A Hard Pill to Swallow: Spillovers of the Opioid Epidemic on Educational Progress

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Abstract

This paper provides novel estimates of the causal effects of exposure to the opioid epidemic on educational progress for California students. I develop a new time-varying instrument for prescription opioids derived from Purdue Pharma's evolving marketing strategy, which targeted areas with high rates of different diseases over time. Moving from the 25th to the 75th percentile of instrumented opioids per capita, test scores fall by 0.65–1.57% of the mean. High school exit exam pass rates fall by a greater magnitude. Ninth- and tenth-grade dropout rates increase. Estimates from IV regressions are larger in magnitude than those using OLS.

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1 Introduction

A large and robust literature has documented the devastating effects of the opioid epidemic on adult well-being (Maclean et al., 2020); a more recent and burgeoning literature has explored some of the spillovers of the opioid epidemic on children (Brundage and Levine, 2019; Buckles, Evans, and Leiber, 2020). However, there is still much we do not know about the effects of the opioid epidemic on children—particularly the causal effect of the epidemic on human capital accumulation. This is an important omission, as the number of children in the United States living with an adult with opioid use disorder grew by 30% between 2002 and 2017, from 423,000 to 548,000 (Bullinger and Wing, 2019). Existing quasi-experimental research indicates that the opioid epidemic has hurt children along numerous dimensions including birth outcomes and family stability (Arteaga and Barone, 2022; Buckles, Evans, and Leiber, 2020). Shorter gestation inhibits fetal brain development, and family instability further limits the ability of parents to invest in their children's human capital development. These mechanisms—along with numerous indirect effects, including negative spillovers from affected peers—provide reason to be concerned about the effects of the opioid crisis on children's academic achievement and attainment. This paper provides novel estimates of the causal effects of exposure to the opioid epidemic on educational progress for California students.

As prescription opioid use in a community is likely related to both observable and unobservable factors that affect human capital development, I use an instrumental variable strategy to estimate the causal effect of community opioid use on education outcomes. I use newly released documents from the UCSF Opioid Industry Documents Library to construct a new time-varying instrument for prescription opioids that follows the changes in marketing strategy described in internal Purdue Pharma documents.[1] This newly proposed instrument is motivated by marketing strategy documents released in response to a lawsuit by the South Florida Sun Sentinel and Orlando Sentinel to make additional records public. Although Purdue Pharma's initial marketing strategy targeted oncologists, the 2000, 2001,

[1]The UCSF Opioid Industry Documents Library launched in 2021 is funded in part by settlement funds from public interest lawsuits against Purdue Pharma by state governments. As of February 2024, this library contained 3,171,159 documents from the proceedings of the numerous lawsuits against Purdue Pharma and other related entities in the pharmaceutical industry.

and 2002 OxyContin Marketing Budget Plans all indicate a shift to potentially lucrative areas in the non-cancer pain market. In particular, these documents describe the evolution of Purdue Pharma's marketing strategy in the early 2000s to build on the momentum previously established with the targeting of oncologists through a redirection of detailers to rheumatologists and other providers treating patients with osteoarthritis. In order to identify the local markets where detailing would be more profitable, pharmaceutical companies have used health data, both public and proprietary, to identify geographical variation in osteoarthritis prevalence and other health conditions over time. Knee replacement surgery is a common procedure to treat osteoarthritis in the elderly. Thus, the interaction of the 1990s cancer rates with contemporaneous knee replacements per capita provides a new time-varying instrument for per capita prescription opioids via Purdue's shifting marketing strategy. This instrument for prescription opioids allows for the identification of the causal effects of the opioid epidemic on educational outcomes.

This study builds on the work by Arteaga and Barone (2022), who first proposed using cancer rates in the mid 1990s as an instrument for the growth of prescription opioids to identify the effects of said growth on opioid mortality, SNAP usage, and birth outcomes. This key paper in the opioids literature recognized that the pharmaceutical company Purdue Pharma, whose marketing strategy drove the early years of the opioid epidemic, initially targeted areas with a high number of cancer patients. Purdue Pharma targeted these areas because, in the late 1990s, the medical community was much more accepting of prescribing opioids to cancer patients than to other patients with chronic pain. A limitation of using 1990s cancer rates as an instrument in the context of my study, however, is that this instrument is time-invariant, precluding the use of county fixed effects. My new instrument allows for identification without additional assumptions regarding the sufficiency of conditioning on only observable variation across counties to meet the exclusion restriction.[2] This time-varying instrument has particular value in in my context, where local unobservable heterogeneity in education inputs captured by county fixed effects may play an important role in determining outcomes.

[2]The authors support their identification strategy by providing reduced form evidence that outcomes followed similar trends in areas with high and low cancer rates prior to the introduction of Oxycontin; but this approach also requires panel data spanning back into the early 1990s, which is unavailable for the educational outcomes I study.

Using newly aggregated and harmonized California education data pulled from the Wayback Machine and other Internet sources, I find strong evidence that the opioid epidemic in communities adversely affected educational progress for children on a wide range of test scores and related outcomes. Moreover, these adverse effects are substantially underestimated by OLS. Although the popular press has associated the opioid epidemic with poor economic conditions, the majority of opioids are prescribed to employed people with private health insurance and not to low-income people on Medicaid (Currie et al., 2019). Thus, the relationship between community opioid use and educational outcomes in OLS regression may be biased upward by higher employment rates among affected families and by other positive factors contributing to private insurance use in a county.

Moving from the 25th to the 75th percentile of instrumented per capita prescription opioids, standardized test scores fall by 0.65% to 1.57% of the mean. High school exit exam scores fall by a similar magnitude, and pass rates fall more dramatically by 3% to 4% percent of mean pass rates. The larger effect sizes found for pass rates suggest that the opioid epidemic has been even more detrimental to the learning of students at the left tail of the achievement distribution. I find no evidence of overall changes in dropout rates, but ninth- and tenth-grade dropout rates increase, suggesting a shift toward students dropping out earlier, conditional on dropping out of high school at all. The magnitude of effects I find in California are comparable to the effect that Aizer et al. (2018) find for the test scores of third graders in Rhode Island when serum lead increases from zero detectable lead to the average level of detectable lead. These results are robust to alternate specifications, including using Arteaga and Barone's (2022) original instrument and using opioid hospitalization rates instead of opioid shipment rates as the measure of community opioid use.

This paper highlights that the impact of the opioid epidemic on education is larger than what has been documented by prior literature. Comparing with Cotti et al. (2020), who provide the richest set of controls in the descriptive literature, the instrumental variable models in this paper find aggregate effects that are 20 to 40 percent larger, measured with much more precision. These substantial negative impacts suggest direct effects on human capital accumulation, which have important implications for long-run economic outcomes of affected children. These estimates bridge a knowledge gap in the academic literature and inform potential policy action to combat the intergenerational impacts of the epidemic.

2 Background and Conceptual Framework

Existing quasi-experimental studies have not looked at the effects of the opioid crisis on education. Most of the existing economics literature studying the effects of the opioid epidemic on children has relied on identification stemming from differences in state-level policies, which has limited the outcomes researchers can evaluate.[3] Since nation-wide education data are not available for years prior to 2009, which is nearly the peak of the second wave of the opioid epidemic, effects of the opioid epidemic on educational outcomes are particularly difficult to study using identification from state-level policies. One notable exception in the literature that uses local variation in the intensity of the opioid epidemic to identify causal effects of the opioid epidemic on children is the work of Evans, Harris, and Kessler (2022). Evans, Harris, and Kessler (2022) use an identification strategy at the county level that exploits the reformulation of OxyContin in 2010 as an exogenous shock to opioid users, and they show that the reformulation of OxyContin actually increased child abuse and neglect as addicts substituted away from prescription opioids and toward heroin. Yet the identification strategy employed by Evans, Harris, and Kessler (2022) is limited to measuring the effects of heroin use in the second wave of the opioid epidemic. I show that negative affects on education began in the first wave of the opioid epidemic, which was characterized by the abuse of prescription opioids.

Past work evaluating the relationship between the opioid epidemic and education has primarily been descriptive. Using test-score data from the Stanford Educational Data Archive (SEDA) for 2009 through 2014, Darolia, Owen, and Tyler (2023) document a negative relationship between a county's drug-related mortality rate and standardized test scores. Using the same data, Drescher and colleagues (2023) estimate a negative association between community opioid prescribing and learning rates as measured by the linear grade slope on average test scores. Cotti, Gordanier, and Ozturk (2020) use a longer panel from South Carolina

[3] Buckles, Evans, and Leiber (2020) exploit differences in state-level triplicate prescription pad programs to estimate the causal effect of the opioid epidemic on children living away from parents and find that, had the opioid epidemic not worsened after 1996, 1.5 million fewer children under the age of 17 would have been living away from their parents in 2015. Bullinger and Ward (2021) study the effects of prescription drug monitoring programs, Good Samaritan laws, pain clinic regulations, and naloxone access laws—all again at the state level—on foster care entrance rates but find mixed results in terms of magnitude and direction of effects. Gihleb, Giuntella, and Zhang (2019) and Evans, Harris, and Kessler (2022) study the effects of mandatory prescription drug monitoring programs, but they find conflicting evidence with respect to the effects of these programs on child abuse and neglect.

and also find a negative correlation between county-level opioid prescribing and student test scores for white students. There are, however, important confounds that weaken the relationship between opioids and adverse educational outcomes in descriptive work. Because the majority of opioids are initially prescribed to employed people with private health insurance (Currie et al., 2019), there is reason to believe that the relative (initial) stability of many people addicted to opioids may obscure the negative impacts of this drug use on their children. Thus, descriptive evaluations of the relationship between the opioid epidemic and education may understate the magnitude of the problem, as these communities may also have advantages with respect to investment in children's education.

There are several mechanisms through which the opioid epidemic may adversely impact human capital development. The economics literature has documented that the opioid epidemic has increased non-marital births, reduced pregnancy duration, decreased Apgar scores, increased the frequency with which children live with relatives other than their parents, and ultimately increased foster care entry (Bullinger and Ward, 2019; Buckles et al., 2022; Arteaga and Barone, 2022). Poor birth outcomes reflect reduced fetal brain development, with lasting effects on IQ and educational attainment (Black et al., 2007). The increase in foster care entry attributable to the opioid crisis also suggests parental opioid use as an underlying cause of child abuse and neglect, which represent extreme forms of low parental investment in children as another mechanism. Although the literature on the causal effects of *marginal* foster care placement on child outcomes shows mixed results, the effects of removal on educational outcomes are more clearly positive when parents of removed children make sufficient improvements to their parenting skills to enable reunification—further supporting the role of home environment in human capital acquisition (Gross and Baron, 2022).

Community-level factors such as the degradation of social cohesion and the diminishing availability of community role models are more difficult to quantify, but descriptive and theoretical work from social work research suggests potentially large effects of community-wide spillovers of the opioid epidemic on children and parents whose neighbors are affected by addiction (Drescher et al., 2023). Neighborhoods with higher social cohesion have lower rates of child neglect, which may suggest that neighbors sometimes make investments in children beyond their own (Maguire-Jack and Showalter, 2016). When a child's neighbors are affected by opioid addiction, the capacity of the neighborhood to invest in the child's development is diminished. Further research provides evidence that community role models may shape children's attitudes toward education, with downstream consequences on children's behavior in school (Hurd et al., 2009). When more adults in a community suffer from addiction, the availability of positive role models is reduced. Children who live with adults who are addicted to opioids may also have negative peer effects in the classroom. This prediction is in line with Carrell et al. (2018), who find that children's learning is adversely impacted by exposure to "disruptive peers" linked to domestic violence. Finally, there may be diversion of resources to public health efforts to address addiction at the expense of education spending and other programs benefiting children.[4]

While children with direct exposure to the opioid crisis through addicted family members may be more negatively impacted, community-level opioid use is likely sufficient to worsen a child's environment. Because the measures of opioid use utilized in my analysis are measured at the county-level, the effects I find reflect a combination of the effects of community-level opioid use and the intent-to-treat effects of familial opioid use.

The predictions for differences in effects of the opioid crisis for younger versus older children are ambiguous. On one hand, younger children are predicted to be more sensitive to negative inputs when brain plasticity is the highest. On the other hand, past academic achievement is part of the educational achievement production function, which implies that the negative effects of the opioid epidemic could build across years. Aggregate changes in adverse effects with student age will depend on the relative importance of brain plasticity and the ability of students to build upon past learning. The relative importance of these factors may also vary by school subject, as some areas of schooling are more dependent on mastery of prior material in school. Reading at home is important for students' verbal skills, but opportunities to practice math at home are more limited (Guryan et al, 2014). Considering the effects of pre-K as an early positive shock to academic achievement, Gormley at al. (2017) find that Tulsa's pre-K program initially had large positive impacts on language skills, but, by seventh grade, only positive effects on math test scores remained. Past research has also indicated that student response to school inputs are generally larger for math than for language skills (Agüero et al, 20221; Clotfelter et al., 2007), providing an additional

[4]See Darolia et al. (2023) for a more extensive discussion of these mechanisms.

mechanism for differential effects by age and subject as students cumulatively spend relatively more time in school and less time with their families as they get older.

3 Data

3.1 Health and Demographic Data

Prescription opioid data come from the digitized records of the Automation of Reports and Consolidated Orders System (ARCOS) of the Drug Enforcement Administration (DEA) provided by Arteaga and Barone (2022). These include oxycodone, codeine, morphine, fentanyl, hydrocodone, hydromorphone, and meperidine in morphine-equivalent milligrams. The data are available at the 3-digit ZIP level, but I crosswalk these data to the county level using Geocorr from the Missouri Census Data Center. ARCOS is a drug reporting system that tracks the flow of prescription drugs that are regulated by the Drug Enforcement Administration under the Controlled Substances Act. These drugs are monitored from the point of manufacture to the point of distribution (U.S. DOJ).

Cancer mortality rates from 1994 to 2017 used in the main analysis come from the CDC Wonder system, which reports mortality statistics at the county level. Cancer mortality is defined as deaths with ICD-9 codes 140 through 239 and ICD-10 codes C00 through D48 (Neoplasms). The CDC transitioned to the ICD-10 in 1999. Knee replacement data for 1997 through 2015 come from the Dartmouth Atlas. Cross-sectional cancer rates at the county level averaged over 1994 to 1996 and panel knee replacement rates at the year–county level are used to construct my instrument for prescription opioids. Cancer rates after 1996 are used as controls. Additional mortality data used in robustness checks come from the restricted-use National Vitals Statistic System (NVSS). These microdata include the deaths of all individuals who died between 1992 and 2013 (inclusive) and include cause of death and county identifiers.

Opioid-related hospitalization data, which I use as an alternate measure of the intensity of the opioid epidemic, come from two sources. For years 2006 through 2018, these measures are reported on the California Overdose Surveillance Dashboard at the county level. For years 2001 through 2005, I collapse the Public Patient Discharge Data from the California Department of Health Care Access and Information. These data include all discharges from California acute care hospitals. I define opioid-related hospitalizations in the same way as the California Overdose Surveillance Dashboard. A hospitalization is included if either the Principle Diagnosis Code is listed as one of ICD-9 codes 965.00, 965.01, 965.02, or 965.09, or there is any listed external cause of injury with ICD-9 codes E850.0, E850.1, or E850.2[2]. For most observations, patient county of residence is reported. In case of county masking, I assign patients to counties using ZIP5 where available and ZIP3 if ZIP5 is masked. For 2006, a year for which I have both data sources, the correlation between the number of opioid-related hospitalizations in the California Overdose Surveillance Dashboard and in the Public Patient Discharge Data is over 0.99. This finding alleviates the concern that the two data sources are not comparable.

In robustness checks using Arteaga and Barone's (2022) original cross-sectional instrument, I use county-level demographic controls from the Survey of Epidemiology and End Results (SEER) from 1998 through 2017. Demographic controls include the share of the population that is white, the share of the population that is Black, the share of the population that is Hispanic, the share of the population that is female, the share of the population that is under one year of age, the share of the population between ages 18 and 65, and the share of population over age 65. I also add additional time-invariant controls from the 2000 Decennial Census including the percentage of adults in a county with a college degree, the share of the county below the poverty line, the population density, and the mean commute time for workers living in the county. Because this alternate instrument does not allow for the use of county fixed effects, these additional controls are used to control for some observable sources of variation across counties that may relate to cancer rates, educational outcomes, prescription opioid use, or some combination thereof. The time-invariant controls are absorbed by the county fixed effects that are included in the primary specifications using the new instrument.

3.2 Education Data

Education data—including standardized test scores, high school dropout rates, and SAT participation rates—come from the California Department of Education website, either directly or via archived Web pages on the Wayback Machine. In some cases where the Wayback

[2]ICD-9 codes 965.00, 965.01, 965.02, and 965.09 refer to "Poisoning by opium (alkaloids), unspecified," "Poisoning by heroin," "Poisoning by methadone," and "Poisoning by other opiates and related narcotics," respectively. ICD-9 codes E850.0, E850.1, and E850.2 refer to "Accidental poisoning by heroin," "Accidental poisoning by methadone," and "Accidental poisoning by other opiates and related narcotics," respectively.

Machine had not archived actual data files but had archived data-file URLs, data were also accessible directly from the Web even though the California Department of Education had long since removed the associated landing page. Data are either available at the school, district, or county level, depending on the year and the source. I harmonize variables across years and collapse all data to the county level to create a balanced panel of educational outcomes spanning the first and second waves of the opioid epidemic.[5]

One of the primary sources for test-score data comes from the California Standardized Testing and Reporting (STAR) exams, which were administered in California public schools between 1998 and 2013.[6] The components of the exam, as well as which grades were tested, varied over the course of the STAR program. However, all second through sixth graders and all second through eleventh graders took the same form of the California Standards Tests in math and in English Language Arts (ELA), respectively, throughout most of the years that the STAR exams were used. Many California public schools begin dividing math students into different tracks by difficulty level in seventh grade, a practice that resulted in different students in the same grade participating in different exams (e.g., geometry versus algebra)[7]. STAR exam scores are available via the Wayback Machine starting with the first exams in 1998, but I restrict the primary analytic sample to 2002 onward to account for substantial changes to the structure of the ELA exam starting in 2002.

I also use data from the California High School Exit Exam (CAHSEE). California public schools began administering the CAHSEE in 2001 and started requiring students to pass both the math and the English sections of the CAHSEE beginning with the class of 2006, who first took the exam as tenth graders in 2004. The CAHSEE was last administered in 2015, after which it was suspended as a graduation requirement. With the exception of the "trial" year of 2001, high schoolers could begin taking the CAHSEE in their sophomore year and could retake the test until they had passed both sections. In practice, most California high schoolers took and passed both sections of the CAHSEE in their sophomore year of high school. CAHSEE scores are available starting in 2001.

[5] I plan to make this dataset available as a public good for other economics and education researchers.

[6] In 2014, the STAR exams were replaced with the California Assessment of Student Performance and Progress (CAASPP) System. This study does not evaluate changes in CAASPP System scores as they may not be directly comparable to STAR exam scores.

[7] Anecdotally, this system also resulted in some gaming by schools in which students sometimes took a different math exam than the exam corresponding to the class they actually took in a given year.

High school dropout rates are available from 1992 through 2017. SAT take-up rates are available for 1999 through 2015. California also administers physical fitness exams to students in grades five, seven, and nine. These exams come from the Cooper Institute's FitnessGram program and include six different areas: aerobic capacity, body composition (BMI), upper body strength, abdominal strength, trunk extensions, and overall flexibility. Until 2021, all six parts were required, after which the body composition exam became optional. Fitness scores are available for 1999 and then again for 2001 through 2015.

To summarize, all educational outcomes are measured at the county level, with years analyzed subject to data availability and consistency. In my analysis, I use STAR exam scores starting in 2002, CAHSEE exam scores starting in 2001, high school dropout rates starting in 1997, SAT participation rates starting in 1999, and fitness scores starting in 1999 (but excluding the missing year of 2000)—all after the launch of OxyContin in 1996.

4 Empirical Strategy

As discussed earlier, opioid use is not random in the population. Although opioid *death* rates are higher for low-income individuals, the prescription opioid epidemic started and grew with increased prescribing to relatively economically well-off individuals (Currie and Schwandt, 2021). Between 2006 and 2014, 85% of opioids were purchased using employer-sponsored health insurance, and more highly educated counties had higher per capita opioid prescribing (Currie et al., 2019). Thus, counties with higher opioid prescribing may also be counties with ex ante higher parental and community inputs into children's education. To address spacial endogeneity in the growth of the opioid epidemic, I use a new, time-varying instrumental variable, which builds upon the instrument proposed in Arteaga and Barone (2022).

As described in depth in Arteaga and Barone (2022), the introduction of OxyContin in 1996 and subsequent marketing by its manufacturer, Purdue Pharma, dramatically affected the trajectory of the opioid epidemic in the United States. OxyContin differed from previous popular prescription opioid medications in that it was longer acting and did not include a second analgesic such as ibuprofen or acetaminophen to constrain the amount of oxycodone that could be ingested at a time.[8] These two characteristics made OxyContin more addic-

[8]Adding ibuprofen or acetaminophen to opioid medications limits consumption because these additives

tive and more easily abused. Simultaneously, Purdue Pharma launched an unprecedentedly large marketing campaign to change physician prescribing behavior. Although most data that would directly measure Purdue Pharma's marketing efforts are not publicly available, Arteaga and Barone (2022) evaluate initial unsealed court records from the numerous criminal and civil lawsuits brought against Purdue Pharma and document that Purdue Pharma's marketing strategy directly targeted the cancer-pain market, which they further substantiate by showing a strong relationship between mid-1990s cancer rates and limited marketing data that are available via the CMS Open Payments database and Massachusetts court records. Purdue Pharma specifically began their marketing of OxyContin to the cancer-pain market and then expanded efforts in commuting zones that were early and enthusiastic adopters of the new drug. This historical background motivates their use of cancer rates just prior to OxyContin's launch as an instrument for the growth of the opioid epidemic. Arteaga and Barone (2022) argue that local cancer rates in 1994 through 1996 can serve as a proxy for areas with many cancer patients at the time of OxyContin's launch in 1996. Thus, they use these cancer rates as an instrument for the growth of prescription opioids. Figure 1A and 1B show that this geospatial relationship between cancer rates in the mid-1990s and opioids per capita at the peak of the prescription opioid epidemic holds for California counties. Demonstrating this relationship in the context of California in particular is important because California was among the five states with a triplicate prescription program, which reduced (but did not eliminate) the amount of marketing Purdue Pharma pursued in California compared to non-triplicate states (Alpert et al., 2022). Table 1 shows California-specific means of opioids per capita in 2000, in 2015, and over the 16-year period between 2000 and 2015.

The time-invariant nature of their instrument, however, precludes the use of county fixed effects. Arteaga and Barone (2022) partially mitigate this limitation of their instrument through the use of long changes, but the identification assumptions in their approach are relatively strong in the context of education and potentially sensitive to the choice of base year.[9] Interpretation of second-stage results from instrumental variables regressions is

can cause complications such as gastrointestinal bleeding or acute liver failure if more than the directed dosage is taken.

[9]Spierdijk (2022) also notes that fixed effects estimators can be recast as the "weighted matrix average of differences estimators," suggesting fewer researcher degrees of freedom when using fixed effects.

also more complicated with the long-difference estimator, reducing comparability with other studies in the education domain. For these reasons, I develop a new instrument to overcome these limitations, incorporating new information about the trajectory of Purdue Pharma's marketing strategy.

Using new court documents from the UCSF Opioid Industry Documents Library, I document the next step in Purdue Pharma's evolving marketing strategy. Although the initial marketing strategy targeted oncologists, one of the first areas of expansion identified in Purdue Pharma's marketing meetings was the arthritis market. The 2000, 2001, and 2002 OxyContin Marketing Budget Plans all stress the targeting of rheumatologists and patients with osteoarthritis (see Appendix Figure A1). After a successful penetration of the cancer market, the non-cancer pain market clearly became Purdue Pharma's target in the early 2000s (see Appendix Figure A2). This documented shift in marketing priorities motivates my new time-varying instrument, which accounts for both the initial marketing strategy and the growing marketing in areas that already had a higher presence of physician detailing. This relationship is seen in Figure 2, which shows the average opioids per capita in counties with above-median knee replacements[10] and below-median knee replacements, split by whether the county had above-median 1990s cancer rates or below-median 1990s cancer rates. After 2000, counties with high knee replacement rates experienced a rapid growth in opioids per capita and diverged from counties with low replacement rates, but only when the 1990s cancer rates had been high. Figure 3 shows a snapshot of the distribution of knee replacements per capita in California in 2010 for comparison with the distribution of 1990s cancer rates and with opioids per capita as shown in Figure 1.

I thus build upon past work and create a new marketing instrument by interacting the 1990s cancer rates with contemporaneous knee replacements per capita to provide a new time-varying instrument that proxies for Purdue Pharma's marketing strategy across time and space. The UCSF court documents also indicate that Purdue Pharma increased targeting of patients with back pain, with certain types of injuries, and with neuropathic pain, but I focus on knee replacements (used to treat osteoarthritis) because, unlike the other conditions targeted, osteoarthritis is easily verifiable via imaging and other diagnostic tests.[11] This

[10]Knee replacement surgery is primarily used to for the treatment of osteoarthritis when conservative measures fail to relieve pain

[11]Hip replacements are also often used to treat deterioration from osteoarthritis, but hip replacement

aspect of osteoarthritis is important because it limits the concern that drug-seeking behavior may drive the instrument.

The Centers for Medicare and Medicaid launched the Medicare Part D Overutilization Monitoring System in the later half of 2013 to combat opioid prescribing to the elderly, reducing the profitability of marketing opioids to physicians serving the osteoarthritis market (CMS, 2015). Thus, to strengthen my instrument, my primary analyses are restricted to years before 2014.[12]

My instrument that proxies for marketing behaviors is defined as follows:

$$\text{Marketing}_{ct} = \text{Mean Cancer 94-96}_c * \frac{\text{Adjusted Knee Replacements}_{ct}}{\text{County Population}_{ct}} \tag{1}$$

The main specification is as follows:

First Stage:

$$\text{Presc. Opioids}_{\ ct} = \alpha_1 + \phi \text{Marketing}_{\ ct} + \psi \text{Cancer Rate}_{ct} + \chi \text{Percent FFS}_{ct} + \xi_c + \gamma_t + v_{ct} \tag{2}$$

Second Stage:

$$y_{ct} = \tau_1 + \beta \ \widehat{\text{Presc. Opioids}}_{\ ct} + \zeta \text{Cancer Rate}_{ct} + \kappa \text{Percent FFS}_{ct} + \eta_c + \lambda_t + \varepsilon_{ct} \tag{3}$$

where c indexes counties and t indexes time in years. County fixed effects control for all time-invariant variation in outcomes specific to each county. Year fixed effects control for variation in outcomes that is common to all counties in California within a year. I also control for the contemporaneous cancer rate in each county in each year as well as the percent of the population over 65 in fee-for-service Medicare, as the Dartmouth Atlas does not include Medicare Advantage. Standard errors are clustered at the county level and regressions are weighted by the relevant county-level population in each specification.

The parameter β represents the effect of opioid prescriptions per capita induced by Purdue Pharma's marketing strategy on each educational outcome. In order for this marketing

surgery is much less common, has a shorter recovery time, and is associated with much less pain than knee replacement surgery.

[12] Results are similar with the inclusion of additional years of data where available, though the instrument is somewhat weaker.

proxy to be a valid instrument, it must be strongly correlated with prescription opioids per capita but uncorrelated with the error term in the second stage. The population of California provides a large sample size, and I show that the first stage is strong. To further ameliorate concerns regarding weak instruments, however, I also report the Anderson–Rubin p-value and the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022) for each regression. I also consider "placebo" instruments that use other measures of healthcare intensity from the Dartmouth Atlas that are unrelated to opioid marketing to provide evidence that effects are not confounded by common health shocks to counties that could violate the exclusion restriction. California has a total of 58 counties, but data from only 53 counties are available in the ARCOS data. The dropped counties are relatively small. With 53 counties, using Angrist and Pischke's (2008) "rule of 42," I am left with a suitably large number of counties to cluster standard errors.

5 Results

5.1 Primary Results

5.1.1 First Stage

While the strength of the first stage varies with the number of years of data available for each outcome and the weighting variable used, the first stage is generally strong. Table 2 shows the first stage estimate for a range of analytic samples.[13] Using the effective F-statistic developed by Montiel Olea and Pflueger (2013), this statistic ranges between 11.5 and 14.5. The first stage coefficient on the marketing instrument ranges from 19.5 to 30, depending on the sample used in the estimation. Moving from the 25th percentile to the 75th percentile of the marketing instrument corresponds to approximately a 45 to 70 percent increase in prescription opioids per capita, depending on the set of years and weights used in the analysis.[14] Table 3 shows the estimates from placebo instruments that use other measures

[13] The samples vary somewhat since the number of years of data available are different across outcomes.

[14] To better understand the way that 1990s cancer rates and knee replacement rates correspond to the marketing instrument, consider two hypothetical counties, one at the 25th percentile of the instrument and the other at the 75th percentile of the instrument for the years 2002 to 2013. If these two counties had the same 1990s average cancer rate, the county at the 75th percentile would have a knee replacement rate approximately 55 percent higher than the county at the 25th percentile. If these two counties had the same knee replacement rate in a given year, the county at the 75th percentile would have a 1990s cancer rate approximately 55 percent higher than the county at the 25th percentile. The CDF of the marketing instrument for this sample is shown in Appendix Figure A3.

of healthcare utilization in Medicare that are unrelated to opioid marketing instead of knee replacements. None of the six placebo instruments shown in columns 2 through 7 has a significant first stage. These results provide reassurance that the subsequent second stage results are not driven by common health shocks to the population or by the density of the population over age 65 (i.e., the Medicare population) that could create violations of the exclusion restriction.

I further support the validity of my marketing instrument by estimating the reduced form effect of the marketing variable and the effect of instrumented prescription opioids on mortality using data spanning the entire country from 2000 to 2013, the primary period of analysis in this study. I estimate these effects on three measures of opioid mortality at the county level: (1) overall drug overdoses, (2) drug overdoses involving opioids, and (2) drug overdoses involving prescription opioids following the definitions used in Alper et al. (2022). I also estimate the effects of the instrument and of instrumented prescription opioids on two placebo outcomes: (1) deaths from alcohol poisoning and (2) deaths from cardiac disease. Both the reduced form and the instrumental variables estimates support the validity of the instrument. All three measures of opioid deaths have a strong relationship with the marketing instrument and with instrumented prescription opioids. Neither of the placebo mortality outcomes is related to the marketing instrument or with instrumented prescription opioids. The instrument is also (unsurprisingly) much stronger in the national sample with an F-stat of 69.

5.1.2 Student Outcomes

I find strong and consistent evidence that community prescription opioid use decreased STAR exam scores in both math and ELA across the grade distribution. As seen in Tables 4A and 5A, moving from the 25th to the 75th percentile of instrumented prescription opioids per capita, math and ELA test scores fall by 0.65% to 1.57% of the mean in test scores. This magnitude of effects is comparable to the effect that Aizer et al. (2018) find for the test scores of third graders in Rhode Island moving from zero detectable lead to the average level of detectable lead. The point estimates become smaller in magnitude with grade level for ELA scores and larger in magnitude with grade level for math scores, but these differences are not statistically significant. This result provides suggestive evidence that children's language skills may be more adversely affected by community opioid use at younger ages and children's mathematical skills may be more adversely affected by community opioid use at older ages. The point estimate of the effect size for math scores is 54% bigger in sixth grade than in second grade. The point estimate of the effect size for ELA scores is 10% smaller in sixth grade than in second grade, and the effect size continues to fall beyond sixth grade. With more grades for comparison for ELA test scores, the trend toward decreasing effect sizes with each grade in school is visually more apparent in Figure 5. Again, however, the confidence intervals for the effect sizes for ELA scores in grades 2 and grade 11 overlap. This pattern may emerge if ELA skills are relatively more sensitive to reduced inputs in early childhood when language plasticity is the highest. Comparing Table 4A to Table 4B and Table 5A to Table 5B, the instrumental variables models indicate much larger effect sizes than the OLS models, suggesting an upward bias from omitted variables in the absence of the instrument, pushing the coefficient toward zero.

The STAR exam content reflects standards that are specific to each grade level. The CAHSEE exams, by contrast, provide a single measure of student mastery of high school standards. Estimates of the effects of community prescription opioid use on CAHSEE scores and pass rates presented in Table 6 similarly indicate strong negative effects on student learning. Moving from the 25th to the 75th percentile of instrumented prescription opioids per capita, math scores (in column 1) fall by 0.89% and ELA scores (in column 3) fall by 0.59% of the mean. These estimates are of a similar magnitude to those measuring the effects on STAR exam scores. The similarity in the magnitudes of the effects on STAR exams and CAHSEE exams is reassuring, as these exams are given to the same students but at different times in the school year. Moving from the 25th to the 75th percentile of instrumented prescription opioids per capita, pass rates for math and ELA exams (in columns 2 and 4, respectively) fall by three to four percent of the mean pass rates. The fact that the effect sizes for pass rates are larger than the effect sizes for mean scores may reflect more adverse effects of the opioid crisis for students at the left tail of the distribution. This suggests that students who are already struggling to meet educational standards may be more impacted by the spillovers of community opioid use. This result is consistent with Aizer et al. (2018), who find larger effect sizes for the probability of students being below proficient than for mean test scores for students exposed to lead. All estimates with the instrumental variables model in Table 6A are much larger in magnitude than the OLS estimates in Table 6B, again suggesting the importance of accounting for omitted variable bias.

Turning to measures reflective of educational attainment, Table 7 shows the effects of opioids per capita on high school dropout rates for each of grades 9 through 12, overall high school dropout rates, and SAT take-up rates, which are an indicator for college readiness. Changes in overall dropout rates are not significant, but ninth- and (marginally) tenth-grade dropout rates increase with instrumented prescription opioids per capita. This result suggests that, conditional on dropping out of high school, students affected by the opioid crisis drop out at an earlier time, reducing total years of schooling for marginal students. This effect provides evidence that the opioid epidemic has reduced educational attainment as well as achievement for the most vulnerable students. Estimates of the returns to schooling in the United States vary substantially in the existing literature, but there is clear evidence that human capital accumulation matters for long-term outcomes, even among students who do not obtain a degree (Deming, 2023). Table 7 also shows a negative effect of opioids on SAT take-up. Comparing Panel A, which shows instrumental variable estimates, and Panel B, which shows OLS estimates, we yet again see that OLS estimates are biased toward zero.

I also test for effects on physical fitness test scores, but estimates are noisy and show no clear pattern. The sign of point estimates vary both across different elements of the physical fitness exam and across grades measured. These results are not surprising, as most (but not all) of the mechanisms by which community opioid use are likely to affect children operate more strongly through cognitive and emotional channels than through physiological channels. Community opioid use has the potential for numerous types of spillovers on children whose parents may not take opioids themselves. For example, the negative externalities of disruptive peers in the classroom would not have physical effects. Although prenatal exposure to opioids may have strong physiological effects on children, these effects would take many years to manifest, and it is unlikely that accidental opioid poisonings of children would be frequent enough to drive substantial concurrent physical effects. Estimates for physical fitness scores for Grade 7 are presented in Table 8 and for Grade 5 and Grade 9 in the appendix.

5.2 Heterogeneity Analysis

5.2.1 Gender and Socioeconomic Status

Past work measuring gender differences in response to other forms of disadvantage including race, parental martial status, and socioeconomic status has generally found that boys are more sensitive to adversity than girls are (Bertrand and Pan, 2013; Chetty et al, 2016; Autor et al., 2019). Within a community, high-income families may also be able to buffer their children against the adverse effects of the opioid epidemic through private resources unavailable to low-income families. Thus, one might expect differences in the effects of the opioid crisis both by gender and by socioeconomic status. Standardized-test–score reporting practices have changed over time to include many different student subgroups of interest, but STAR test scores by sex and by socioeconomic status were reliably reported by most counties between 2002 and 2013. According to the California Department of Education, students are considered to be socioeconomically disadvantaged if one of the follow conditions is met: "1. neither of the student's parents has received a high school diploma; 2. the student is eligible for or participating in the Free Meal program or Reduced-Price Meal program; 3. the student is eligible for or participating in the Title I Part C Migrant program; 4. the student was considered Homeless; 5. the student was Foster Program Eligible; 6. the student was Directly Certified; 7. the student was enrolled in a Juvenile Course School; 8. the student is eligible as Tribal Foster Youth."

Figures 6A and 6B demonstrate the effect size with respect to test scores moving from the 25th percentile to the 75th percentile of instrumented opioids per capita by grade and gender for STAR math scores and STAR ELA scores, respectively. These figures provide no evidence of heterogeneous treatment effects by gender, with remarkably similar estimates for each group in each grade. Although the past economics literature has typically found that boys' educational outcomes are more affected by adverse childhood experiences, gender gaps in responses to adversity are much lower for test scores than they are for more extreme outcomes such as suspension (Autor et al., 2019). This finding is consistent with the broader literature indicating that girls tend to have less dispersion in outcomes than do boys, leading to a concentration of extreme adverse outcomes among boys. Because I measure only aggregated test scores by gender, my analysis may be missing heterogeneous treatment effects by gender for outcomes not measurable in my data including suspensions and expulsions from school.

Figures 7A and 7B demonstrate the effect size with respect to test scores moving from the 25th percentile to the 75th percentile of instrumented opioids per capita by grade and socioeconomic status for STAR Math scores and STAR ELA scores, respectively. These figures similarly provide no evidence of heterogeneous treatment effects by socioeconomic status, with clearly overlapping confidence intervals in each grade. The point estimates of treatment effects are a little smaller for economically disadvantaged students, so not all estimates are statistically significant for this subgroup; these estimates remain indistinguishable, however, from those from the test scores of students who are not economically disadvantaged. The fact that treatment effects are negative and precise for non-economically disadvantaged students in every grade for both math and ELA tests provides further evidence that the opioid epidemic has had far reaching consequences for individuals across the income distribution. At the same time, test scores are lower on average for economically disadvantaged students, so similar percent reductions in test scores may have more serious consequences for those students.

5.2.2 Treatment Dynamics

As discussed in Section 2, there are many different channels through which the opioid epidemic may adversely affect human capital development. While my primary analysis focuses on contemporaneous measures of community opioid use that best reflect the acute stress of the crisis, many of the mechanisms may have lagged effects that would take time to be reflected in test scores. One would also expect potentially larger lagged effects as prescription opioid users who were initially prescribed opioids for more medically appropriate causes develop inappropriate opioid use over time. Unfortunately, even pooling test scores across grade levels, I lack statistical power to detect significant differences between the effects of contemporaneous opioids per capita and lagged opioids per capita on test scores. The point estimates, however, are in the expected direction, with larger effects of lagged opioids. Results are presented for lags up to five years in Appendix Figures A4 and A5.

6 Robustness Checks

6.1 Using the Cross-Sectional Cancer Instrument

I also estimate all models using the Arteaga and Barone's (2022) original cross-sectional cancer instrument. My preferred specifications use my time-variant instrument because the inclusion of county fixed effects implies weaker identification assumptions in the complex context of childhood education. However, Arteaga and Barone's (2022) instrument and their approach of expressing variables in terms of long changes is conceptually useful because long changes reflect the *cumulative* exposure to community opioid use that students faced.

This alternate specification is as follows:

First Stage:

$$\Delta \text{ Presc. Opioids }_{ct} = \alpha_1 + \phi \text{ Cancer } MR_{ct_0} + \alpha \Delta X_{ct} + \xi Y_c + \gamma_t + v_{ct} \tag{4}$$

Second Stage:

$$\Delta y_{ct} = \tau_1 + \beta \Delta \text{ Presc. Opioids }_{ct} + \tau \Delta X_{ct} + \eta Y_c + \lambda_t + \varepsilon_{ct} \tag{5}$$

where c indexes counties, t indexes time in years, and t_0 is the average of the 1994 to 1996 period. For any random variable $W_{ct}, \Delta W_{ct}$ equals the difference $W_{ct} - W_{c1}$. The vector ΔX_{ct} represents time- and county-varying control variables, including county-level demographics and contemporaneous cancer rates. The vector Y_c represents additional county-level controls from the 2000 Decennial Census that are not reliably measured on a yearly basis, including the percentage of adults in a county with a college degree, the share of the county below the poverty line, the population density, and the mean commute time for workers living in the county. Year fixed effects control for variation in outcomes that is common to all counties in California within a year. Standard errors are clustered at the county level and regressions are weighted by the relevant student population in each specification.

Here, the parameter β represents the effect of a change in opioid prescriptions per capita since the baseline year on the change in educational outcomes measured since that same baseline year.[3] The first stage estimates are presented in Appendix Table A4. Results are presented in Appendix Tables A5 through A9. Generally, estimates are consistent but with larger standard errors than the estimates in my preferred specifications. As in my preferred specifications, the instrumental variables estimates indicate that the OLS estimates are biased toward zero.

6.2 Using Opioid Hospitalization Rates

My main specifications use opioid shipments as the local measure of the intensity of the opioid epidemic, as the ARCOS data provide a less noisy measure of opioid use than do data on opioid hospitalizations. There are, however, two notable pitfalls with utilizing opioid shipments as a measure of community opioid use that using opioid hospitalizations as an alternative measure avoids. First, one threat to identification in my preferred specifications would be potential changes over time in the exportation of prescription opioids across county borders. Opioid hospitalizations more consistently reflect where opioid use occurred over time because ambulance catchment zones are independent of opioid trafficking. Second, ARCOS opioid-shipment data are a measure of community opioid use, but they are not a direct measure of community opioid abuse, the later of which is more likely to negatively affect children. Opioid hospitalizations better reflect inappropriate use of opioids.

To alleviate both of these concerns, I re-estimate the instrumental variables models to measure the effects of the opioid epidemic on educational outcomes using opioid hospitalizations per capita instead of opioid prescriptions per capita as the measure of the intensity of the opioid epidemic. The first stage estimates, presented in Appendix Table A10, are similar in strength to those of the primary specification. Estimates, which are presented in Appendix Tables A11 through A15, are also broadly similar using this measure. The similarity in estimates suggests that the areas with high prescription opioid use driven by Purdue Pharma's marketing strategy are also the same areas with increased opioid abuse during this time period, which is consistent with the dominance of prescription opioids during this phase of the opioid epidemic.

[3] Arteaga and Barone (2022) always use the baseline of year 1997 for opioids per capita, but I prefer to use the earliest baseline year that is available for each outcome for ease of interpretation, because most of my outcomes are only measured starting later than 1997.

7 Conclusion

These results provide strong evidence that the opioid epidemic slowed educational progress in California. The reduction in test scores from the opioid epidemic are both pervasive across grade levels and subjects and economically significant in magnitude. To provide another point of reference, a one standard deviation increase in instrumented prescription opioids per capita corresponds to a decease in average test scores equivalent to 30 percent of the difference in third grade math test scores between socioeconomically disadvantaged students and non-socioeconomically disadvantaged students in California. At a time when test scores and educational attainment improved overall, counties that had greater changes in prescription opioids had smaller improvements in educational outcomes. These results are unlikely merely to reflect regression to the mean, as effects are small in OLS estimates. Despite the popular (and mostly unsubstantiated) narrative that the opioid epidemic was caused by economic distress, most prescription opioids are—and were—purchased by people with private health insurance, who are likely employed (Currie and Schwandt, 2021). Thus, counties that would be more affected by the opioid epidemic may be positively selected with respect to educational outcomes for the children of these more highly employed adults, suggesting one clear source of omitted variable bias in the OLS regressions.

An important limitation of this paper is that I am constrained in evaluating the specific mechanisms by which opioid use affects educational outcomes. Future work should investigate the effects of community opioid use on school attendance, suspensions, and expulsion. These outcomes may be able to indicate behavioral and socio-emotional channels that affect test scores. Children with conduct disorder, for example, often have high rates of suspension and expulsion. Children with conduct disorder also have worse academic performance (Currie and Stabile, 2009). Another limitation of these analyses is that ARCOS opioid-shipment data are a measure of community opioid use but not a direct measure of parental opioid abuse, the latter of which is more likely to negatively affect children. Thus, I am unable to determine to what degree the effects measured in this paper are attributable to the intent-to-treat effects of having a parent who uses opioids versus the community-wide spillovers of the opioid epidemic that affect children without direct exposure. Further data linkages could enable such estimates.

This paper provides the first quasi-experimental estimates of the effects of the opioid epidemic on children's educational outcomes, providing new evidence on the intergenerational impacts of the opioid crisis. Given data availability, the effects mostly pertain to the first and second waves of the opioid epidemic, prior to the widespread use of fentanyl. Yet even in this ongoing third wave of the epidemic, opioid prescribing remains high, contributing to the creation of new opioid addiction with resultant negative effects on children (Currie and Schwandt, 2021). My analysis is also restricted to California, but California is the most populous state in the United States and has a diverse population that reflects much of the demographic variation found throughout the country. Future work is needed to fully understand the mechanisms behind these negative effects of the opioid crisis on childhood human capital accumulation as well as on other potential spillovers on the health, well-being, and development of children affected by community opioid use.

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Figures

Figure 1A. 1990s Cancer Mortality

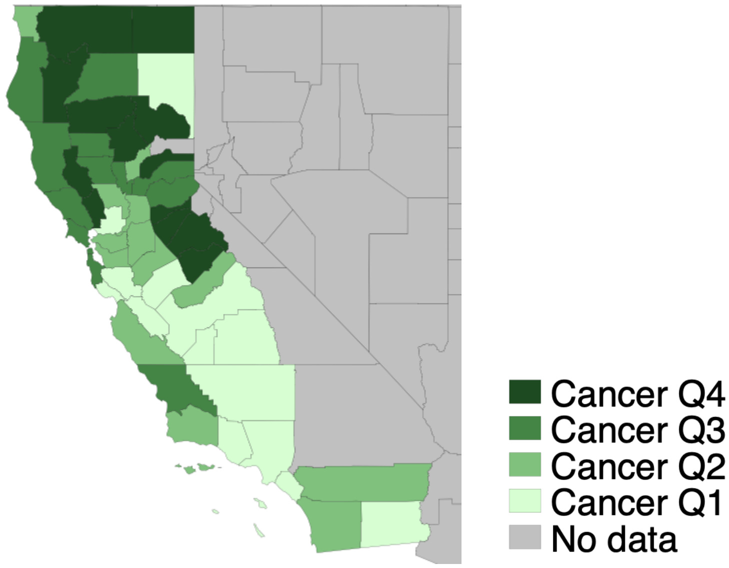

Figure Notes: This figure shows counties in California by their quartile in the state distribution of the average cancer mortality rate in 1994 through 1996. Counties in darker green had higher cancer mortality.

Figure 1B. Opioids Per Capita in 2010

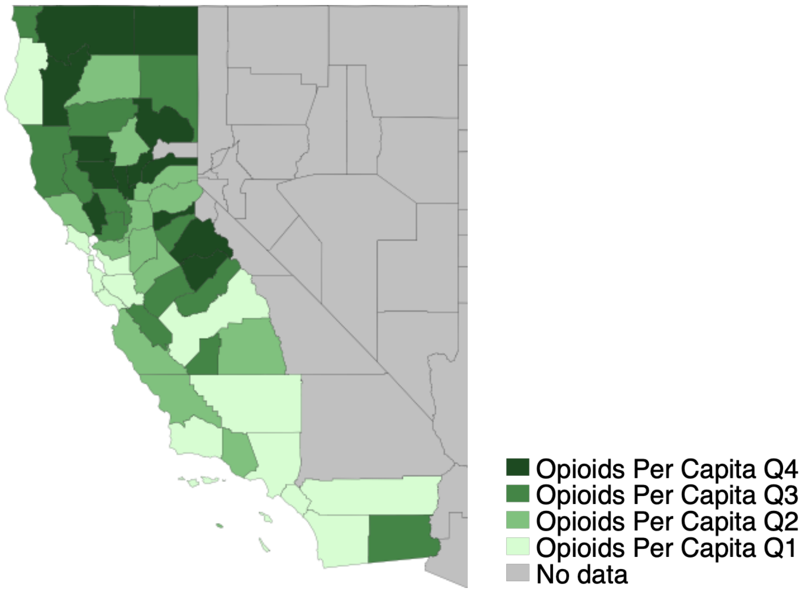

Figure Notes: This figure shows counties in California by their quartile in the state distribution of opioid shipments per capita in 2010. Counties in darker green had more opioids per capita in that year.

Figure 2. Knee Replacements, Cancer, and Opioids in California

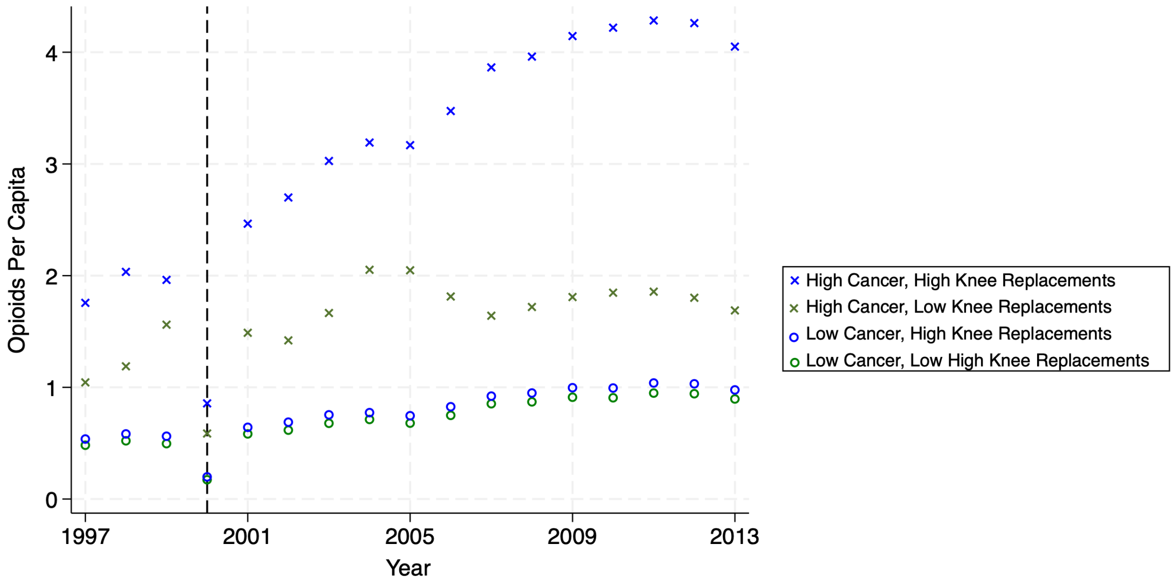

Figure Notes: This figure shows the average opioids per capita in counties with above-median knee replacements (in blue) and below-median knee replacements (in green), split by above-median 1990s cancer rates (in xs) and below-median 1990s cancer rates (in os). The drop in opioids per capita in 2000 is an artifact of how ARCOS reported shipments in that year, which is absorbed by year fixed effects in any analysis that uses data from 2000.

Figure 3. Knee Replacements Per Capita in 2010

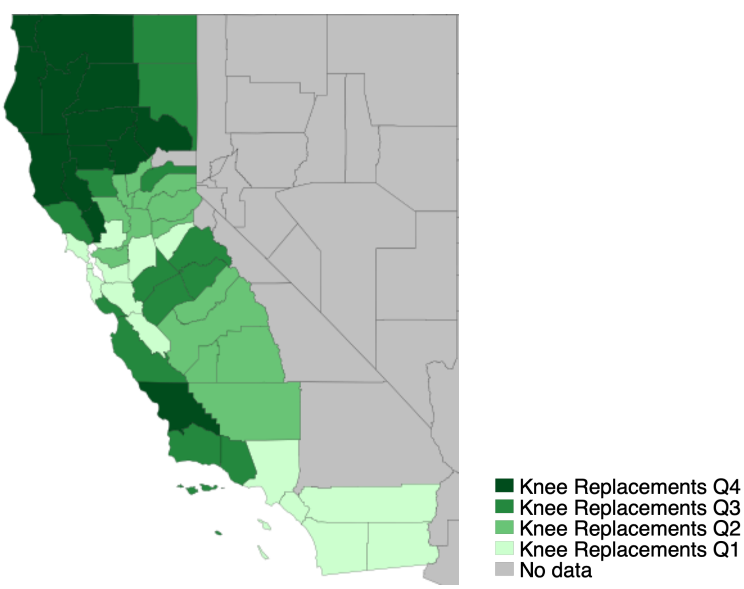

Figure Notes: This figure shows counties in California by their quartile in the state distribution of knee replacements per capita in 2010. Counties in darker green had more knee replacements per capita in that year.

Figure 4. STAR Math Effect Size by Grade

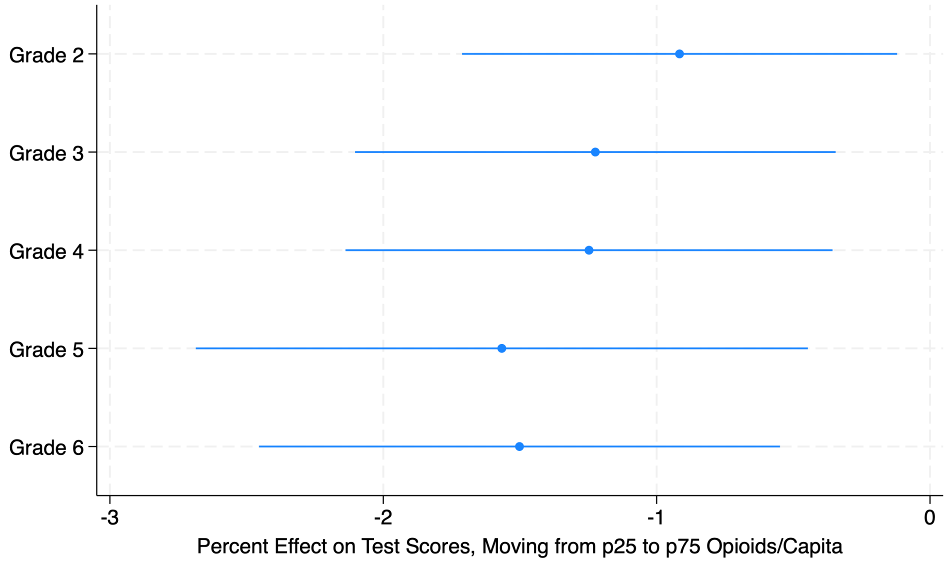

Figure Notes: This figure shows the percent decrease in test scores by grade when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval.

Figure 5. STAR ELA Effect Size by Grade

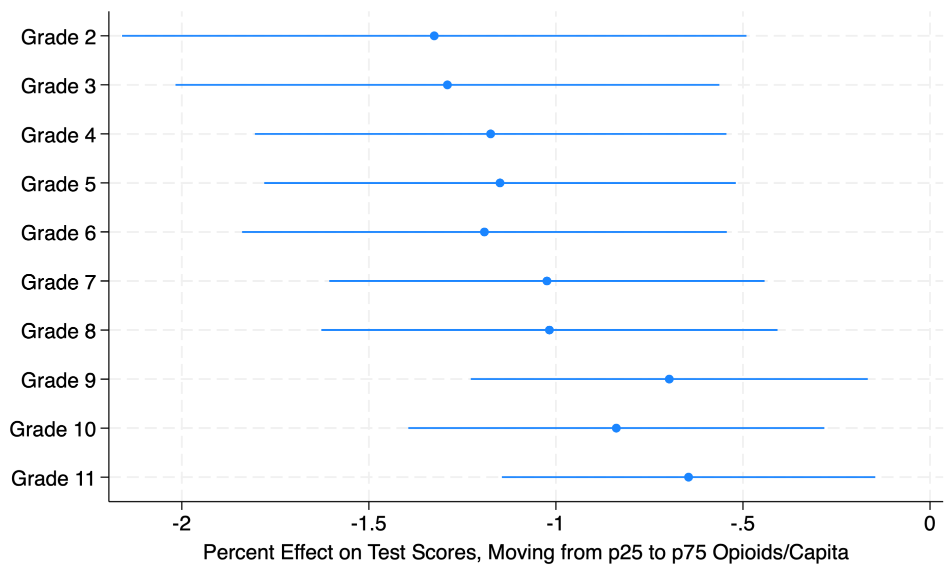

Figure Notes: This figure shows the percent decrease in test scores by grade when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval.

Figure 6A. STAR Math Effect Size by Grade and Gender

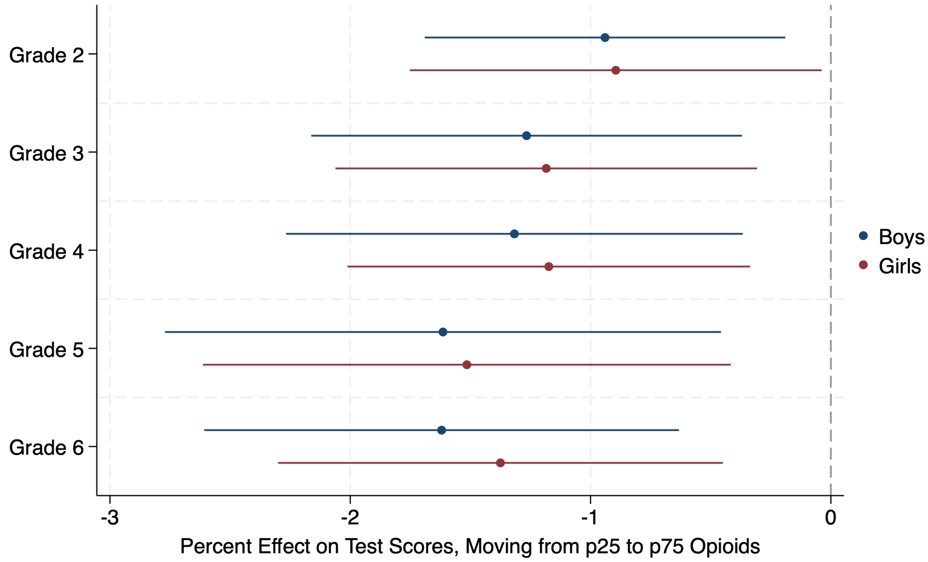

Figure Notes: This figure shows the percent decrease in test scores by grade and by gender when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval.

Figure 6B. STAR ELA Effect Size by Grade and Gender

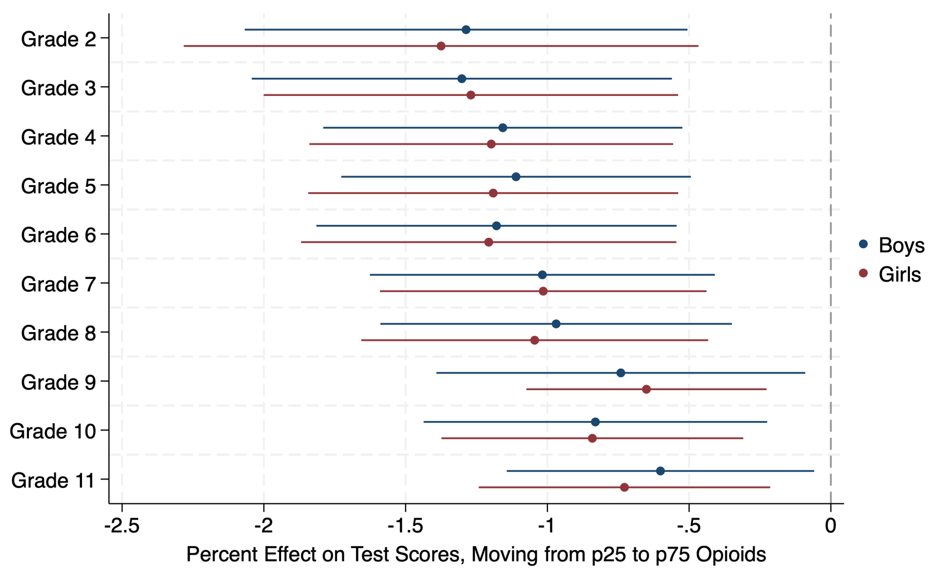

Figure Notes: This figure shows the percent decrease in test scores by grade and by gender when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval.

Figure 7A. STAR Math Effect Size by Grade and Socioeconomic Status

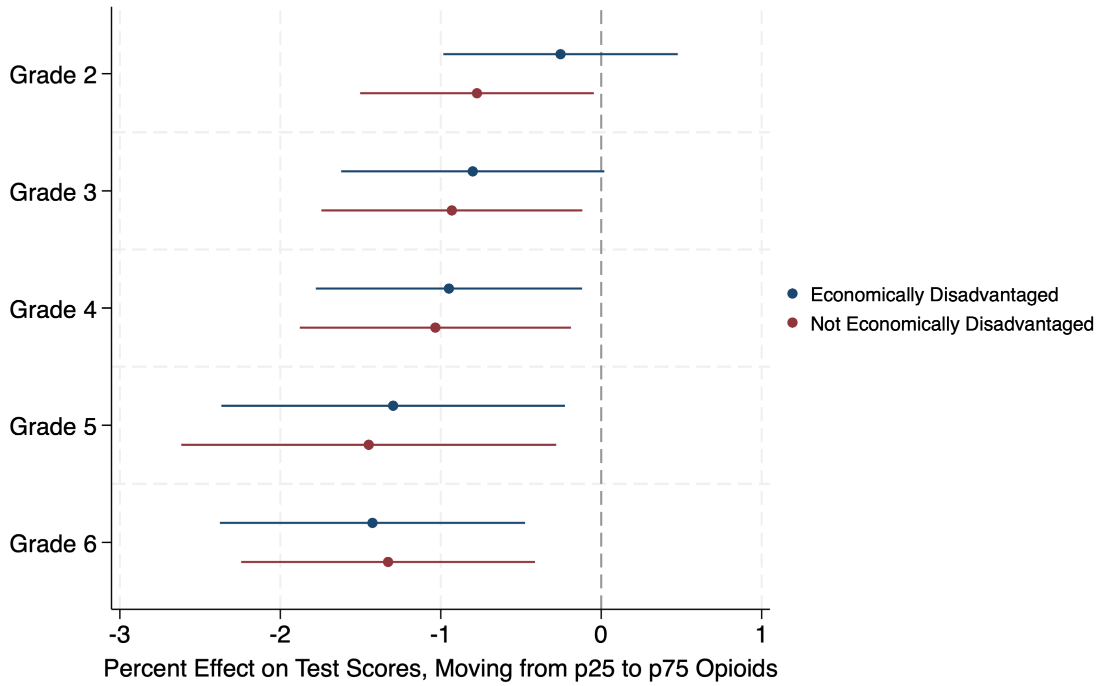

Figure Notes: This figure shows the percent decrease in test scores by grade and by socioeconomic status when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval. According to the California Department of Education, students are considered to be socioeconomically disadvantaged if one of the follow conditions is met: "1. neither of the student's parents has received a high school diploma; 2. the student is eligible for or participating in the Free Meal program or Reduced-Price Meal program; 3. the student is eligible for or participating in the Title I Part C Migrant program; 4. the student was considered Homeless; 5. the student was Foster Program Eligible; 6. the student was Directly Certified; 7. the student was enrolled in a Juvenile Course School; 8. the student is eligible as Tribal Foster Youth."

Figure 7B. STAR ELA Effect Size by Grade and Socioeconomic Status

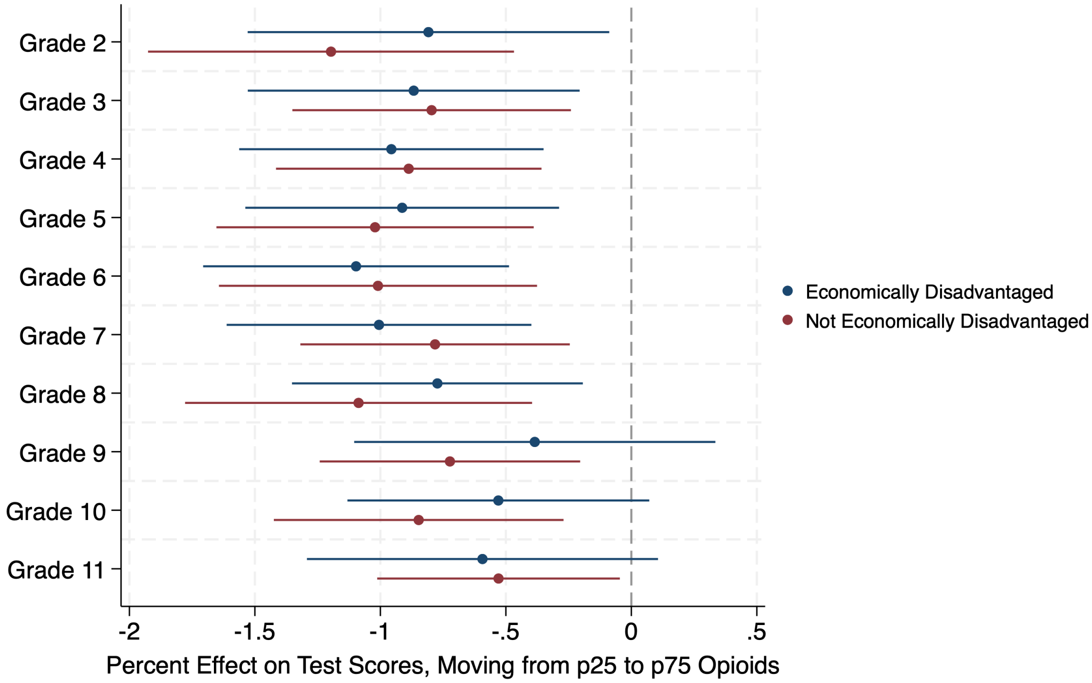

Figure Notes: This figure shows the percent decrease in test scores by grade and by socioeconomic status when instrumented opioids per capita move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval. According to the California Department of Education, students are considered to be socioeconomically disadvantaged if one of the follow conditions is met: "1. neither of the student's parents has received a high school diploma; 2. the student is eligible for or participating in the Free Meal program or Reduced-Price Meal program; 3. the student is eligible for or participating in the Title I Part C Migrant program; 4. the student was considered Homeless; 5. the student was Foster Program Eligible; 6. the student was Directly Certified; 7. the student was enrolled in a Juvenile Course School; 8. the student is eligible as Tribal Foster Youth."

Tables

Table 1. Summary Statistics

Variable	Mean	SD	N
Opioids Per Capita, 2000–2015	1.17	2.71	848
Opioids Per Capita 2000	0.28	0.65	53
Opioids Per Capita 2015	1.23	2.88	53
Cancer Deaths Per 100K, 1994–1996	164.4	26.7	53
Knee Replacement Rate Per 1K Medicare Enrollees	6.28	1.24	848

Weighted by county population.

Table 2. First Stage Estimates

VARIABLES	(1) Opioids Per Capita	(2) Opioids/Capita	(3) Opioids/Capita	(4) Opioids/Capita	(5) Opioids/Capita	(6) Opioids/Capita
Marketing	19.621***	19.526***	21.45***	20.98***	30.26***	30.98***
	(5.662)	(5.654)	(6.07)	(5.99)	(7.98)	(8.17)
Constant	1.942**	1.938**	1.69**	1.63**	3.27***	3.03***
	(0.758)	(0.756)	(0.76)	(0.76)	(1.05)	(0.99)
Observations	636	636	689	689	901	795
R-squared	0.976	0.976	0.97	0.97	0.91	0.92
Effective F-stat	11.6	11.52	12.23	12.12	14.33	14.53
Instrument Mean	.0708	.0708	.0704	.0709	.0632	.0650
Sample	STAR Math G2	STAR ELA G2	CAHSEE Math	CAHSEE ELA	G9 Dropouts	SAT

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. First Stage Placebo Instruments

VARIABLES	(1) Opioids/Cap.	(2) Opioids/Cap.	(3) Opioids/Cap.	(4) Opioids/Cap.	(5) Opioids/Cap.	(6) Opioids/Cap.	(7) Opioids/Cap.
Real Instrument	30.52***						
	(8.21)						
Cancer x CE		-23.58					
		(14.36)					
Cancer x VR			0.00				
			(0.00)				
Cancer x CABG				-12.11*			
				(7.15)			
Cancer x TURP					-0.00		
					(0.00)		
Cancer x Aneurysm						0.00	
						(0.00)	
Cancer x PCI							-6.91
							(5.65)
Constant	2.82**	2.08*	2.50*	1.68	2.51*	2.53*	1.99
	(1.10)	(1.23)	(1.28)	(1.14)	(1.27)	(1.27)	(1.21)
Observations	742	742	742	742	742	742	742
R-squared	0.94	0.93	0.93	0.93	0.93	0.93	0.93
Effective F-stat	13.72	2.5	.05	2.71	.24	.89	1.48
Instrument	Cancer x Knee Replacements	Cancer x Carotid Endarterectomy	Cancer x Valve Replacement	Cancer x CABG	Cancer x TURP	Cancer x A.A. Aneurysm Repair	Cancer x PCI

Standard errors clustered at the county level. Regressions weighted by population. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. STAR Exam Math

VARIABLES	(1) G2	(2) G3	(3) G4	(4) G5	(5) G6
A. Instrumental Variables					
Opioids per Capita	-4.33**	-5.84***	-5.86***	-7.24***	-6.66***
	(1.92)	(2.14)	(2.14)	(2.64)	(2.16)
[tF 0.05 se]	[2.8988]	[3.2568]	[3.2488]	[4.0162]	[3.2845]
{AR p-value}	{.0295}	{.0056}	{.0007}	{.0012}	{.0002}
R-squared	0.92	0.97	0.97	0.97	0.93
Effective F-Stat	11.6	11.41	11.43	11.44	11.4
Effect Size	-.92	-1.22	-1.25	-1.57	-1.5
B. OLS					
Opioids per Capita	-1.90***	-2.10***	-1.86***	-2.16***	-1.93***
	(0.63)	(0.65)	(0.58)	(0.70)	(0.62)
R-squared	0.96	0.98	0.98	0.98	0.98
Effect Size	-.4	-.44	-.4	-.47	-.43
Observations	636	636	636	636	636
Outcome Mean	370.66	374.39	368.86	362.89	348.07

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. STAR Exam ELA

VARIABLES	(1) G2	(2) G3	(3) G4	(4) G5	(5) G6	(6) G7	(7) G8	(8) G9	(9) G10	(10) G11
A. Instrumental Variables										
Opioids per Capita	-5.84***	-5.49***	-5.33***	-5.10***	-5.23***	-4.52***	-4.45***	-3.07**	-3.59***	-2.73**
	(1.88)	(1.58)	(1.46)	(1.43)	(1.45)	(1.31)	(1.36)	(1.19)	(1.22)	(1.08)
[tF 0.05 se]	[2.8471]	[2.4069]	[2.2375]	[2.1722]	[2.2127]	[2.018]	[2.092]	[1.8327]	[1.8849]	[1.6946]
{AR p-value}	{.0011}	{.0007}	{.0001}	{ <.0001}	{.0001}	{.0001}	{.0001}	{.0037}	{.0009}	{.0067}
R-squared	0.94	0.91	0.97	0.96	0.96	0.97	0.97	0.97	0.95	0.94
Effective F-Stat	11.52	11.38	11.21	11.4	11.4	11.11	11.22	11.22	11.01	10.65
Effect Size	-1.33	-1.29	-1.17	-1.15	-1.19	-1.02	-1.02	-.70	-.84	-.65
B. OLS										
Opioids per Capita	-1.89***	-1.53***	-1.76***	-1.33***	-1.39***	-1.40***	-1.37***	-1.08***	-1.26***	-1.07***
	(0.64)	(0.51)	(0.48)	(0.40)	(0.45)	(0.30)	(0.37)	(0.27)	(0.35)	(0.31)
R-squared	0.97	0.97	0.99	0.98	0.99	0.99	0.99	0.99	0.98	0.97
Effect Size	-.43	-.36	-.39	-.3	-.32	-.32	-.31	-.24	-.29	-.25
Observations	636	636	636	636	636	636	636	636	636	636
Outcome Mean	346.14	334.22	356.36	348.21	344.85	346.55	343.79	345.8	336.29	331.51

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. CAHSEE

VARIABLES	(1) Math Scores	(2) Math Pass Rate	(3) ELA Scores	(4) ELA Pass Rate
A. Instrumental Variables				
Opioids per Capita	-4.34***	-3.98***	-2.856***	-3.40***
	(1.17)	(1.44)	(0.963)	(1.23)
[tF 0.05 se]	[1.7487]	[2.1578]	[1.4485]	[1.8493]
{AR p-value}	{.0001}	{.0089}	{.004}	{.0069}
R-squared	0.94	0.97	0.970	0.89
Effective F-Stat	12.23	12.23	12.12	12.12
Effect Size	-.89	-4.33	-.59	-3.45
B. OLS				
Opioids per Capita	-1.25***	-1.01*	-0.69**	-0.81**
	(0.37)	(0.50)	(0.29)	(0.40)
R-squared	0.97	0.98	0.98	0.94
Effect Size	-.25	-1.1	-.14	-.82
Observations	689	689	689	689
Outcome Mean	378.75	70.98	375.03	76.37

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). CAHSEE test scores are available starting in 2001.

*** p<0.01, ** p<0.05, * p<0.1

Table 7. Dropout and SAT Take-Up

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dropouts G9	Dropouts G10	Dropouts G11	Dropouts G12	Dropouts Total	SAT Take-Up
A. Instrumental Variables						
Opioids per Capita	0.0030***	0.0014*	0.0004	-0.0006	0.0020	-0.0096**
	(0.0009)	(0.0008)	(0.0009)	(0.0061)	(0.0023)	(0.0041)
[tF 0.05 se]	[.0013]	[.0012]	[.0013]	[.0088]	[.0033]	[.0058]
{AR p-value}	{.0018}	{.0876}	{.6894}	{.9198}	{.3976}	{.0212}
R-squared	0.3064	0.4035	0.4108	0.5538	0.4980	0.5660
Effective F-Stat	14.33	14.14	13.85	13.96	14.08	14.53
Effect Size	9.95	4.64	1.24	-2	3.33	-1.71
B. OLS						
Opioids per Capita	0.0009**	0.0004	0.0007	0.0033	0.0018	-0.0025*
	(0.0004)	(0.0004)	(0.0005)	(0.0037)	(0.0016)	(0.0013)
R-squared	0.7532	0.7847	0.6805	0.7608	0.7347	0.9480
Effect Size	2.88	1.46	2.4	10.86	3.01	-.45
Observations	901	901	901	901	901	795
Outcome Mean	.02	.02	.02	.02	.04	.41

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Physical Fitness Grade 7

VARIABLES	(1) Aerobic Capacity	(2) Body Comp	(3) Upper Body	(4) Ab Strength	(5) Trunk Ext	(6) Flexibility
A. Instrumental Variables						
Opioids per Capita	-1.00*	0.83	-0.87	-0.72*	-0.01	-0.56
	(0.54)	(0.80)	(0.56)	(0.40)	(0.80)	(0.71)
[tF 0.05 se]	[.7908]	[1.1724]	[.8157]	[.5909]	[1.1742]	[1.0373]
{AR p-value}	{.0574}	{.2938}	{.1234}	{.0867}	{.9929}	{.4423}
R-squared	0.60	0.87	0.70	0.29	0.28	0.70
Effective F-Stat	13.41	13.41	13.41	13.41	13.41	13.41
Effect Size	-1.05	.84	-.83	-.57	-.01	-.5
B.OLS						
Opioids per Capita	-0.59***	-0.13	0.03	0.02	0.37	0.00
	(0.21)	(0.13)	(0.21)	(0.19)	(0.23)	(0.28)
R-squared	0.87	0.92	0.83	0.74	0.57	0.77
Effect Size	-.62	-.14	.03	.02	.27	0
Observations	741	741	741	741	741	741
Outcome Mean	62.4	64.98	68.55	83.58	88.87	74.77

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure A1. Clips from the 2000, 2001, and 2002 OxyContin Marketing Plans

- Effective in non-malignant pain states. In 2000, OxyContin Tablets will be more aggressively promoted for use in the non-malignant pain market. The most common diagnoses for non-malignant pain are back pain, osteoarthritis, injury, and trauma pain. The major competitors for these diagnoses will be oxycodone and hydrocodone combination products, as well as Ultram. OxyContin Tablets will be positioned as providing the equivalent efficacy and safety of combination opioids, with early onset of pain relief and the benefit of a q12h dosing schedule. The promotional efforts will focus on specific disease syndromes such as back pain, osteoarthritis, reflex sympathetic dystrophy, trauma/injury, neuropathic type pains, etc.

Effective in non-malignant pain states. In 2001 OxyContin Tablets will continue to be aggressively promoted for use in the non-malignant pain market. The most common diagnoses for non-malignant pain are back pain, osteoarthritis, injury, and trauma pain. The major competitors for these diagnoses will be oxycodone and hydrocodone combination products. OxyContin Tablets will be positioned as providing the equivalent efficacy and safety of combination opioids, with early onset of pain relief and the benefit of a q12h dosing schedule. The promotional efforts will focus on specific disease syndromes such as back pain, osteoarthritis, reflex sympathetic dystrophy, trauma/injury, neuropathic type pains, etc.

- In 2002 OxyContin Tablets will continue to be promoted for use in the non-malignant pain market. The most common diagnoses that result in non-malignant pain are back pain, osteoarthritis, injury, and trauma. The major competitors for these diagnoses will be oxycodone and hydrocodone combination products.

Figure A2. OxyContin Overall Strategy, 2002 OxyContin Marketing Plan

OxyContin Tablets began a market penetration campaign in cancer pain. This was imperative based on acceptability of oxycodone in cancer pain. In addition, this initiative was imperative to penetrate the barriers by managed care organizations.

After the initial penetration phase and widespread formulary acceptance of OxyContin Tablets by Managed Care, the promotional initiative focused on market expansion in noncancer pain through aggressive promotion and education on proper pain management. In addition, the American Pain Society and AAPM introduced a position paper on the aggressive and appropriate treatment of nonmalignant pain, employing the use of opioids. Purdue continued the growth of OxyContin Tablets by educating physicians on the benefits of OxyContin Tablets in non-cancer pain through patient profiles and case studies. Patients who had suffered for long periods of time were soon telling their physicians that OxyContin Tablets "gave me my life back."

Figure A3. Cumulative Distribution Function of the Marketing Instrument

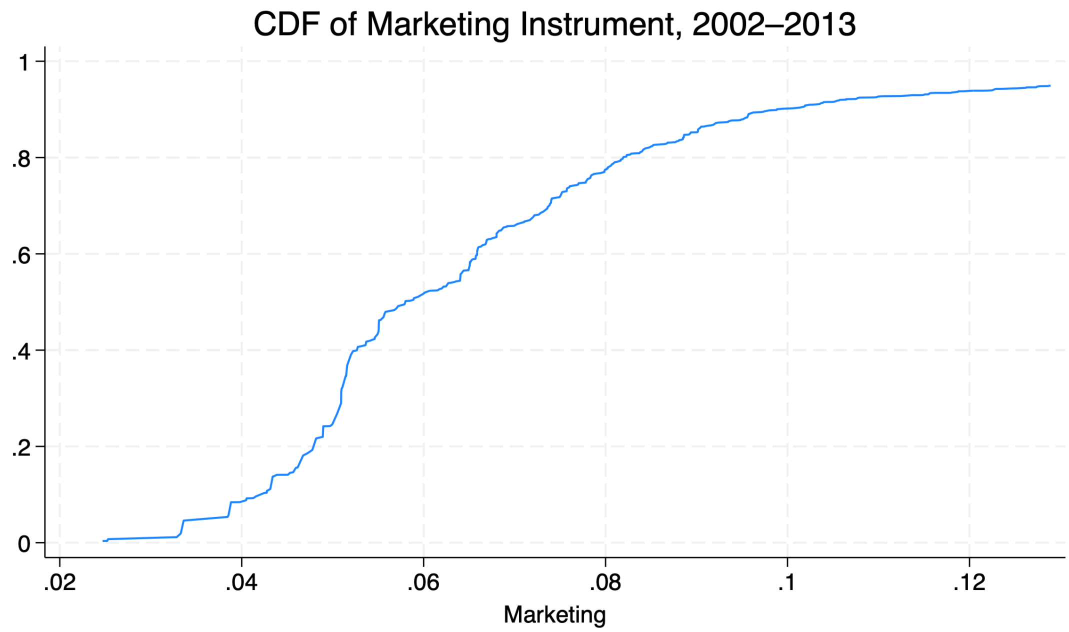

Figure Notes: Weighted by number of students. This sample corresponds to the estimates for the first stage shown in Table 2, Column 1.

Figure A4. Effect of Lagged Instrumented Opioids on Math Scores

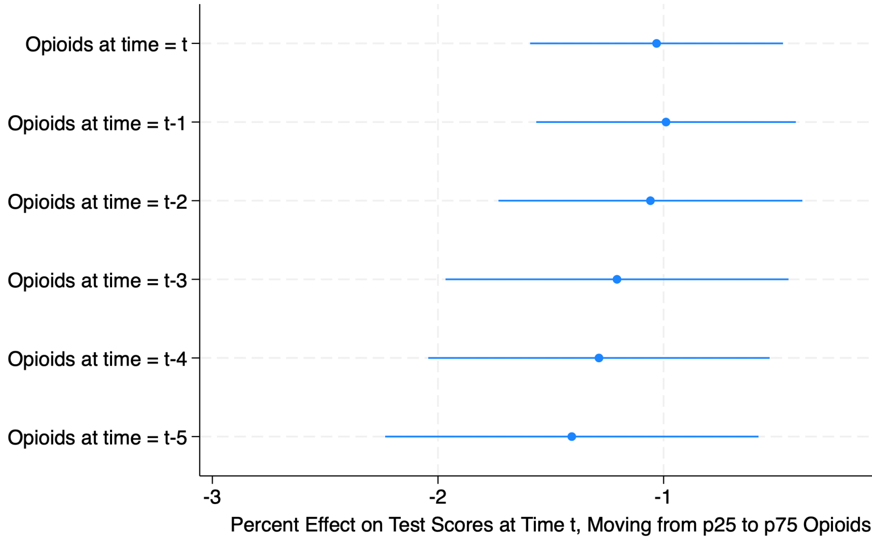

Figure Notes: This figure shows the percent decrease in test scores in time t when instrumented opioids per capita in time t through time t-5 move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval. All grade levels are pooled in the analysis for power and grade fixed effects are added to the model.

Figure A5. Effect of Lagged Instrumented Opioids on ELA Scores

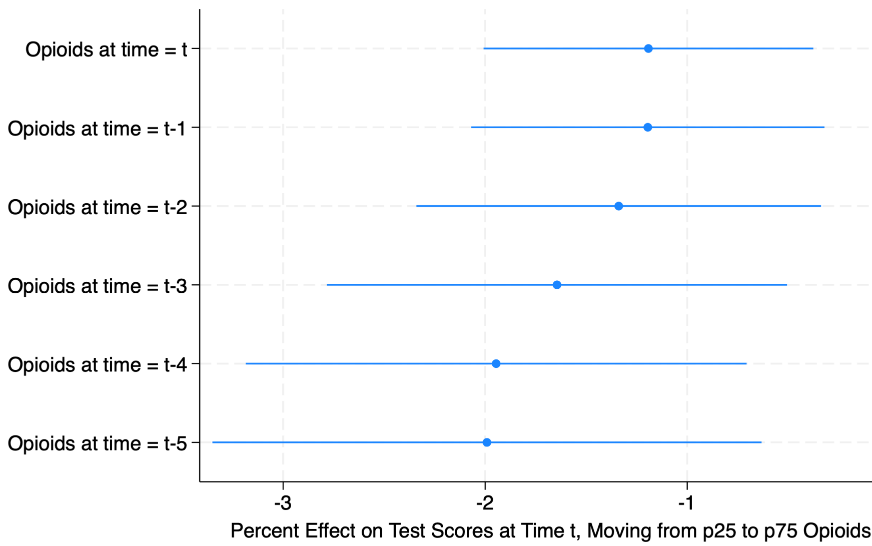

Figure Notes: This figure shows the percent decrease in test scores in time t when instrumented opioids per capita in time t through time t-5 move from the 25th percentile to the 75th percentile. The bands on either side of the plotted coefficients represent the 95% confidence interval. All grade levels are pooled in the analysis for power and grade fixed effects are added to the model.

Table A1. Effects of Prescription Opioids on National Mortality

VARIABLES	(1) Rx Opioid	(2) Rx Opioid	(3) Opioid	(4) Opioid	(5) Overdose	(6) Overdose	(7) Alc. Poison	(8) Alc. Poison	(9) Cardiac	(10) Cardiac
Marketing	.0501**		.0764***		.1288***		-.0036		-.1378	
	(.0217)		(.0252)		(.0349)		(.0030)		(.2689)	
Opioids/Cap.		.0041**		.0063***		.0107***		-.0003		-.0113
		(.0017)		(.0021)		(.0026))		(.0002)		(.0210)
{AR p-value}		{.0147}		{.0014}		{.0001}		{.224}		{.592}
Observations	43,654	43,654	43,654	43,654	43,654	43,654	43,654	43,654	43,654	43,654
R-squared	.657	-.115	.682	-0.221	.707	-.307	.333	-.007	.939	.030
Outcome Mean	.0358	.0358	.0495	.0495	.1080	.1080	.0041	.0041	2.816	2.816
Effective F-stat		68.97		68.97		68.97		68.97		68.97
Model	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV

Estimation at the county-year level. Standard errors clustered at the county level. Regressions weighted by county population. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and state by year fixed effects. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value. Death rates expressed per 1,000 residents.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2. Physical Fitness Grade 5

VARIABLES	(1) Aerobic Capacity	(2) Body Comp	(3) Upper Body	(4) Ab Strength	(5) Trunk Ext	(6) Flexibility
A. Instrumental Variables						
Opioids per Capita	0.46	0.96	0.87	0.45	-0.10	0.34
	(0.75)	(0.81)	(0.63)	(0.37)	(0.76)	(0.69)
[tF 0.05 se]	[1.0875]	[1.1837]	[.9244]	[.5461]	[1.102]	[1.0074]
{AR p-value}	{.5454}	{.2558}	{.1247}	{.1959}	{.8938}	{.6235}
R-squared	0.64	0.90	0.57	0.29	0.30	0.60
Effective F-Stat	13.49	13.49	13.49	13.49	13.49	13.49
Effect Size	.5	.98	.85	.37	-.08	.32
A. OLS						
Opioids per Capita	0.10	0.11	-0.12	-0.05	-0.00	0.10
	(0.26)	(0.19)	(0.17)	(0.16)	(0.29)	(0.21)
R-squared	0.83	0.93	0.79	0.68	0.55	0.72
Effect Size	.11	.11	-.12	-.04	0	.1
Observations	741	741	741	741	741	741
Outcome Mean	61.18	64.18	66.76	79.56	86.93	67.97

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3. Physical Fitness Grade 9

VARIABLES	(1) Aerobic Capacity	(2) Body Comp	(3) Upper Body	(4) Ab Strength	(5) Trunk Ext	(6) Flexibility
A. Instrumental Variables						
Opioids per Capita	-2.20***	0.88	-0.66	-0.96	-0.08	-1.50
	(0.83)	(1.11)	(0.86)	(0.70)	(1.12)	(0.97)
[tF 0.05 se]	[1.2525]	[1.6794]	[1.3032]	[1.0587]	[1.6954]	[1.4657]
{AR p-value}	{.009}	{.4272}	{.4748}	{.2118}	{.9417}	{.1636}
R-squared	0.81	0.73	0.75	0.54	0.63	0.78
Effective F-Stat	12.23	12.23	12.23	12.23	12.23	12.23
Effect Size	-2.55	.87	-.61	-.75	-.06	-1.3
B. OLS						
Opioids per Capita	-1.19***	-0.15	-0.60	-0.75**	-0.40	-1.10**
	(0.40)	(0.17)	(0.38)	(0.32)	(0.36)	(0.47)
R-squared	0.90	0.85	0.80	0.73	0.69	0.81
Effect Size	-1.39	-.15	-.55	-.59	-.3	-.95
Observations	741	741	741	741	741	741
Outcome Mean	56.64	66.33	71.15	83.58	87.06	75.82

Standard errors clustered at the county level. Regressions weighted by number of students. Effect size indicates the percent change in the dependent variable relative to its mean when opioids per capita increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1

Table A4: First Stage, Cross-Sectional Cancer Instrument

VARIABLES	(1) Δ Opioids/Capita	(2) Δ Op./Cap.	(3) Δ Op./Cap.	(4) Δ Op./Cap.	(5) Δ Op./Cap.	(6) Δ Op./Cap.	(7) Δ Op./Cap.
Cancer Mort.	0.0178***	0.0176***	0.0104***	0.0103***	0.0245***	0.0261***	0.0248***
	(0.00475)	(0.00466)	(0.00302)	(0.00301)	(0.00555)	(0.00593)	(0.00606)
Constant	-1.628	-1.705	-0.550	-0.547	-3.079*	-4.060**	-1.901
	(1.442)	(1.432)	(1.037)	(1.036)	(1.782)	(1.974)	(1.914)
Observations	583	583	583	583	1,060	848	954
R-squared	0.347	0.350	0.311	0.311	0.327	0.347	0.321
Effective F-stat	13.96	14.34	11.84	11.81	19.40	19.46	16.74
Sample	Math G2	Math G6	CAHSEE Math	CAHSEE ELA	Dropouts	SAT Takers	Fitness G7

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A5: STAR Exam Math, Cross-Sectional Cancer Instrument

	(1)	(2)	(3)	(4)	(5)
VARIABLES	G2	G3	G4	G5	G6
A. Instrumental Variables					
Δ Opioids Per Capita	-1.64	-2.27*	-3.37**	-4.58**	-2.53***
	(1.14)	(1.23)	(1.54)	(2.08)	(0.94)
[tF 0.05 se]	[1.7007]	[1.8279]	[2.2829]	[3.0684]	[1.3837]
{AR p-value}	{.1769}	{.0415}	{.0009}	{.0018}	{.002}
R-squared	0.81	0.95	0.95	0.94	0.93
Effective F-Stat	13.43	13.43	13.61	13.72	13.81
Effect Size	-1.25	-1.12	-1.94	-2.38	-2.7
B. OLS					
Δ Opioids Per Capita	-0.644*	-0.719**	-0.773*	-0.979*	-0.794**
	(0.328)	(0.331)	(0.421)	(0.542)	(0.366)
R-squared	0.817	0.954	0.962	0.955	0.937
Effect Size	-.49	-.35	-.45	-.51	-.85
Observations	583	583	583	583	583
Mean Score Change	29.74	46.23	39.38	43.64	21.2

Standard errors clustered at the county level. Regressions weighted by number of students. Outcomes are also expressed in terms of changes. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effect size indicates the percent change in the dependent variable relative to its mean when changes in opioids per capita since the base year increase from the 25th to the 75th percentile. The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** p<0.01, ** p<0.05, * p<0.1

Table A6: STAR Exam ELA, Cross-Sectional Cancer Instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
A. IV										
Δ Opioids Per Capita	-2.01*	-0.78	-2.36***	-1.89**	-1.30**	-1.21**	-1.72**	-1.54*	-2.27**	-1.44*
	(1.04)	(0.96)	(0.85)	(0.81)	(0.63)	(0.58)	(0.73)	(0.79)	(1.05)	(0.78)
[tF 0.05 se]	[1.5407]	[1.4309]	[1.2553]	[1.2]	[.9264]	[.8517]	[1.0754]	[1.1548]	[1.5435]	[1.1545]
{AR p-value}	{.0243}	{.4178}	{.0017}	{.0055}	{.0656}	{.0938}	{.0068}	{.0125}	{.0007}	{.0211}
R-squared	0.91	0.90	0.96	0.95	0.96	0.97	0.96	0.94	0.91	0.89
Effective F-Stat	13.43	13.43	13.63	13.73	13.82	13.75	13.64	13.89	13.8	13.81
Effect Size	-1.95	-1.62	-2.14	-1.95	-1.26	-1.09	-1.79	-1.34	-3.57	-2.75
B. OLS										
Δ Opioids Per Capita	-0.361	-0.197	-0.623***	-0.212	-0.360	-0.590***	-0.266	-0.187	-0.323	-0.274
	(0.268)	(0.272)	(0.203)	(0.185)	(0.252)	(0.188)	(0.201)	(0.181)	(0.252)	(0.234)
R-squared	0.920	0.900	0.965	0.963	0.962	0.974	0.968	0.952	0.934	0.902
Effect Size	-.35	-.41	-.56	-.22	-.35	-.53	-.28	-.16	-.51	-.52
Observations	583	583	583	583	583	583	583	583	583	583
Mean Score Change	23.32	10.88	25.04	21.94	23.43	25.33	21.82	25.95	14.4	11.88

Standard errors clustered at the county level. Regressions weighted by number of students. Outcomes are also expressed in terms of changes. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effect size indicates the percent change in the dependent variable relative to its mean when changes in opioids per capita since the base year increase from the 25th to the 75th percentile. The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7: CAHSEE, Cross-Sectional Cancer Instrument

VARIABLES	(1) Δ Math Scores	(2) Δ ELA Scores	(3) Δ Math Pass Rate	(4) Δ ELA Pass Rate
A. Instrumental Variables				
Δ Opioids Per Capita	-2.02*	-1.93**	-2.92**	-1.18
	(1.12)	(0.84)	(1.20)	(0.96)
[tF 0.05 se]	[1.7194]	[1.2886]	[1.8481]	[1.461]
{AR p-value}	{.017}	{.0043}	{.0007}	{.1109}
R-squared	0.91	0.92	0.93	0.88
Effective F-Stat	12.44	12.6	12.44	12.6
Effect Size	-3.17	-1.74	-2.61	-2.27
B. OLS				
Δ Opioids Per Capita	-0.119	-0.216	-0.279	0.124
	(0.213)	(0.151)	(0.189)	(0.228)
R-squared	0.934	0.940	0.955	0.901
Effect Size	-.19	-.2	-.25	.24
Observations	742	742	742	742
Outcome Mean	16.63	28.93	29.18	13.65

Standard errors clustered at the county level. Regressions weighted by number of students. Outcomes are also expressed in terms of changes. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effect size indicates the percent change in the dependent variable relative to its mean when changes in opioids per capita since the base year increase from the 25th to the 75th percentile. The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). CAHSEE test scores are available starting in 2001.

*** p<0.01, ** p<0.05, * p<0.1

Table A8: Dropout and SAT Take-Up, Cross-Sectional Cancer Instrument

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δ Dropout G9	Δ Dropout G10	Δ Dropout G11	Δ Dropout G12	Δ Dropout	Δ SAT Takers
A. Instrumental Variables						
Δ Opioids Per Capita	0.0014	0.0006	0.0004	0.0047	0.0019	-0.01
	(0.0011)	(0.0010)	(0.0014)	(0.0077)	(0.0024)	(0.01)
[tF 0.05 se]	[.0015]	[.0013]	[.0019]	[.0101]	[.0032]	[.0072]
{AR p-value}	{.1846}	{.5742}	{.8001}	{.5580}	{.4327}	{.3392}
R-squared	0.5716	0.4752	0.4405	0.3491	0.3636	0.57
Effective F-Stat	19.78	19.85	19.76	20.52	19.98	18.25
Effect Size	-4.08	-2.5	-5.69	4.43	20.14	-4.72
B. OLS						
Δ Opioids Per Capita	0.000386	4.78e-05	0.000524	0.00628	0.00188	-0.00183
	(0.000366)	(0.000409)	(0.000584)	(0.00534)	(0.00167)	(0.00160)
R-squared	0.583	0.479	0.441	0.351	0.364	0.580
Effect Size	-1.09	-.21	-8.12	5.89	19.39	-1.66
Observations	954	954	954	954	954	848
Outcome Mean	-.011	-.007	-.002	.033	.003	.034

Standard errors clustered at the county level. Regressions weighted by number of students. Outcomes are also expressed in terms of changes. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effect size indicates the percent change in the dependent variable relative to its mean when changes in opioids per capita since the base year increase from the 25th to the 75th percentile. The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1

Table A9: Physical Fitness Grade 7, Cross-Sectional Cancer Instrument

VARIABLES	(1) Δ Aerobic Capacity	(2) Δ Body Comp	(3) Δ Upper Body	(4) Δ Ab Strength	(5) Δ Trunk Ext	(6) Δ Flexibility
A. Instrumental Variables						
Δ Opioids Per Capita	-0.88	0.38	0.12	-0.88	1.49	0.06
	(0.90)	(1.01)	(0.96)	(0.63)	(1.18)	(1.32)
[tF 0.05 se]	[1.1963]	[1.3455]	[1.2736]	[.8356]	[1.572]	[1.7579]
{AR p-value}	{.2902}	{.7065}	{.9038}	{.118}	{.2986}	{.9645}
R-squared	0.37	0.59	0.31	0.13	0.25	0.33
Effective F-Stat	18.81	18.81	18.81	18.81	18.81	18.81
Effect Size	-5.61	-6.11	.34	-9.88	13.29	.19
B. OLS						
Δ Opioids Per Capita	-0.00971	0.284	0.918	0.615	1.462*	0.764
	(0.443)	(0.521)	(0.582)	(0.570)	(0.777)	(0.587)
R-squared	0.398	0.591	0.327	0.237	0.250	0.342
Effect Size	-.06	-4.55	2.65	6.92	13.04	2.46
Observations	795	795	795	795	795	795
Mean Score Change	4.786	-1.916	10.621	2.725	3.437	9.51

Standard errors clustered at the county level. Regressions weighted by number of students. Outcomes are also expressed in terms of changes. All regressions include year fixed effects and a set of control variables including changes in SEERS demographic variables and county characteristics from the 2000 Census. Effect size indicates the percent change in the dependent variable relative to its mean when changes in opioids per capita since the base year increase from the 25th to the 75th percentile. The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1

Table A10: First Stage, Opioid Hospitalizations

VARIABLES	(1) Opioid Hosp	(2) Opioid Hosp	(3) Opioid Hosp	(4) Opioid Hosp	(5) Opioid Hosp	(6) Opioid Hosp
Marketing	92.37***	91.31***	101.46***	97.95***	106.90***	102.48***
	(28.33)	(28.50)	(23.52)	(23.26)	(23.38)	(23.27)
Constant	9.09	9.03	5.41	5.08	6.47	5.93
	(6.03)	(6.03)	(5.15)	(5.03)	(4.97)	(4.97)
Observations	660	660	715	715	715	715
R-squared	0.84	0.84	0.83	0.84	0.84	0.84
Effective F-stat	10.69	10.32	18.68	17.89	21.03	19.69
Instrument Mean	.0686	.0687	.0682	.0688	.0670	.0688
Sample	STAR Math G2	STAR ELA G2	CAHSEE Math	CAHSEE ELA	G9 Dropouts	SAT

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013).

*** p<0.01, ** p<0.05, * p<0.1

Table A11: STAR Exam Math, Opioid Hospitalizations

VARIABLES	(1) G2	(2) G3	(3) G4	(4) G5	(5) G6
A. Instrumental Variables					
Opioid Hospitalizations	-0.85**	-1.10***	-1.18***	-1.44***	-1.35***
	(0.36)	(0.42)	(0.35)	(0.42)	(0.36)
[tF 0.05 se]	[.5793]	[.6664]	[.5481]	[.6535]	[.5481]
{AR p-value}	{.0392}	{.013}	{.0012}	{.0019}	{.0002}
R-squared	0.92	0.97	0.97	0.97	0.93
Effective F-Stat	10.69	10.99	11.04	11.46	11.95
Effect Size	-1.18	-1.51	-1.64	-2.02	-1.98
B.OLS					
Opioid Hospitalizations	-0.43***	-0.39***	-0.41***	-0.48***	-0.37***
	(0.10)	(0.12)	(0.09)	(0.11)	(0.08)
R-squared	0.96	0.98	0.98	0.98	0.98
Effect Size	-.59	-.54	-.56	-.68	-.54
Observations	660	660	660	660	660
Outcome Mean	369.86	373.57	368.28	362.16	347.55

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioid hospitalizations increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** p<0.01, ** p<0.05, * p<0.1

Table A12: STAR Exam ELA, Opioid Hospitalizations

VARIABLES	(1) G2	(2) G3	(3) G4	(4) G5	(5) G6	(6) G7	(7) G8	(8) G9	(9) G10	(10) G11
A. Instrumental Variables										
Opioid Hosp./Cap.	-1.25***	-1.17***	-1.15***	-1.07***	-1.10***	-0.91***	-0.92***	-0.61**	-0.73***	-0.54**
	(0.33)	(0.34)	(0.29)	(0.26)	(0.26)	(0.24)	(0.27)	(0.26)	(0.27)	(0.27)
[tF 0.05 se]	[.5336]	[.5426]	[.4621]	[.4104]	[.398]	[.3777]	[.4189]	[.4082]	[.4326]	[.4417]
{AR p-value}	{.0006}	{.0004}	{<.0001}	{<.0001}	{<.0001}	{.0001}	{.0001}	{.0066}	{.0021}	{.0205}
R-squared	0.94	0.90	0.96	0.95	0.96	0.97	0.97	0.97	0.94	0.92
Effective F-Stat	10.32	10.85	10.46	11.35	11.86	10.9	11.41	11.13	10.48	10.01
Effect Size	-1.84	-1.79	-1.64	-1.57	-1.63	-1.35	-1.37	-.9	-1.11	-.84
B.OLS										
Opioid Hosp./Cap.	-0.42***	-0.30***	-0.30***	-0.26***	-0.28***	-0.20***	-0.21***	-0.10**	-0.13***	-0.02
	(0.11)	(0.09)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
R-squared	0.98	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.97
Effect Size	-.62	-.46	-.43	-.39	-.41	-.3	-.31	-.15	-.19	-.03
Observations	660	660	660	660	660	660	660	660	660	660
Outcome Mean	345.56	333.57	355.79	347.69	344.44	345.92	343.19	345.26	335.7	330.86

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioid hospitalizations increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). STAR test scores are available between 2002 and 2013.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A13: CAHSEE, Opioid Hospitalizations

VARIABLES	(1) Math Scores	(2) Math Pass Rate	(3) ELA Scores	(4) ELA Pass Rate
A. Instrumental Variables				
Opioid Hospitalizations	-0.81***	-0.87***	-0.616***	-0.71***
	(0.20)	(0.25)	(0.173)	(0.20)
[tF 0.05 se]	[.2574]	[.3247]	[.2295]	[.2615]
{AR p-value}	{.0004}	{.0027}	{.0013}	{.0033}
R-squared	0.95	0.97	0.972	0.90
Effective F-Stat	18.68	18.68	17.89	17.89
Effect Size	-1.08	-6.22	-.84	-4.73
B. OLS				
Opioid Hospitalizations	-0.22***	-0.26**	-0.19***	-0.22**
	(0.07)	(0.11)	(0.06)	(0.09)
R-squared	0.97	0.98	0.98	0.95
Effect Size	-.3	-1.84	-.26	-1.44
Observations	715	715	715	715
Outcome Mean	378.28	70.66	374.62	76.17

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioid hospitalizations increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022). CAHSEE test scores are available starting in 2001.

*** p<0.01, ** p<0.05, * p<0.1

Table A14: Dropout and SAT Take-Up, Opioid Hospitalizations

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dropouts G9	Dropouts G10	Dropouts G11	Dropouts G12	Dropouts Total	SAT Take-Up
A. Instrumental Variables						
Opioid Hospitalizations	0.0016***	0.0012**	0.0012*	0.0010	0.0015	-0.0025**
	(0.0006)	(0.0006)	(0.0006)	(0.0020)	(0.0009)	(0.0012)
[tF 0.05 se]	[.0008]	[.0007]	[.0008]	[.0025]	[.0012]	[.0016]
{AR p-value}	{.0054}	{.0225}	{.0539}	{.6117}	{.111}	{.0297}
R-squared	0.0630	0.1736	0.2806	0.5295	0.3934	0.5927
Effective F-Stat	21.03	21.01	20.67	19.72	20.83	19.69
Effect Size	41.07	30.73	29.93	25.67	18.69	-3.08
B. OLS						
Opioid Hospitalizations	0.0001	-0.0000	0.0001	0.0005	0.0003	-0.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0009)	(0.0004)	(0.0004)
R-squared	0.6281	0.6872	0.6356	0.7897	0.7360	0.9541
Effect Size	2.34	-.22	3.64	11.49	3.43	-.4
Observations	715	715	715	715	715	715
Outcome Mean	.02	.02	.02	.02	.04	.41

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioid hospitalizations increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A15: Physical Fitness Grade 7, Opioid Hospitalizations

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Aerobic Capacity	Body Comp	Upper Body	Ab Strength	Trunk Ext	Flexibility
A. Instrumental Variables						
Opioid Hospitalizations	-0.24*	0.10	-0.16	-0.19**	-0.10	-0.31**
	(0.14)	(0.10)	(0.11)	(0.10)	(0.17)	(0.15)
[tF 0.05 se]	[.181]	[.1332]	[.1439]	[.1227]	[.2207]	[.1879]
{AR p-value}	{.0889}	{.3146}	{.1563}	{.0872}	{.5651}	{.0728}
R-squared	0.58	0.92	0.67	0.28	0.26	0.70
Effective F-Stat	20.11	20.11	20.11	20.11	20.11	20.11
Effect Size	-1.96	.82	-1.17	-1.14	-.59	-2.07
B.OLS						
Opioid Hospitalizations	-0.01	-0.03	-0.05	-0.05	-0.04	-0.09
	(0.05)	(0.03)	(0.04)	(0.05)	(0.07)	(0.06)
R-squared	0.88	0.94	0.83	0.74	0.60	0.79
Effect Size	-.09	-.21	-.39	-.33	-.21	-.59
Observations	715	715	715	715	715	715
Outcome Mean	61.96	64.74	69.16	83.73	89.12	75

Standard errors clustered at the county level. Regressions weighted by number of students. All regressions include controls for contemporaneous cancer rates, the percent of the population over 65 in FFS Medicare, and county and year fixed effects. Effect size indicates the percent change in the dependent variable relative to its mean when opioid hospitalizations increase from the 25th to the 75th percentile. Effective F-stat is the effective first-stage F statistic as in Montiel Olea and Pflueger (2013). The AR p-value is the Anderson-Rubin p-value and the [tF 0.05 se] is the tF-adjusted standard error for the 5% significance level from Lee, McCrary, Moreira, and Porter (2022).

*** p<0.01, ** p<0.05, * p<0.1