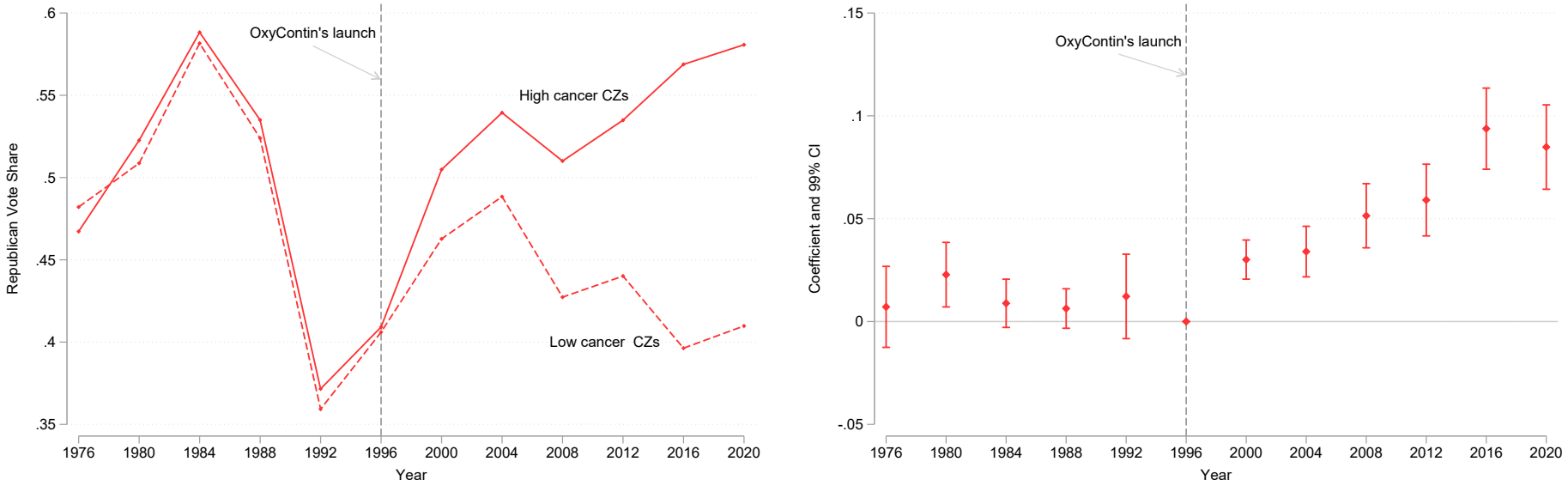
Notes: All variables are coded such that higher values represent liberal/progressive views. ANES Immigration is the thermometer regarding illegal immigration. ANES Abortion corresponds to the item "By law, when should abortion be allowed?" and takes values 1 to 4, where 1="By law, abortion should never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

A Additional Figures

Figure A1: Republican Vote Share: Presidential Elections

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

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

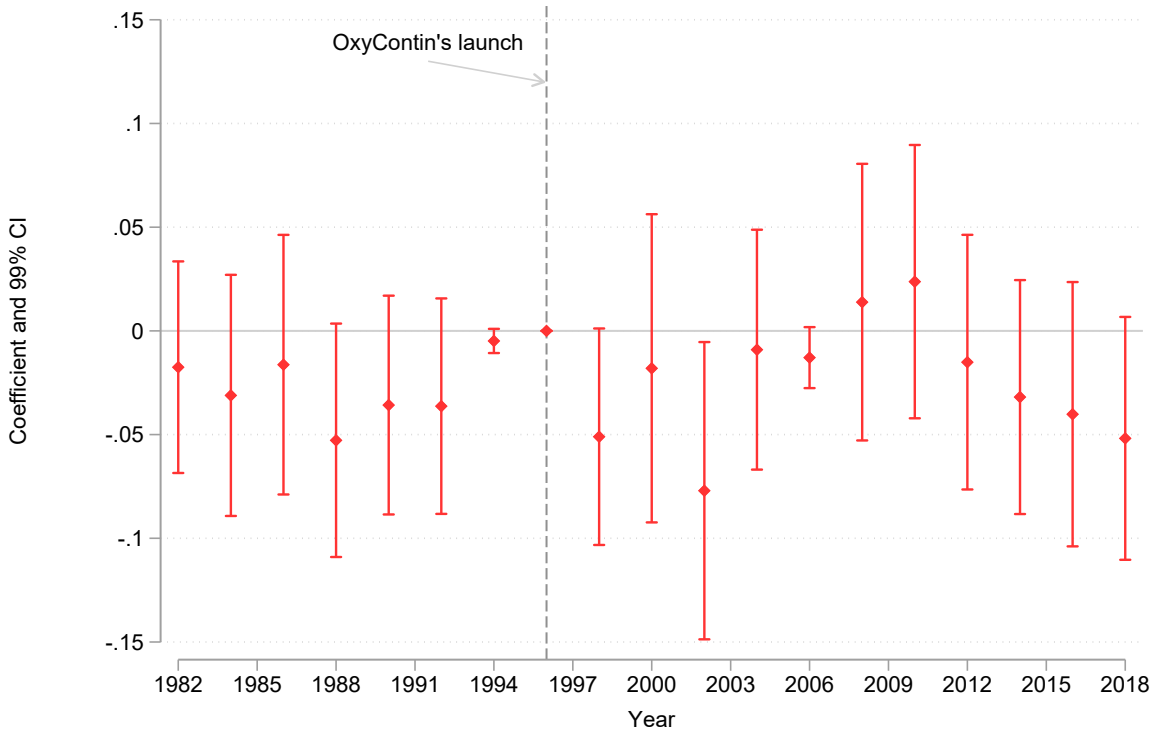


Notes: Panel (a) of this figure shows the evolution of the share of votes for Republican candidates in presidential elections in the bottom (dashed line) and top (solid lines) quartiles of the cancer mortality distribution before the launch of OxyContin. Panel (b) presents estimates of the dynamic relationship between the share of votes for Republican candidates and cancer mortality, our proxy of exposure to the opioid epidemic. We do not reject the null hypothesis that the estimated coefficients before 1996 ($\phi_{1976}, \phi_{1980}, \ldots, \phi_{1992}$) are jointly equal to zero. The p value of these tests is presented in the figures. This figure is referenced in Section V.

Figure A2: Turnout Rates

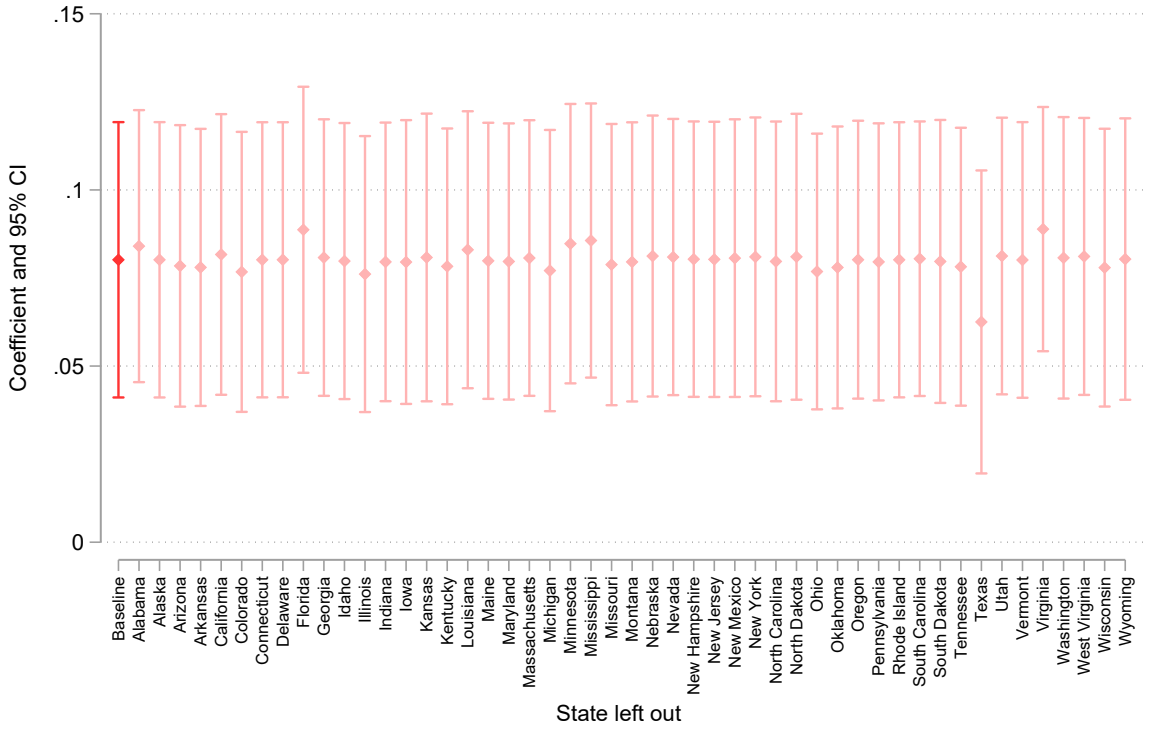
Notes: Panel (a) shows the evolution of turnout rates during presidential election years. Panel (b) presents estimates of the dynamic relationship between turnout rates and mid-1990s cancer mortality, our proxy of exposure to the opioid epidemic. This figure is referenced in Section V.

Figure A3: Tone of Immigration Speeches



Notes: This figure presents estimates of the effects of opioid epidemic exposure on the tone of speeches on immigration given in Congress by House members. Lower values represent a more anti-immigrant tone. This figure is referenced in Section V.

Figure A4: 2020 Coefficients – Leaving One State Out



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