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What We RANDomly Did Not Learn: *Wave Zero* of the U.S. Opioid Epidemic

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Abstract

Opioid-related deaths have contributed to the recent decline in U.S. life expectancy, yet the period preceding the opioid epidemic remains understudied. This article addresses this gap by leveraging the 1974-1982 RAND Health Insurance Experiment. We document novel facts about the widespread use of prescribed opioids, prescriber characteristics, and diagnoses linked to opioid prescriptions in *Wave Zero*. Additionally, we exploit random assignment to health insurance plans to estimate how opioid use adjusts to changes in plan generosity. More generous plans increase use by raising outpatient visits and providers' likelihood of prescribing opioids. We discuss implications for understanding the onset of the opioid epidemic.

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1 Introduction

The narcotics epidemic in the United States is a leading factor in the unprecedented rise in all-cause midlife mortality among white non-Hispanic Americans after 1998, a trend not seen in other industrialized countries (Case and Deaton, 2015). The crisis evolved in three waves: the first, beginning in the mid-1990s, was driven by prescription opioids; the second, between 2010 and 2014, saw a surge in heroin use; and the third is marked by the widespread use of synthetic opioids (Maclean et al., 2020). The literature has studied demand- and supply-side explanations for the origins of the crisis, including worsening economic conditions (Case and Deaton, 2017; Ruhm, 2019; Pierce and Schott, 2020), increased production and marketing campaigns for opioids (Van Zee, 2009; Alpert et al., 2022; Arteaga and Barone, 2022), and a change in physicians' prescribing practices (Quinones, 2015; Case and Deaton, 2020). Although the opioid epidemic is an essential contributor to the first sustained decline in life expectancy since the 1918 influenza epidemic (Case and Deaton, 2020), the circumstances that preceded the first wave of the opioid crisis remain largely unexplored.

In this paper, we address two important gaps in our understanding of the prelude to the U.S. opioid epidemic by exploiting the unique timing, research design, and richness of the RAND Health Insurance Experiment (HIE), a large-scale Randomized Controlled Trial conducted between 1974 and 1982. Our first contribution is to document novel descriptive facts about the widespread use of prescribed opioid painkillers in the 1970s and early 1980s—what we refer to as *Wave Zero*—, two decades before what scholars commonly identify as the start of the opioid epidemic. The RAND HIE data, rarely used to study historical opioid prescribing, provide a unique window into this formative period. Leveraging its detailed claims and prescription records, we characterize prescribing patterns, profile prescriber types, identify the clinical contexts in which opioids were used, and trace the most commonly dispensed opioid medications of the time. In doing so, we shed light on a largely overlooked chapter in the history of one of the largest public health crises in the U.S.

Our second contribution is to provide causal estimates of how prescription opioid use responds to changes in patient health insurance generosity, decomposing these effects into patient- and provider-driven channels. The first channel is provider access: increased provider contact mechanically increases prescribing opportunities. The second channel reflects providers' role along the *prescribing* margin—deciding whether to write opioid prescriptions once patients present. The third channel is the patient's decision along the *filling* margin—whether to fill a written prescription. While it is widely believed that the opioid crisis was fueled primarily by prescribers rather than consumers, who are seen as passively receiving and filling prescriptions, there is limited evidence supporting this view, largely due to data limitations. Unlike typical claims data that capture only filled prescriptions, our data uniquely distinguish between *unwritten* and *unfilled* prescriptions, enabling direct analysis of this last margin.

Our empirical work begins with novel descriptive facts essential to understanding the opioid landscape before 1990. Despite the RAND HIE being conducted before the first wave of the opioid epidemic in the 1990s (CDC, 2021), opioid use was already prevalent at that time. We find that 56% of painkiller prescriptions filled were for opioids, 10.8% of individuals under age 65 had at least one opioid prescription filled in a given year, and 3.9% filled two or more. To put these numbers into perspective, in 2010, 16.2% of the non-elderly U.S. population filled at least one opioid prescription and 6.8% filled two or more.[1] In addition, we document that prescribed opioid painkiller use was consistently higher among white non-Hispanics than blacks or Hispanics, aligning with the surge in deaths of despair primarily among white non-Hispanics at the onset of the opioid crisis (Case and Deaton, 2020). We also find no differences in prescribed opioid painkiller use between urban and rural areas at the extensive margin. This is somewhat unexpected, as rural areas typically have fewer pre-

[1] Authors' calculations based on the 2010 Medical Expenditure Panel Survey.

scribers. However, the prevalence of labor-intensive occupations like mining and agriculture, along with associated pain, may have contributed to similar levels of opioid use.

Second, we examine the role of prescribers. Studies suggest that opioids were initially prescribed primarily by specialists; however, in the 1990s, pharmaceutical marketing campaigns targeting general practitioners played a pivotal role in shifting prescribing patterns (GAO, 2003; Van Zee, 2009; Alpert et al., 2022; Arteaga and Barone, 2022), ultimately positioning them as the primary opioid prescribers (Schnell, 2025). We are among the first to provide empirical evidence supporting this claim, focusing on the landscape prior to the opioid crisis. Our findings show that opioids were primarily prescribed by specialists (42%), followed by general practitioners (34%). A novel contribution of our study is the recognition that dentists played a non-negligible role in opioid prescribing, accounting for 20% of opioid prescriptions in a nationally representative, non-elderly population. We also document that general practitioners (GPs) initially prescribed opioids more conservatively than specialists (i.e., fewer days of supply and lower MME per day), leaving room for increased prescribing. The 1996 OxyContin marketing campaign targeted this gap by promoting opioids for non-cancer chronic pain, thereby lowering prescribing thresholds for GPs.

Third, we leverage detailed claim-level data on diagnosis codes associated with prescribed opioid painkillers to address the widely held view that opioids were initially prescribed mainly for severe, acute, or end-of-life pain. We analyze diagnosis codes linked to opioid prescriptions and find that 17% were associated with pain-related diagnoses and only 3% with cancer-related ones. These findings suggest that prescribing opioids for chronic non-cancer pain was already common before the epidemic, anticipating trends seen in later decades.

Focusing on our second contribution, we provide the first experimental evidence on how prescription opioid use responds to changes in patients health insurance generosity in a general population. By exploiting the random assignment of families to insurance plans, we find that prescribed opioid purchases decrease significantly as health insurance generosity declines, at both extensive and intensive margins. These results contribute to the literature examining the responsiveness of prescription opioid consumption to out-of-pocket costs, which has largely focused on older populations and relied on variation from the introduction of Medicare Part D (see, e.g., Einav, Finkelstein, and Polyakova (2018); Soni (2019); Powell, Pacula, and Taylor (2020)) or the 2008 expansion of Oregon's Medicaid program (see, e.g., Baicker et al. (2017)).

We then decompose the price response into three mechanisms: (i) decreased outpatient provider visits, (ii) decreased writing of prescriptions, and (iii) decreased filling of prescriptions. We find that the causal decline in opioid painkiller use as health insurance generosity decreases is partly mediated by patients' reduced utilization of provider visits (i.e., patient-initiated behavior). This result aligns with the original RAND investigators who documented that higher cost-sharing leads to substantial reductions in outpatient services (Manning et al., 1987). More recently, the Oregon Health Insurance Experiment found that gaining Medicaid coverage increased outpatient visits among previously uninsured adults (Finkelstein et al., 2012). Similarly, Card, Dobkin, and Maestas (2008) showed that crossing the Medicare eligibility threshold at age 65 led to a sharp rise in outpatient care, consistent with expanded coverage driving increased utilization. Chandra, Gruber, and McKnight (2010) further demonstrated that more generous outpatient coverage among Medicare beneficiaries reduces cost-related underuse and lowers rates of avoidable hospitalizations. Taken together, this literature—and our own findings—highlight the sensitivity of outpatient utilization to patients' financial exposure.[2]

While prior work has documented how patient behavior mediates the response to insur-

[2] See Baicker and Goldman (2011) for a review of this literature.

ance generosity, far less is known about how providers adjust their treatment decisions in response to patients' financial exposure. This gap is especially pronounced in the context of prescribing behavior, where data limitations typically prevent researchers from distinguishing between written and filled prescriptions. Leveraging unique data that allow us to observe this distinction, we provide the first direct causal evidence that providers also play an important role in mediating the response of opioid use to patient cost-sharing. We show that, conditional on an outpatient visit and controlling for selection on pain and health, providers are 24.9% less likely to write an opioid prescription as plan generosity decreases from full insurance to a high-deductible plan.

If clinical need were the sole determinant of prescribing, variation in plan generosity would be inconsequential. Instead, the gradient observed in our results suggests that prescribers respond to patients' out-of-pocket costs. This behavior is well-grounded in principal-agent theory, where physicians acting in the best interest of the patient internalize affordability constraints when making prescribing decisions (McGuire, 2000). While this empirical behavior is novel in the prescribing margin, it aligns with a broader literature documenting how physicians consider factors beyond clinical need when making treatment decisions.[3] Our findings echo Card, Dobkin, and Maestas (2009), who show that individuals just above the Medicare

[3]Other than patient insurance coverage, a growing body of influential work shows that physicians' treatment decisions are also shaped by their financial incentives and exposure to legal liability. For financial incentives, see, e.g., Clemens and Gottlieb (2014) who show that physicians adjust treatment intensity in response to Medicare payment changes, Gaynor, Mehta, and Richards-Shubik (2023), who find that dialysis providers adjust drug administration in response to changes in Medicare reimbursement contracts, and Dickstein (2017), who finds that financial incentives lead capitated physicians, who are paid a fixed amount per patient regardless of services provided, to favor treatments that reduce the need for follow-up care. For liability-driven behavior, see, e.g., the seminal study by Kessler and McClellan (1996), who find that malpractice reforms reduce the use of intensive procedures, and Currie and MacLeod (2008), who show that reforms favoring fewer procedures reduce the use of labor induction, stimulation, and C-sections, whereas caps on malpractice damages increase them.

eligibility threshold (age 65) experience a marked increase in in-hospital procedures, implying that providers adjust treatment intensity when insurance coverage expands. Carrera et al. (2018) also show that physicians are capable of recognizing patients' responsiveness to cost-sharing and adjust their prescribing patterns accordingly, although such adjustments occur only in the presence of broad and significant changes in prices. Our findings contribute to this literature by showing that insurance generosity influences the initial prescribing decision, highlighting the prescriber as an active agent in shaping access to treatment. This is particularly salient in the case of opioids, where prescription initiation is itself a key margin of interest and what ignited the first wave of the crisis.

Finally, we examine the *filling* margin. A large literature documents that patient cost-sharing influences prescription drug utilization, but most studies conflate prescriber behavior with patient adherence, obscuring the distinct mechanisms through which insurance generosity affects drug access. We address this identification challenge by estimating the effect of plan generosity on patient-level adherence separately from the effect on prescribing. Our results show that although four out of five opioid prescriptions are filled, the fill rate is insensitive to variation in plan generosity—even after conditioning on patient and prescriber characteristics. This suggests that for highly salient conditions such as acute pain, insurance design primarily affects the supply side—whether a prescription is written—rather than patient demand conditional on having received one. These findings underscore the importance of distinguishing between prescribing and adherence margins, particularly for therapeutic classes where the costs of non-adherence are less immediate or salient.

Beyond the contributions outlined above, our paper makes several additional contributions to the existing literature. First, we add to the body of work exploring the origins of the opioid crisis (see, e.g., Alpert et al. (2022); Arteaga and Barone (2022); Powell, Pacula, and

Taylor (2020); Case and Deaton (2020); Cutler and Glaeser (2021)).[4] While most existing research begins its analysis in 1996—when OxyContin was first introduced—epidemics of this scale do not emerge overnight. Our key contribution is to examine the prelude to the modern opioid crisis, a period we refer to as *Wave Zero*, when the conditions for the coming epidemic were already beginning to take shape. Our paper also contributes to the broader literature on the origins and evolution of health epidemics more generally (see, e.g., Adda (2016); Anderson (2018); Beach, Clay, and Saavedra (2022); Oster (2005)). Specifically, we identify general patterns in provider prescribing and patient utilization that are critical for understanding the dynamics of healthcare crises.

Second, this paper contributes to the literature on the role of supply, specifically physicians, during the opioid crisis (see, e.g., Currie, Li, and Schnell (2023); Schnell and Currie (2018); Barnett, Olenski, and Jena (2017); Schnell (2025); Eichmeyer and Zhang (2023, 2022)). A related strand of research explores policies aimed at reducing opioid prescribing, such as the implementation of prescription monitoring programs (Buchmueller and Carey, 2018; Alpert, Dykstra, and Jacobson, 2024; Nguyen, Meille, and Buchmueller, 2023; Kim, 2021) and changes to national prescribing guidelines (Sacks et al., 2021; Stein et al., 2022; Allen, Bradford, and Durrance, 2024). We contribute to this extensive body of literature by offering a comprehensive analysis of the prescribers and the diagnosis codes linked to opioid prescriptions, as well as the prescriber types and prescription characteristics of competing non-opioid painkillers. Our findings highlight potential gaps that pharmaceutical companies capitalized on in the 1990s to expand the market for opioid prescribing.

Third, we contribute to the broad literature studying the price elasticity of demand

[4] A related body of research focuses on understanding the factors driving the subsequent waves of the opioid crisis (see, e.g., Alpert, Powell, and Pacula (2018); Donahoe and Soliman (2025); Evans, Lieber, and Power (2019); Powell and Pacula (2021)).

for prescription drugs (see, e.g., Einav, Finkelstein, and Schrimpf (2015); Aron-Dine et al. (2015); Leibowitz, Manning, and Newhouse (1985); Newhouse et al. (1993)), and addictive substances other than prescribed opioid drugs (see, e.g., Nisbet and Vakil (1972), Grossman and Chaloupka (1998); Chaloupka and Pacula (2000); Dave (2006); Van Ours (1995); Olmstead et al. (2015); Saffer and Chaloupka (1999)). Lastly, our paper relates to recent studies underscoring the continued relevance of the RAND HIE to address current policy questions (see, e.g., Diaz-Campo (2023); Hodor (2021); Lin and Sacks (2019); Aron-Dine, Einav, and Finkelstein (2013); Vera-Hernandez (2003)).

The rest of the paper is structured as follows. In Section 2, we provide a brief overview of the historical context of opioid use in the U.S. during the nineteenth and twentieth centuries. Section 3 describes the data used for the analysis. In Section 4, we present novel facts regarding the prelude to the U.S. opioid crisis. Section 5 examines the response of prescribed painkiller consumption to changes in insurance generosity. Section 6 addresses potential threats to the validity of our identification strategy and presents robustness checks. Section 7 decomposes the response to changes in insurance generosity into provider- and patient-driven mechanisms. Finally, Section 8 offers concluding remarks.

2 Historical Background

In this section, we present a brief examination of the historical context surrounding opioid use in the U.S. in the nineteenth and twentieth centuries. Three disruptive inventions set the tone for the nineteenth century: morphine was distilled from opium for the first time in 1804, the hypodermic syringe was invented in 1853, and heroin was first synthesized from boiling morphine in 1874. The context in the late nineteenth century was characterized by the wide availability of morphine and opium, marketed aggressively not only for adults but also to pacify children. In 1898, the German drug company Bayer introduced heroin for medical use, commercializing it as a cough, cold, and pain remedy.

Perhaps unsurprisingly, at the beginning of the twentieth century, there was a narcotic problem of considerable dimensions (Quinones, 2015), referred as the iatrogenic wave of opium and morphine addiction by Macy (2018) and as the first great American opioid epidemic by Case and Deaton (2020). This public health crisis prompted increased intervention by the federal government, culminating in the introduction of the Harrison Narcotics Tax Act in 1914. This landmark legislation aimed to restrict the distribution and sales of narcotics, signifying the first comprehensive legal framework to regulate whole classes of drugs. However, the alarm was not raised solely within the U.S. Convened by the U.S., the 1909 Shanghai Opium Commission summit meeting marked the first international effort to prohibit the trade of narcotic substances (Keefer and Loayza, 2010).

The Harrison Narcotics Tax Act managed to curb the illicit use of opioids for some time. However, in the early 1970s, the administration of President Nixon acknowledged the resurgence of drug abuse, with a particular emphasis on heroin addiction, as a significant public health concern. This realization was largely triggered by the observed prevalence of substance abuse among military personnel deployed in Vietnam (Case and Deaton, 2020). Using a representative sample of enlisted Army men who left Vietnam in September 1971, Robins (1993) documented that 45% of Army enlisted had tried narcotics, and around 20% self-reported being addicted to narcotics. However, opioid use was not limited to adults during that period. In 1975, 5.7% of Grade 12 children reported using narcotics other than heroin in the last 12 months (Miech et al., 2023). Concurrently, fentanyl had already been introduced in 1968 for general anesthesia, establishing itself as a staple in anesthesia practice for the ensuing five decades. The Controlled Substances Act was established in 1970 to regulate the manufacture, importation, possession, use, and distribution of certain substances.

The legislation created five schedules, with the Drug Enforcement Administration (DEA) and the Food Drug Administration (FDA) in charge of determining which substances are included in each schedule.

The surge in the population of disabled veterans during the period spanning the 1940s to the 1960s prompted a heightened emphasis on pain and its treatment. The inception of pain as a distinct field within the medical domain took shape in the 1970s, reflected in the establishment of the Pain Journal and the International Association for the Study of Pain. Perceptions of under treatment of pain surged, partly influenced by the introduction of the gate control theory of pain (Melzack and Wall, 1965) and the McGill Pain Questionaire (Melzack, 1975), widely employed for the multidimensional assessment of pain.

Early in 1980, the New England Journal of Medicine published a letter authored by Janer Porter and Hershel Jick, reporting the findings of a study that scrutinized medical records of 11,882 opioid-naïve patients who had undergone hospitalization and received minimal opioid doses. The study revealed that merely four of those patients had developed addiction (Porter and Jick, 1980). Subsequently, this letter gained widespread citation, often invoked to assert the non-addictive nature of opioids. Later, in 1984, Purdue released MS Contin, a timed-release morphine painkiller marketed to cancer patients. In 1986, the Pain Journal published a study reviewing the cases of thirty-eight cancer patients with chronic pain treated with opioids for at least four years. The study found that only two patients became addicted, both with a history of prior drug abuse, suggesting that opioids were not inherently addictive (Portenoy and Foley, 1986). The concept of pain continued to evolve throughout the 1980s, reaching a pivotal moment with the official recognition of pain as the fifth vital sign by the American Pain Society in 1995.

3 Data

Our analysis relies on rich claim-level data from the RAND HIE, a large-scale randomized controlled trial of alternative health insurance plans conducted between 1974 and 1982 in the U.S. A total of 8,254 individuals were randomly assigned to one of six groups of fee-for-service (FFS) plans or to a prepaid group practice, for either three or five years. The FFS plans varied along two principal dimensions: (1) the coinsurance rate, which is the fraction of the bill paid by the patient, and (2) the maximum dollar expenditure (MDE), which caps the family OOP expenditures. Four of the six groups of plans set their coinsurance rates at either 0 (free care), 25, 50, or 95 percent. There was a group of "mixed coinsurance" plans, with a 25 percent coinsurance rate for most services but 50 percent for dental and outpatient mental health services. Finally, the "individual deductible" plan had a coinsurance rate of 95 percent for outpatient services but 0 percent for inpatient services. Except for the free-care plan, each plan had a MDE of either 5, 10, or 15 percent of family income in the previous year. For a detailed description of the RAND HIE, see Newhouse et al. (1993).

We combine line-item records from several RAND HIE claims files: (1) services rendered in outpatient settings, (2) drugs prescribed in outpatient settings, and (3) drugs purchased from pharmacies. A typical line-item record contains several variables including, but not limited to, patient and provider identifiers, service date, diagnoses and procedure codes, total line-item cost, and the portion paid OOP by the patient. We further use the eligibility and demographic files to build the family composition and define the participation periods for each member.

We make three restrictions to construct our sample. First, we drop the years in which the individuals do not participate in full and all years thereafter, except for newborns. Second, we drop the year in which individuals move and therefore switch plans, and all years thereafter. Third, we drop individuals enrolled in the prepaid group practice because the method of care delivery is substantially different from the FFS plans. After these restrictions, our sample has 20,004 individual-year observations with 5,922 unique individuals and 3,100 unique families.[5]

The line-item records related to drugs purchased provide comprehensive information on medication characteristics, including the National Drug Code (NDC), generic drug codes, drug therapeutic codes, dosage instructions (i.e., quantity, form, frequency, strength), and prescription status. We classify a drug as a painkiller if its associated drug therapeutic codes fall under strong analgesics, mild analgesics, or anti-rheumatic agents. To identify opioid drugs, we use data from the 2020 CDC Oral MME Conversion file, containing all opioid analgesics that are normally prescribed in outpatient settings, dispensed by retail pharmacies, and controlled by the Drug Enforcement Administration (DEA).[6]

Since this paper focuses on pills prescribed for pain relief, we sequentially apply three exclusion criteria to build our pharmacy claims dataset. First, we exclude opioid records that fall outside our definition of painkillers.[7] Second, we exclude painkillers available over the counter (OTC).[8] Third, we only keep painkillers in tablet or capsule form.[9] Our cleaned pharmacy claims dataset contains 9214 records of pain pills sold by prescription only: 5149 opioids and 4065 non-opioids.[10]

[5]Appendix OA.1.2 shows the remaining number of observations after each sample restriction.

[6]We exclude opioid treatment drugs, such as methadone and naltrexone. There are only 8 pharmacy claims involving opioid treatment drugs in our sample.

[7]Opioids that are not prescribed for pain relief account for 25.94% of the opioid pharmacy claims in our sample. These non-painkiller opioids are mostly prescribed as antitussive agents (78.98%), expectorants and inhalants (28.63%), and/or antidiarrheals (7.82%). Percentages add up to more than 100% because pharmacy claims can have up to five different drug therapeutic codes.

[8]OTC painkillers account for 5.19% of the painkiller pharmacy claims in our sample.

[9]We drop 1.93% of the remaining records at this final stage.

[10]Appendix OA.1.3 presents the details to identify prescription-only painkillers in the RAND HIE data.

With these data in hand, we generate three key variables for each opioid painkiller purchase: (a) days of supply, (b) MME per day, and (c) an indicator for high-dose opioid purchase. We follow the CDC guidelines and define these variables as follows:

$$\text{days of supply} = \frac{\text{number of units}}{\text{quantity per intake} \times \text{intakes per day}} \tag{1a}$$

$$\text{MME per day} = \text{strength per unit} \times \frac{\text{number of units}}{\text{days of supply}} \times \text{MME conversion factor} \tag{1b}$$

$$\text{high-dose} = \mathbb{1}[\text{MME per day} \geq 90] \tag{1c}$$

where the variables *number of units*, *quantity per intake*, *intakes per day*, and *strength per unit* come directly from the claim records, and *MME conversion factor* comes from the CDC Oral MME Conversion file. Lastly, we generate three variables for each physician outpatient visit: (a) an indicator for any visit, (b) an indicator for any opioid prescription written, conditional on a provider visit, and (c) an indicator for whether the prescription was filled, conditional on a provider visit and an opioid prescription.

The line-item claim records related to services rendered in outpatient settings provide comprehensive information on ambulatory visits to healthcare providers. These services can come from (a) independent physicians and health professionals, or (b) dentists. We exclude hospital claims for outpatient services performed by physicians acting as employees. Specific information includes the reasons/symptoms for the visit, the diagnosis and procedure codes, the charge for the service, the date and place of the service, among other variables.

Table 1 presents descriptive statistics for the sample used in the analysis. Panel A reports demographic characteristics and self-reported measures of pain and health from the baseline questionnaire. Individuals in the sample are predominantly women (51.7%), with the majority residing in urban areas (65.6%). A large proportion of individuals are under 18 years old (45.3%). The sample is composed of 78.3% white non-Hispanic individuals and 18.7% black non-Hispanic individuals.[11] At enrollment, most individuals report experiencing no or minimal pain (74.6%) and rate their health as good or excellent (80.1%).[12]

4 The Stage for the Modern Opioid Crisis: *Wave Zero*

In this section, we draw on data from the RAND Experiment outlined in Section 3 to contextualize opioid utilization during the late 1970s and early 1980s. We begin by presenting statistics related to opioid utilization. Next, we focus on the characteristics of opioid prescribers and the most commonly prescribed opioid drugs. Finally, we examine diagnosis codes to explore the diseases, symptoms, and potential injuries that led to prescribed opioid use.

Panel B of Table 1 provides descriptive statistics on the utilization of prescription-only painkillers, distinguishing between opioid and non-opioid medications. Prescribed painkiller purchases, while not widespread, are clearly present across a significant portion of the sample, with 15.5% of individual-year observations including at least one. Prescribed opioid painkillers are more frequent than their non-opioid counterpart: 10.8% of individual-year

[11] Race and ethnicity data were collected only for the family heads in the RAND HIE. We assign the race/ethnicity of the family head to all family members. In the rare instance of two family heads, we prioritize the male.

[12] Appendix OA.1.1 presents additional details regarding the self-reported measures of pain in the RAND HIE data.

Table 1: Summary Statistics: RAND Health Insurance Experiment, 1974-1982

	MEAN	SD	N
Panel A: Sample Demographics			
1. Share female	0.517	0.500	5922
2. Share urban	0.656	0.475	5922
Age Category at Baseline			
3. Share under 18	0.453	0.498	5922
4. Share 18–24	0.105	0.306	5922
5. Share 25–34	0.187	0.390	5922
6. Share 35–44	0.111	0.314	5922
7. Share 45–54	0.091	0.288	5922
8. Share 55–64	0.053	0.225	5922
Race and Ethnicity			
9. Share non-Hispanic white	0.783	0.412	5922
10. Share non-Hispanic black	0.187	0.390	5922
11. Share Hispanic	0.006	0.074	5922
12. Share other	0.008	0.092	5922
13. Share missing	0.016	0.127	5922
Pain Level at Baseline			
14. A great deal	0.037	0.189	5922
15. Some pain	0.109	0.311	5922
16. A little pain	0.327	0.469	5922
17. No pain at all	0.419	0.493	5922
18. Missing	0.108	0.310	5922
Health Status at Baseline			
19. Poor	0.015	0.123	5922
20. Fair	0.076	0.265	5922
21. Good	0.348	0.476	5922
22. Excellent	0.453	0.498	5922
23. Missing	0.108	0.310	5922
Panel B: Painkiller Prescriptions Filled			
All Painkillers			
24. Share with any prescription filled	0.155	0.362	20004
25. Share with two or more prescriptions filled	0.073	0.261	20004
26. Number of prescriptions filled | any purchase	2.964	4.849	3109
27. Annual days of supply | any purchase	29.844	71.983	3109
Opioids			
28. Share with any prescription filled	0.108	0.310	20004
29. Share with two or more prescriptions filled	0.039	0.195	20004
30. Number of prescriptions filled | any purchase	2.383	4.449	2161
31. Annual days of supply | any purchase	12.429	36.238	2161
32. MME per day per prescription filled | any purchase	51.091	36.330	2161
33. Share of high-dose per prescription filled | any purchase	0.136	0.315	2161
Non-Opioids			
34. Share with any prescription filled	0.078	0.269	20004
35. Share with two or more prescriptions filled	0.036	0.186	20004
36. Number of prescriptions filled | any purchase	2.591	3.040	1569
37. Annual days of supply | any purchase	42.017	80.858	1569

Notes: This table presents summary statistics for our RAND HIE analysis sample. Each row reports raw means and standard deviations at the individual-year level for various variables. The variables are organized into two panels. The first panel reports demographic characteristics and self-reported measures of pain and health from the baseline questionnaire, using observations from the first year only. The second panel provides measures of prescribed painkiller utilization, distinguishing between opioid and non-opioid painkillers.

observations contain at least one opioid painkiller purchase against 7.8% for non-opioids.[13] Additionally, 3.9% of individual-year observations include two or more opioid painkiller pur-

[13] Our statistics for non-opioid painkillers refer to prescription-only and do not account for OTC purchases.

chases, a commonly used proxy for heavy use of opioids (Cutler and Glaeser, 2021). Among individual-year pairs with at least one opioid painkiller purchase, the average number of opioid prescriptions filled per person is 2.38, with an average annual supply of 12.4 days, an average MME per day per prescription of 51.1, and an average share of high-dose prescriptions of 13.6%.

Our results provide the first evidence that opioid consumption was already prevalent in the 1970s and early 1980s, more than a decade prior to the onset of the opioid epidemic in 1996. To contextualize our findings, we use data from the 1996 Medical Expenditure Panel Survey (MEPS), which show that 16.2% of the non-elderly U.S. population filled at least one opioid prescription, and 6.8% filled two or more.[14] Among opioid users, the average number of prescriptions was 2.47.[15] As expected, usage was lower in the 1974-1982 RAND data compared to 1996, as the RAND survey reflects opioid consumption more than a decade earlier and before the onset of the modern opioid crisis. All of these figures rose sharply in the 2000s. By 2010, 17.6% of the non-elderly U.S. population filled at least one opioid prescription, 8.0% filled two or more, and the average number of opioid prescriptions had increased to 3.79.[16]

[14]See Figure OA.2.1 in Appendix OA.2 for the evolution of opioid usage among the non-elderly population using data from the MEPS between 1996 and 2016. Cutler and Glaeser (2021) also use the MEPS to report similar statistics, focusing on the population aged 15 and older. Because the RAND HIE oversampled low-income families, we also report figures by poverty line in Figure OA.2.2. Opioid usage was highest among low-income individuals (i.e., those with income below 200% of the poverty line). The RAND HIE sample is most comparable to the population group between 200% and 400% of the poverty line (Newhouse et al., 1993), among whom 16.7% filled at least one opioid prescription and 6.8% filled two or more in 1996.

[15]See Figure OA.2.3 in Appendix OA.2 for the evolution of number of opioid prescriptions filled in the MEPS between 1996 and 2016. MEPS does not report days of supply information prior to 2010. Therefore, we are unable to systematically document average days of supply and its derived variables (e.g., MME per day).

[16]Authors' calculations based on the 2010 Medical Expenditure Panel Survey (MEPS).

4.1 Patient Opioid Utilization

This section documents relevant patterns in prescribed opioid and non-opioid painkiller use across different demographic and geographic groups.

First, we analyze several measures of prescribed analgesic use at the individual-year level. Prescribed opioid painkiller use is notably more prevalent among women at both the extensive and intensive margins. Compared to men, women exhibit greater opioid prescription uptake (12.0% versus 9.0%; Figure 1a) and are more likely to fill multiple opioid prescriptions (5.0% versus 3.0%; Figure 1b). Conditional on at least one purchase within the year, women have a higher per capita annual number of opioid prescriptions filled than men, averaging 2.64 versus 2.00 (Figure 1c), have longer days of supply (14.16 versus 9.84; Figure 1d), and higher average MME per day (52.5 versus 49.0; Figure 1e), which translates to 15% of women (with nonzero opioid prescriptions) filling at least one high-dose opioid prescription per year (versus 11% for men; Figure 1f).[17] A similar pattern is observed for prescribed non-opioid painkillers, which also show higher prevalence among women at both margins.

We document a similar gender pattern in opioid utilization in the 1996 MEPS. For example, Figure OA.2.4 shows that women were more likely than men to fill at least one prescription (18.6% versus 13.8%).[18] The gender patterns of opioid use are not replicated in opioid mortality though. Case and Deaton (2020) show that "deaths of despair" were

[17]Figures on utilization at the intensive margin (i.e., number of purchases, days of supply, MME per day, and share of high-dose) are calculated using individual-year observations with nonzero purchases. Figure OA.2.5 presents analogous subfigures incorporating individual-year observations with zero use.

[18]Cutler and Glaeser (2021) document a comparable gender pattern in opioid utilization using the 1996 MEPS, though they focus on the share taking two or more prescriptions among individuals aged 15 and older. By contrast, our figures are based on the population under age 65.

more prevalent among men at the onset of the epidemic. However, this is not necessarily contradictory, as the measures differ in nature. Mortality rates capture the ultimate consequence of substance use, while opioid use patterns reflect the prevalence and intensity of consumption without directly accounting for its fatal outcomes.

Second, we find no differences in prescribed opioid painkiller use between urban and rural areas at the extensive margins (Figures 2a and 2b).[19] However, individuals in rural areas fill more prescriptions and receive longer average days of supply (Figures 2c and 2d). These findings may seem surprising, given the expectation that individuals in rural areas face reduced access to healthcare providers and, consequently, fewer prescriptions. However, labor-intensive occupations such as mining and agriculture, along with the associated pain, may be more prevalent in rural areas and could contribute to comparable levels of opioid use.[20] These patterns are consistent with 1996 MEPS data, which also show similar levels of opioid use in rural and urban areas (Figure OA.2.4), although subsequent increases were more pronounced in rural regions. Notably, we also document that the prevalence of prescribed non-opioid painkillers is higher in urban areas, both at the extensive margin and in terms of average days of supply.

Third, focusing on race and ethnicity, we find that prescribed opioid painkiller use is higher among white non-Hispanics than among Black individuals or Hispanics (Figures 3a and 3b).[21] Conditional on filling at least one opioid prescription in a given year, white non-Hispanics also exhibit greater per capita annual opioid purchases (2.49 versus 2.00 and

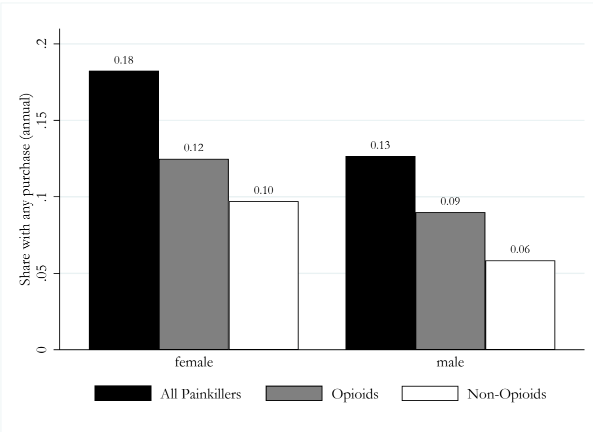
[19]Figure OA.2.6 presents analogous subfigures incorporating individual-year observations with zero use.

[20]Consistent with this hypothesis, we document that self-reported pain at baseline in our RAND HIE sample is higher in rural compared to urban areas. Specifically, the share of individuals reporting at least some pain is 0.22 in rural areas and 0.14 in urban areas, with the difference being statistically significant (p-value= 0.000).

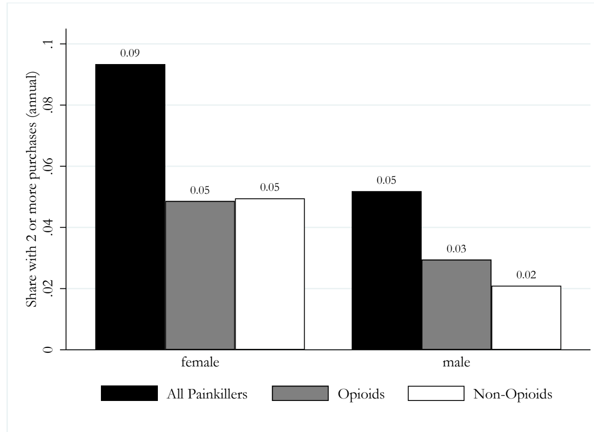
[21]Figure OA.2.7 presents analogous subfigures incorporating individual-year observations with zero use.

Figure 1: Prescribed Painkiller Utilization by Gender

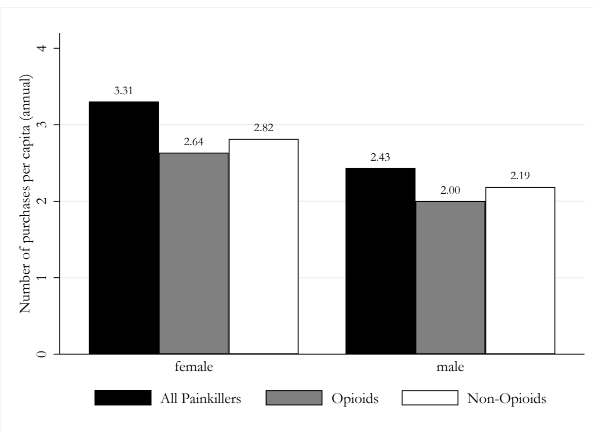
(a) Share with Any Purchase



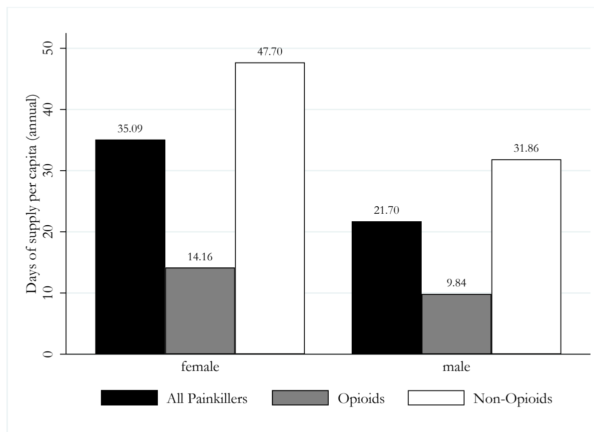
(b) Share with Two or More Purchases



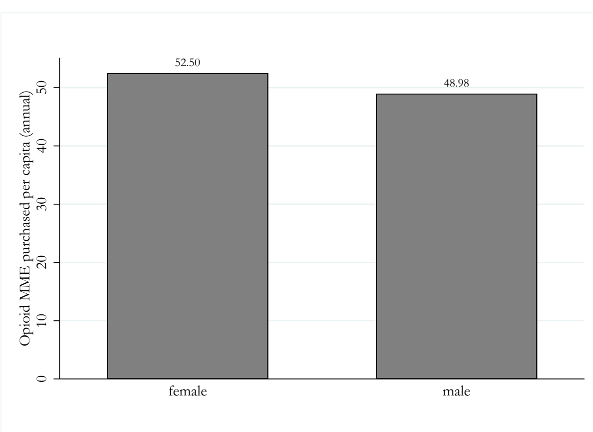
(c) Average Number of Purchases Per Capita



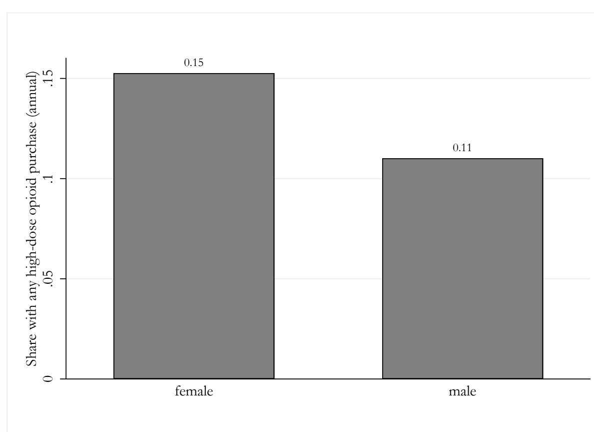
(d) Average Annual Days of Supply Per Capita



(e) Average MME Per Day Per Capita



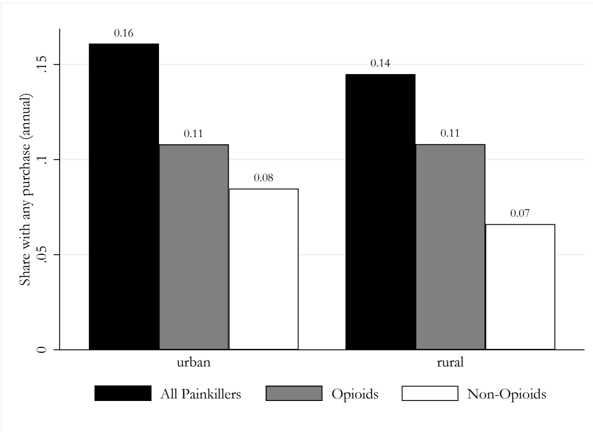
(f) Share with Any High-Dose Opioid



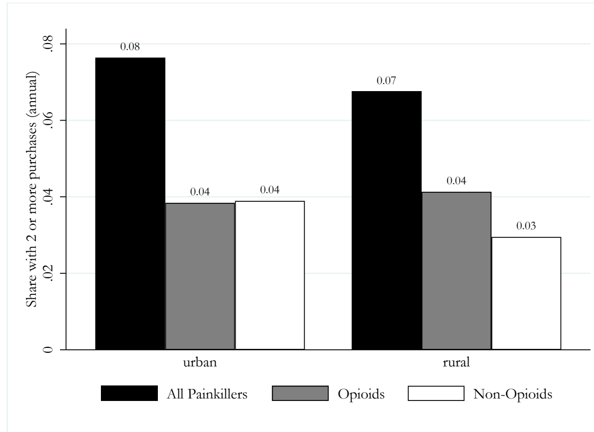
Notes: These figures depict several measures of prescribed painkiller utilization by gender and type of prescribed painkiller (i.e., opioid and non-opioid). Figures 1 and 1b use all individual-year pairs in our RAND HIE analysis sample. Figures 1c, 1d, 1e, and 1f are restricted to individual-year pairs with at least one prescribed painkiller. Specifically, figures focusing on opioid (non-opioid) painkillers include only individual-year observations with at least one prescribed opioid (non-opioid). Similarly, figures covering all prescribed painkillers include individual-year observations with at least one prescribed opioid and/or non-opioid.

Figure 2: Opioid Utilization by Location

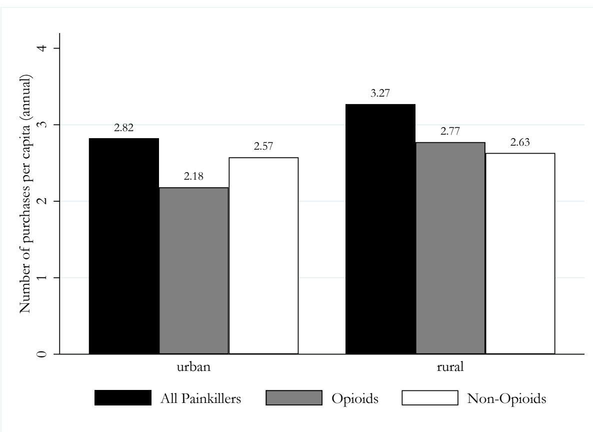
(a) Share with Any Purchase



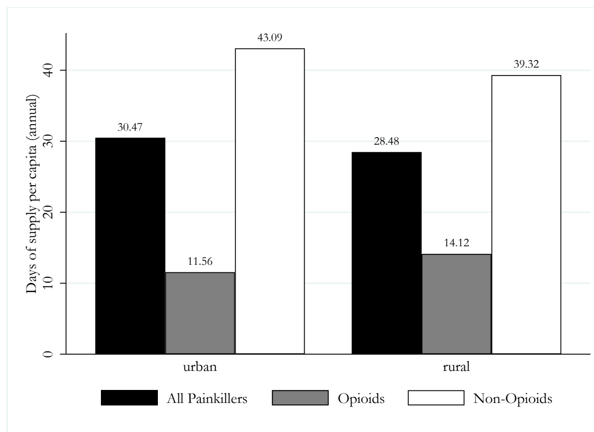
(b) Share with Two or More Purchases



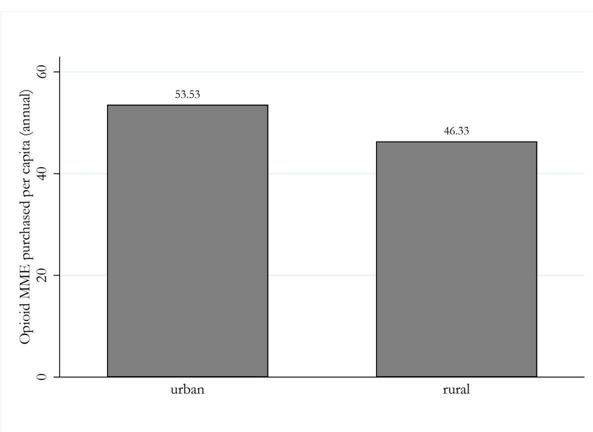
(c) Average Number of Purchases Per Capita



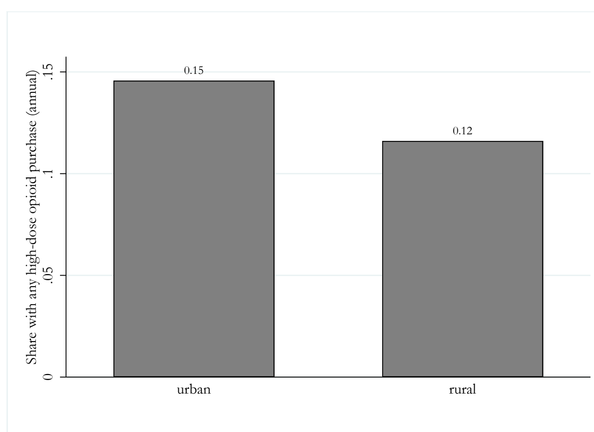
(d) Average Annual Days of Supply Per Capita



(e) Average MME Per Day Per Capita



(f) Share with Any High-Dose Opioid



Notes: These figures depict several measures of prescribed painkiller utilization by location (i.e., rural or urban) and type of prescribed painkiller (i.e., opioid and non-opioid). Figures 2 and 2b use all individual-year pairs in our RAND HIE analysis sample. Figures 2c, 2d, 2e, and 2f are restricted to individual-year pairs with at least one prescribed painkiller. Specifically, figures focusing on opioid (non-opioid) painkillers include only individual-year observations with at least one prescribed opioid (non-opioid). Similarly, figures covering all prescribed painkillers include individual-year observations with at least one prescribed opioid and/or non-opioid.

1.38; Figure 3c) and longer average days of supply (13.48 versus 8.38 and 4.33; Figure 3d). Notably, similar racial-ethnic disparities emerge for prescribed non-opioid painkiller as well.

These findings are consistent with patterns observed in the 1996 MEPS. Figure OA.2.4 shows that white non-Hispanics were more likely to have filled at least one opioid prescription (17.9%) compared to Black non-Hispanics (12.9%) and Hispanics (12.3%). The ethnic disparities documented here are also consistent with those in Case and Deaton (2020), who found that deaths of despair were less prevalent among Black individuals and remained relatively stable during the early years of the opioid crisis (up to the mid-2000s), while mortality rates among white individuals, primarily among non-Hispanics, increased significantly. The differences between white and Black individuals are often attributed to disparities in health insurance access and generosity. However, given the random assignment of families to insurance plans in the RAND HIE, this explanation is unlikely to account for the observed patterns. Ethnic disparities in opioid purchases may stem from taste-based discrimination by physicians. For instance, a widely controversial textbook offering guidance on when to administer pain relief to people from different ethnic backgrounds, suggests that black individuals often report higher pain intensity than other cultures and have higher pain tolerance (Pearson, 2014). This notion, however, is not evidence-based and has been criticized for encouraging healthcare providers to dismiss patient-reported pain levels (see, e.g., Jaschik (2017); Sini (2017)).

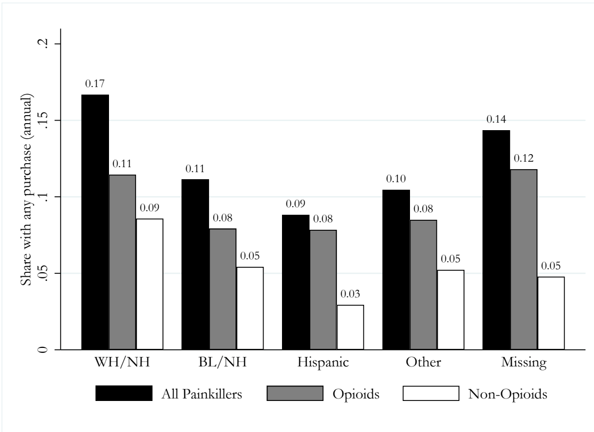
4.2 Opioid Prescribers

In this section, we use claim-level data to examine prescriber characteristics by training (physicians versus dentists) and specialty.[22] Prescribers played a significant role in the onset

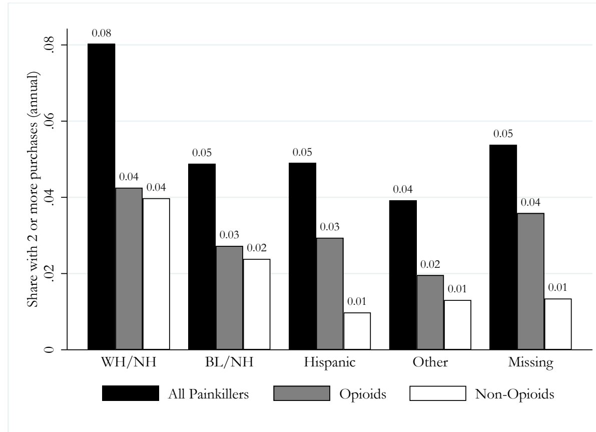
[22]Note that this data is different from the one used in Subsection 4.1 (i.e, individual-year level data). Instead, the data in this section relies on claim-level records, specifically all prescribed painkiller purchases.

Figure 3: Opioid Utilization by Ethnicity

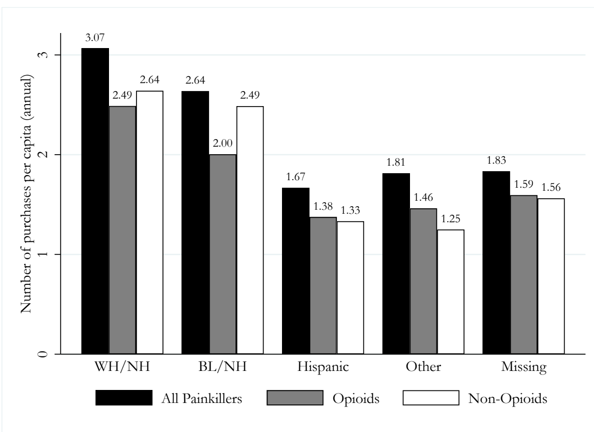
(a) Share with Any Purchase



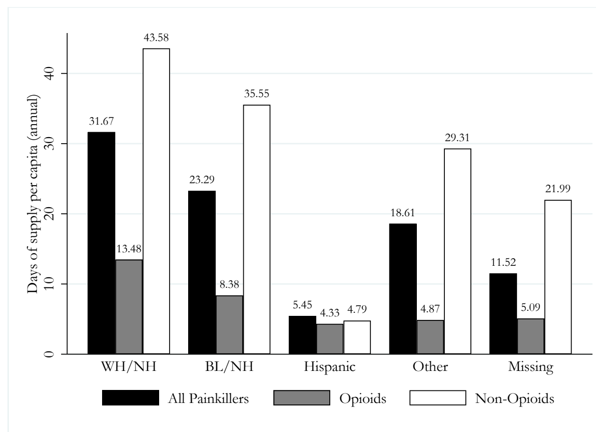
(b) Share with Two or More Purchases



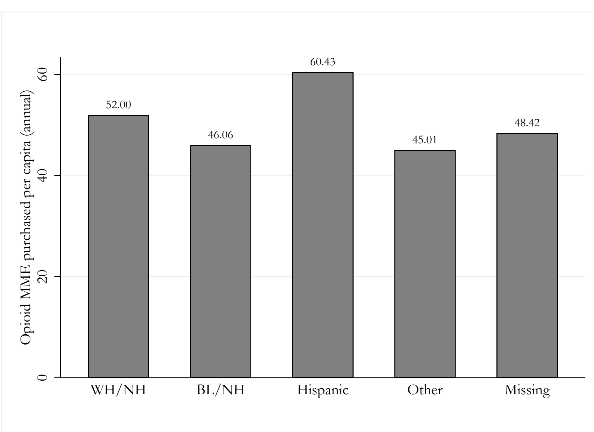
(c) Average Number of Purchases Per Capita



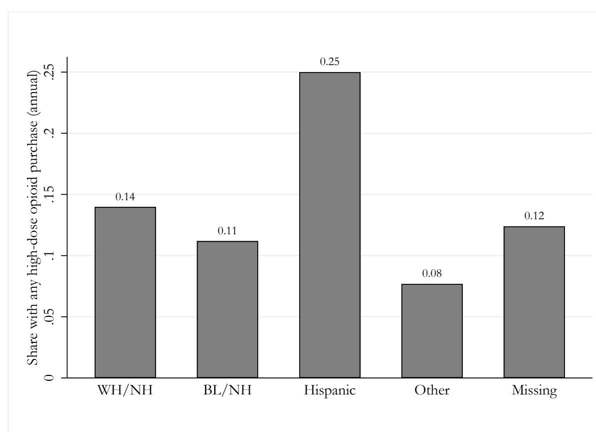
(d) Average Annual Days of Supply Per Capita



(e) Average MME Per Day Per Capita



(f) Share with Any High-Dose Opioid



Notes: These figures depict several measures of prescribed painkiller utilization by ethnicity and type of prescribed painkiller (i.e., opioid and non-opioid). The ethnicity categories include White non-Hispanic (WH/NH), Black non-Hispanic (B/NH), Hispanic, other, and missing. Figures 3 and 3b use all individual-year pairs in our RAND HIE analysis sample. Figures 3c, 3d, 3e, and 3f are restricted to individual-year pairs with at least one prescribed painkiller. Specifically, figures focusing on opioid (non-opioid) painkillers include only individual-year observations with at least one prescribed opioid (non-opioid). Similarly, figures covering all prescribed painkillers include individual-year observations with at least one prescribed opioid and/or non-opioid.

of the modern opioid crisis. First, changing guidelines in the early 1990s encouraged opioid prescribing for pain management (Quinones, 2015). Second, physicians —particularly primary care providers— were targeted by aggressive marketing campaigns for OxyContin (Alpert et al., 2022). Therefore, analyzing prescriber characteristics is crucial to understanding their role in the opioid crisis.

We categorize prescribers into three mutually exclusive groups: general practitioners, specialists, and dentists. General practitioners (GPs) include Doctors of Medicine (MDs) and Doctors of Osteopathy (DOs) with a family practice or general practice specialty. Specialists include MDs and DOs who are not GPs (e.g., cardiologists).[23]

Our analysis of prescribers is based on data from all prescribed painkiller purchases. Descriptive statistics for the data are provided in Table OA.2.1. The data comprises 5,119 and 4,065 opioid and non-opioid painkiller purchases filled, with opioids accounting for 55.9% of all prescribed painkillers. For context, in 2021, opioids comprised 45% of prescribed painkiller purchases.[24] Our figures highlight the widespread use of opioid painkillers in *Wave Zero*, before the onset of the opioid epidemic.

Figure 4a shows that, in the 1970s and early 1980s, opioids were primarily prescribed by specialists (42%), followed by GPs (34%). A notable finding is that dentists played a non-negligible role in opioid prescribing, accounting for 20% of opioid prescriptions. To our knowledge, we are the first to emphasize the role of dentists in opioid prescribing in the prelude of the opioid epidemic. The dominant role of specialists in opioid prescribing until the

[23]Data concerning Doctors of Medicine, Doctors of Osteopathy, or dentists come from the American Medical Association (AMA) 1976 and 1981 data tapes, the American Osteopathic Association (AOA) 1976 data tape, and the American Dental Association (ADA) 1976 data tape, respectively.

[24]Authors' calculations based on the 2021 Medical Expenditure Panel Survey (MEPS). See Appendix OA.3.

1980s did not last long. By 2003, nearly half of all physicians prescribing OxyContin were primary care physicians (GAO, 2003). Using data from 2006-2014, Schnell (2025) find that GPs were the leading opioid prescribers (43%), followed by specialists (39%). The swap in the ranking positions between GPs and specialists from 1974-1982 to 2006-2014 is consistent with pharmaceutical marketing campaigns in the 1990s targeting physicians in general practice. For prescribed non-opioid painkillers the distribution looks strikingly different: GPs and specialists split the non-opioid prescriptions in roughly half, so the role of dentists is negligible (1%).

Opioid prescription patterns varied across prescriber types. First, specialists prescribed opioids with the highest average days of supply (6.33; Figure 4b) and MME per day (57.24; Figure 4c). Consistent with this, 19% of specialists' opioid prescriptions involved high-dose opioids (Figure 4d). Second, opioid prescribing patterns among GPs were more conservative than those of specialists, with fewer average days of supply (5.65), lower MME per day per prescription (52.45), and a lower share of high-dose opioids (11%). Third, dentists were the most conservative prescribers, with the shortest average days of supply per prescription (2.48) and the lowest average MME per day (40.72). Non-opioid painkiller prescriptions follow the same pattern.[25]

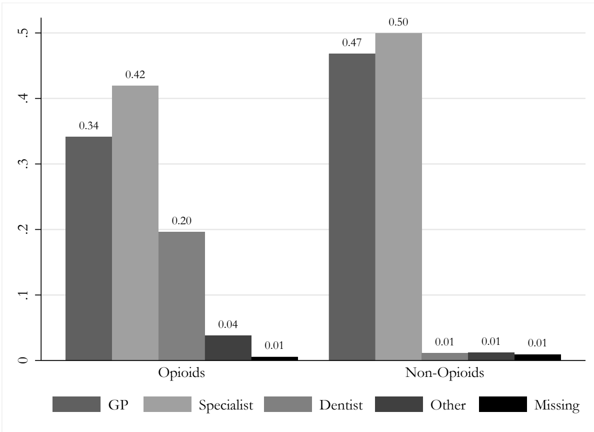
These figures suggest that both GPs and dentists had scope to substitute away from non-opioids to opioids and/or increase opioid prescription generosity relative to specialists, a factor central to the OxyContin marketing campaign in 1996, which specifically targeted primary-care providers (Alpert et al., 2022). However, these observations do not account for the potentially higher pain levels among patients treated by specialists. In this regard, another key aspect of OxyContin's marketing strategy was to promote opioid use for noncancer chronic pain, in an attempt to decrease the pain level threshold above which physicians would

[25] Figure OA.2.8 further decomposes prescription patterns among specialists by their respective specialties.

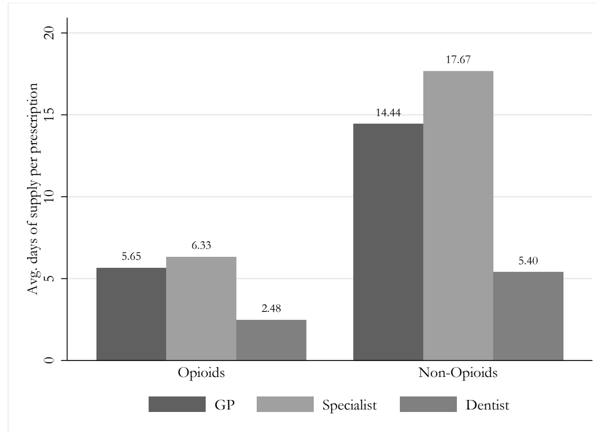
be willing to prescribe opioids. We further discuss this in Subsection 4.4.

Figure 4: Characteristics of Opioid Prescribers

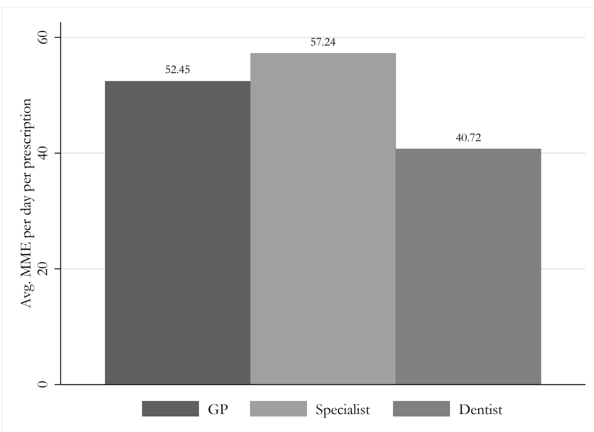
(a) Distribution of Prescribers



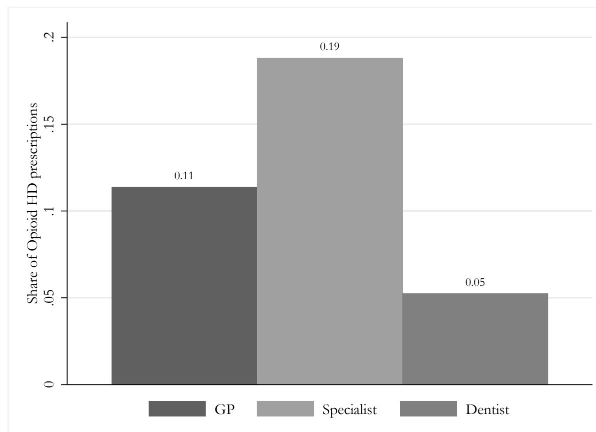
(b) Average Days of Supply per Prescription



(c) Average MME per Day per Prescription



(d) Share of Opioid High-Dose Prescriptions



Notes: These figures depict several characteristics of prescribed painkillers by type of prescriber (i.e., general practitioner, specialist, dentists, other, missing) and type (i.e., opioid and non-opioid). Figures related to prescribed opioid (non-opioid) painkillers employ all opioid (non-opioid) prescriptions in our RAND HIE analysis sample.

4.3 Commonly Prescribed Opioid Drugs

In this section, we document the opioid drugs most commonly prescribed in the 1970s and early 1980s, leveraging the claim-level data on all opioid painkiller purchases described in Subsection 4.2. Figure 5 shows that codeine was the most commonly prescribed opioid, accounting for more than 52% of all opioid purchases. The second most commonly prescribed drug was propoxyphene (24%), which was discontinued in 2010 due to heart-related risks (U.S. Food and Drug Administration, 2010).[26] Notably, oxycodone accounted for only 11% of all opioid purchases, despite later playing a central role in the opioid epidemic (Alpert et al., 2022). Moreover, propoxyphene prescriptions had longer average days of supply (7.52) and more than twice the average MME per day (105.3) compared to other commonly prescribed opioids. The average days of supply per prescription for oxycodone was 6.68, with an average MME per day of 45.6.

To examine shifts in drug distribution between the pre-epidemic and post-epidemic periods, we compare our figures with analogous data from the 2021 Medical Expenditure Panel Survey (MEPS).[27] Table 2 shows the distribution of opioid prescriptions by drug name in MEPS. As shown in the third column, codeine represents only 2.7% of all opioid prescriptions, while propoxyphene has a zero share due to its 2010 discontinuation. Hydrocodone and oxycodone combined account for more than 50% of all opioid prescriptions. These figures reflect the number of prescriptions but do not account for differences in drug potency. The last column of Table 2 adjusts for potency by weighting prescriptions based on their MME. By this measure, oxycodone alone represents 53.3% of all opioid prescriptions, followed by hydrocodone (25.2%) and morphine (10.5%).[28] A similar concentration pattern existed in the 1970s and early 1980s, though with a different dominant drug. Figure 5f shows the MME-weighted distribution of opioids in the RAND data, where propoxyphene accounted

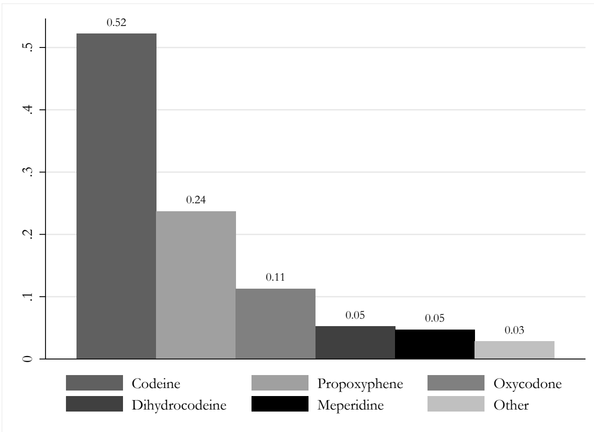
[26]First approved by the FDA in 1957, propoxyphene was an opioid analgesic indicated for the treatment of mild to moderate pain. It was available by prescription in various formulations, both as a single-ingredient product (e.g., Darvon) and in combination with acetaminophen (e.g., Darvocet). The FDA requested the withdrawal of propoxyphene from the U.S. market on November 19, 2010, following two prior withdrawal requests since 1978 and the European market's decision to remove the drug in June 2009.

[27]In Appendix OA.3, we describe the main steps followed to clean the 2021 MEPS data.

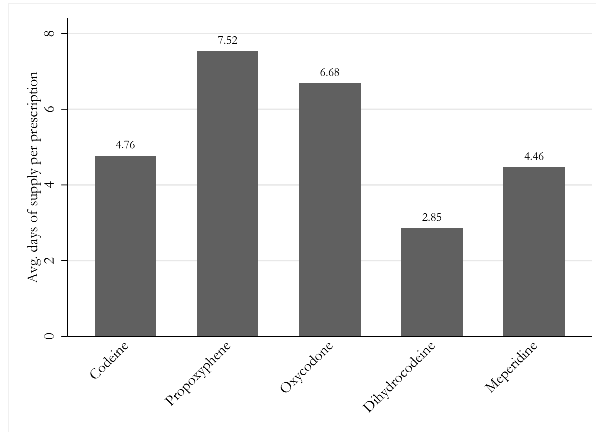
[28]Arteaga and Barone (2022) analyze ARCOS data from 1997 to 2018 and document that the share of oxycodone shipments increased steadily from 1997 to 2010, stabilizing thereafter, while hydrocodone shipments remained relatively stable over the same period.

Figure 5: Most Commonly Prescribed Opioid Drugs

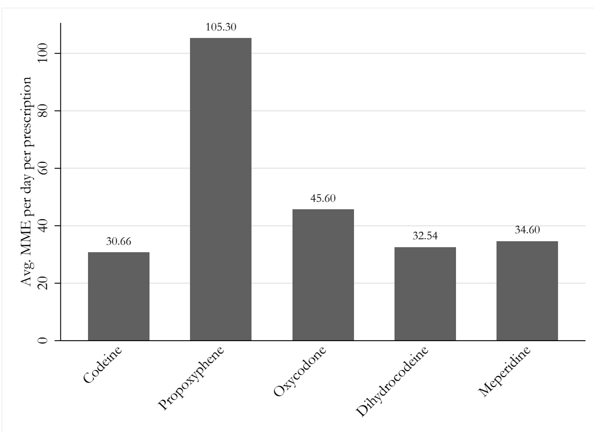
(a) Distribution of Drugs (# of Prescriptions)



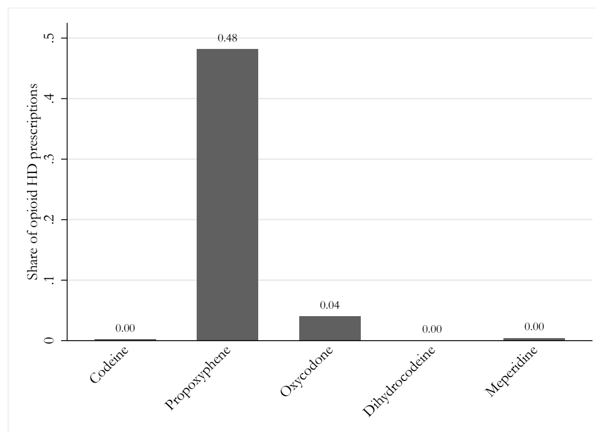
(b) Average Days of Supply per Prescription



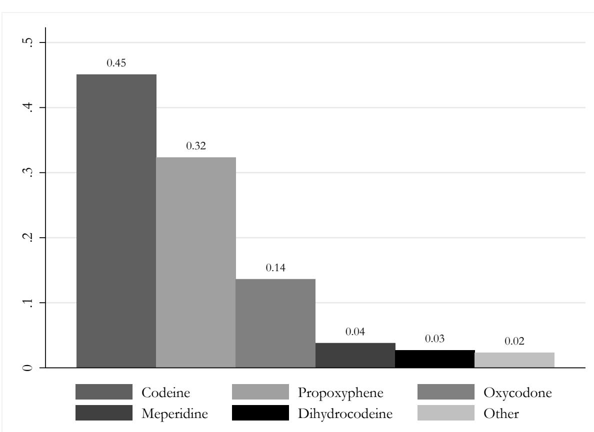
(c) Average MME per Day per Prescription



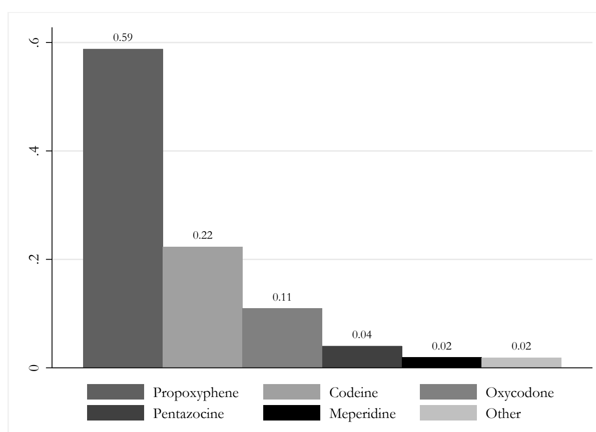
(d) Share of High-Dose Prescriptions



(e) Distribution of Drugs (# of Days of Supply)



(f) Distribution of Drugs (# of MME)



Notes: These figures depict various characteristics of prescribed opioid painkillers by drug type. All figures include opioid prescriptions from our RAND HIE analysis sample.

for 59% of all opioid painkiller prescriptions, followed by codeine (22%) and oxycodone (11%).

Table 2: Opioid Prescriptions in 2021 MEPS by Drug Name

Drug Name	Frequency	Percent (unweighted)	Percent (MEPS weighted)	Percent (MME weighted)	Percent (MEPS & MME weighted)
Codeine	142	2.71	3.21	1.28	1.31
Hydrocodone	1701	32.41	33.64	25.56	25.23
Hydromorphone	76	1.45	1.46	2.34	2.59
Morphine	277	5.28	5.09	12.34	10.52
Oxycodone	1426	27.17	27.73	51.48	53.31
Tramadol	737	14.04	14.01	6.99	7.05
Unknown	890	16.96	14.86		
Total	5249	100.00	100.00	100.00	100.00

Notes: The reported statistics are derived from the MEPS Prescribed Medicine file for 2021. We restrict the sample to opioid painkillers with non-missing drug names purchased by individuals aged 64 or less. Column (1) shows the frequencies of each drug. Columns (2) and (3) show the drug percentages unadjusted and adjusted by MEPS survey weights for national representation, respectively. Column (4) displays percentages weighted by Morphine Milligram Equivalents (MMEs) only. The last column displays percentages weighted by MMEs and adjusted by MEPS survey weights for national representation.

4.4 Common Diagnosis Codes and Reasons for Outpatient Visits Leading to Painkiller Prescriptions

In this section, we examine the primary diagnosis codes linked to prescribed painkiller purchases, alongside the main reported reasons and symptoms associated with the outpatient provider visits that preceded these prescriptions. Unlike diagnosis codes, which are assigned by healthcare providers, reasons and symptoms are typically self-reported by patients. This distinction offers a complementary perspective on the factors contributing to opioid prescriptions.

We begin by focusing on the reasons and symptoms associated with outpatient visits that resulted in painkiller prescriptions. For each painkiller sold by prescription only, we collect reasons recorded in outpatient visit claims within the 30 days preceding the prescription.[29] We group these reasons into clinically relevant categories and construct five indicator variables measuring whether the outpatient visits within the 30 days preceding the prescription had at least one reason related to: (1) cancer, (2) arthritis, (3) pain, (4) injury, and (5) diabetes. Figure 6a presents the share of opioid painkiller purchases involving at least one of several specified reasons.[30]

Approximately 44% of opioid painkiller prescriptions are associated with at least one pain-related reason for the outpatient visits within the past 30 days, whereas only 2% involved a cancer-related reason. Although there is some overlap between pain-related and cancer-related reasons, the gap between their respective shares reveals that a substantial portion of opioid prescriptions were for pain reasons unrelated to cancer. This pattern underscores that opioids were already being widely used to treat chronic non-cancer pain, a practice that escalated and reached a critical point during the first wave of the opioid epidemic.

We observe a similar, though somewhat attenuated, pattern when focusing on diagnosis codes. Consistent with the previous approach, we analyze the 30-day period preceding each prescription and collect the diagnosis codes recorded in outpatient visit claims. Figure 6b displays the share of opioid prescriptions involving at least one of several specified diagnosis codes. We find that 17% of opioid painkiller prescriptions were associated with at least one pain-related diagnosis code within the past 30 days, whereas only 3% involved

[29]In Appendix OA.2 we present the same analysis using 90-day and 180-day windows. The main findings remain robust.

[30]Multiple reasons may be associated with a single opioid purchase. First, individuals may have multiple outpatient healthcare visits within the 180 days preceding the prescription. Second, the RAND HIE data records up to three reasons per line-item claim. Similarly, several diagnosis codes may be linked with a single opioid purchase. In this case, the RAND HIE data include up to four reasons/symptoms per line-item claim.

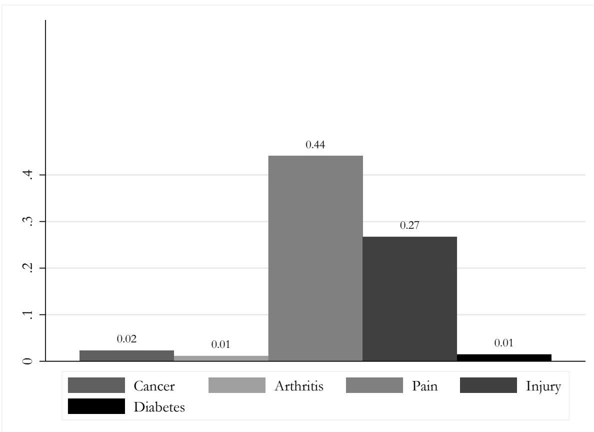
a cancer-related diagnosis code. Although the overall shares are smaller than those based on self-reported reasons, the relative difference between pain and cancer remains substantial.

Lastly, similar patterns arise for non-opioid painkillers (see Figures 6c and 6d). The main distinction is observed in the arthritis category, which accounts for a higher share of both reasons and diagnosis codes relative to opioid painkillers.

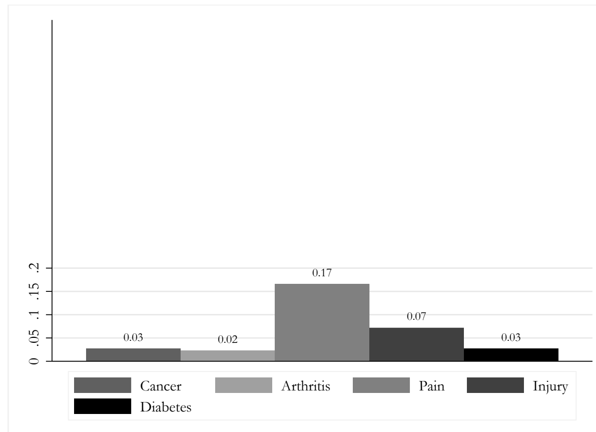
To contextualize our findings, we compare them with those of Daubresse et al. (2013), who analyze diagnosis codes associated with opioid prescriptions in ambulatory care settings between 2006 and 2015. They report that 66.4% of visits involving an opioid prescription were linked to noncancer pain diagnoses, while only 5.1% were associated with cancer-related pain. The predominance of opioid prescribing for pain during the second and third waves of the opioid epidemic is consistent with the focus of pharmaceutical marketing efforts on noncancer pain conditions (Arteaga and Barone, 2022). Reasonably expected, the share of prescriptions linked to cancer diagnoses remained relatively low both prior to and during the epidemic.

Figure 6: Common Diagnosis Codes and Reasons for Healthcare Visits Underlying Painkiller Prescriptions

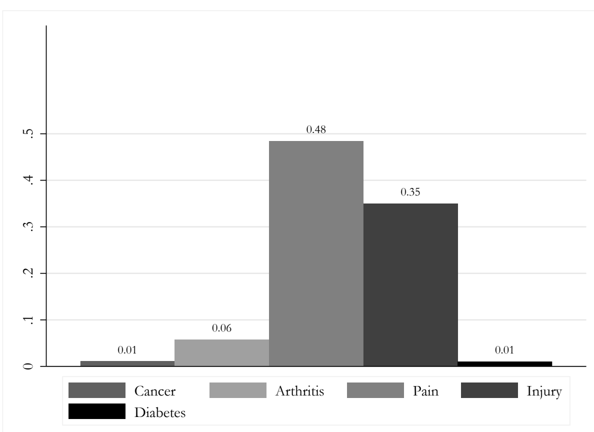
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



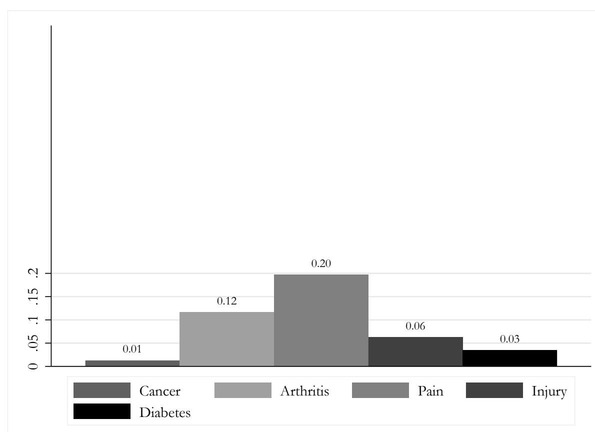
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



(c) Share of Non-Opioid Prescriptions Involving Selected Reasons for Visiting Provider



(d) Share of Non-Opioid Prescriptions Involving Selected Diagnosis Codes



Notes: Figures OA.2.10b and OA.2.10d display, for opioid and non-opioid prescriptions respectively, the average of four indicator variables capturing whether any outpatient visit within the 30 days preceding the prescription involved: (1) at least one diagnosis related to cancer, (2) at least one diagnosis related to arthritis, (3) at least one diagnosis related to pain, (4) at least one diagnosis related to injury, or (5) at least one diagnosis related to diabetes. Figures OA.2.10a and OA.2.10c present analogous measures but focus instead on the reported reasons and symptoms for the visits.

5 Empirical Analysis: Impact of Health Insurance Generosity on Prescribed Painkiller Purchases

In this section, we examine how prescribed painkiller purchases respond to changes in health insurance generosity. To do so, we leverage the random assignment of individuals to health insurance plans in the RAND HIE. We begin by presenting descriptive statistics for our estimation sample by health insurance plan, followed by a discussion of our empirical strategy and main results.

5.1 Descriptive Statistics by Health Insurance Plan

Table 3 describes the most relevant statistics of our sample by plan group. Each of the six columns presents raw means and standard deviations at the person-year level by plan. Each row presents a measure related to the utilization of prescribed painkillers or the use of outpatient provider services. The last three rows at the bottom of the table record the number of unique families, individuals, and individual-years, respectively, by plan.

Free care is the largest plan, encompassing 33.2% of individuals, followed by the individual deductible and 95 percent coinsurance plans, with 21.3% and 19.1% of individuals, respectively. Comparing the highest cost-sharing plan (the 95 percent coinsurance plan) with the free-care plan, the raw means indicate a 9.5%-point (46.1%) decline in the fraction of individuals with at least one prescribed painkiller purchase and a \$11.6 (59.7%) decline in annual spending on prescribed painkillers (in 2019 dollars). Focusing on the fifth row, the share of individuals with at least one opioid prescription filled in a given year ranges from 14.5% in the free-care plan to 7.7% in the least generous plan. On the non-opioid counterpart, the share with at least one non-opioid prescription filled in a given year ranges between 5.4% and 10.4% across plans.

Focusing on rows 16 to 19, outpatient provider visits correlate unequivocally with health insurance generosity. Individuals in the highest cost-sharing plan are 17.4%-points (18.8%) less likely to have an outpatient provider visit in a given year, have 3.5 (38.5%) fewer visits on average, and, as a consequence, spend \$654 (43.2%) less in visits relative to individuals in free care. Thanks to our unique data, rows 19 and 11 present novel evidence on the likelihood of having at least one outpatient visit with an opioid prescription *written*, and on the share of filled opioid prescriptions in a given year, respectively. Individuals in the highest cost-sharing plan are 5.7%-points (31.1%) less likely to receive an opioid prescription in a given year, conditional on having a visit. Conditional on having an opioid prescription, there is a notable decline in the share of filled opioid prescriptions—from 83.9% under the free-care plan to 77.7% under the least generous plan. This drop suggests that higher out-of-pocket costs may discourage some individuals from filling their opioid prescriptions. However, because prescriptions are not randomly assigned, a comparison of raw means does not identify the causal effect of insurance generosity on prescription filling. We return to this issue in the mechanisms section, where we attempt to decompose the response to changes in health insurance generosity into provider-driven versus patient-driven effects.

5.2 Empirical Strategy and Results

Our analysis starts with an overview of the empirical strategy used to assess the response of prescribed painkiller purchases to changes in health insurance generosity. We then present the corresponding results.

Consider an individual i, in calendar year t, enrolled in health insurance plan $p \in \{1, 6\}$, in location l and starting month m. Mimicking the framework from Aron-Dine, Einav, and Finkelstein (2013), hereinafter referred to as AEF, our baseline regression for outcome $Y_{i,t}$ is,

Table 3: Summary Statistics - All Painkillers

	(1)		(2)		(3)		(4)		(5)		(6)	
	Free Care		25% Coinsurance		Mixed Coinsurance		50% Coinsurance		Individual Deductible		95% Coinsurance	
	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD
All Prescribed Painkillers:												
1. Any prescription filled	0.206	(0.40)	0.149	(0.36)	0.148	(0.36)	0.121	(0.33)	0.131	(0.34)	0.111	(0.31)
2. Annual spending (2019 $)	19.509	(103.91)	8.758	(47.00)	11.295	(73.27)	5.420	(27.16)	9.847	(63.35)	7.871	(46.74)
3. Annual days of supply	7.192	(40.74)	3.335	(21.18)	3.727	(23.19)	1.950	(10.81)	3.832	(26.99)	3.174	(23.77)
4. Number of Rx Purchased	0.728	(3.20)	0.355	(1.47)	0.386	(1.57)	0.254	(1.05)	0.337	(1.40)	0.294	(1.44)
Opioids:												
5. Any prescription filled	0.145	(0.35)	0.098	(0.30)	0.102	(0.30)	0.083	(0.28)	0.092	(0.29)	0.077	(0.27)
6. Any high-dose Rx filled	0.031	(0.17)	0.012	(0.11)	0.022	(0.15)	0.007	(0.08)	0.017	(0.13)	0.014	(0.12)
7. Annual spending (2019 $)	8.859	(64.89)	2.939	(15.35)	5.030	(56.40)	2.276	(12.36)	4.289	(39.43)	3.053	(22.12)
8. Annual days of supply	2.105	(16.31)	0.692	(4.18)	1.340	(15.15)	0.588	(4.36)	1.114	(11.69)	0.915	(9.28)
9. Average MME per day	6.327	(20.28)	3.812	(14.91)	4.307	(16.85)	3.623	(16.10)	4.077	(16.32)	3.566	(15.78)
10. Number of Rx Purchased	0.431	(2.52)	0.169	(0.96)	0.202	(1.06)	0.145	(0.72)	0.183	(0.92)	0.150	(0.83)
11. Share filled Rx | Rx	0.839	(0.32)	0.747	(0.40)	0.759	(0.39)	0.803	(0.36)	0.750	(0.39)	0.777	(0.38)
Non-Opioids:												
12. Any prescription filled	0.104	(0.31)	0.081	(0.27)	0.075	(0.26)	0.054	(0.23)	0.065	(0.25)	0.056	(0.23)
13. Annual spending (2019 $)	10.650	(67.34)	5.819	(41.32)	6.265	(39.78)	3.145	(23.54)	5.558	(45.05)	4.818	(37.10)
14. Annual days of supply	5.087	(34.32)	2.643	(19.86)	2.388	(15.52)	1.362	(9.75)	2.718	(23.06)	2.259	(18.01)
15. Number of Rx Purchased	0.296	(1.42)	0.186	(0.96)	0.184	(0.93)	0.109	(0.72)	0.154	(0.88)	0.145	(0.90)
Outpatient Provider Visits:												
16. Any visit	0.925	(0.26)	0.843	(0.36)	0.846	(0.36)	0.837	(0.37)	0.780	(0.41)	0.751	(0.43)
17. Number of visits	9.055	(11.55)	6.778	(11.16)	6.729	(10.17)	6.033	(8.00)	6.365	(9.25)	5.573	(8.88)
18. Annual spending (2019 K$)	1.513	(2.63)	1.044	(2.11)	1.122	(2.45)	0.864	(1.85)	1.076	(2.25)	0.859	(1.99)
19. Any opioid Rx | any visit	0.183	(0.39)	0.148	(0.36)	0.150	(0.36)	0.121	(0.33)	0.148	(0.36)	0.126	(0.33)
# Families	1040		327		285		208		668		572	
# Individuals	1964		663		507		393		1261		1134	
# Individual-years	6724		2333		1704		1417		4087		3739	

Notes: This table reports summary statistics from our RAND HIE analysis sample, by health insurance plan. Each of the six columns presents raw means and standard deviations at the individual-year level by plan. Standard deviations are reported in parentheses beside the mean.

$$Y_{i,t} = \lambda_p + \tau_t + \alpha_{l,m} + \beta X' + \varepsilon_{i,t} \tag{2}$$

where τ_t are calendar year fixed effects, $\alpha_{l,m}$ are location-by-start-month fixed effects, and the vector X contains dummies for gender and age. Specifically, we include a dummy variable for women and a dummy variable for individuals under the age of 18. The main parameters of interest are the health insurance plan fixed effects, λ_p, measuring the average effect of each health insurance plan on the outcome variable $Y_{i,t}$ for adult males. All standard errors are clustered at the family level.

We begin by evaluating the response of all prescribed painkiller purchases (i.e., opioid and non-opioid). We consider four outcomes: (1) a dummy variable for any painkiller purchase in the year, (2) annual spending on painkillers, (3) annual days of supply, and (4) number of prescriptions filled in the year. Annual spending is the sum of both the portion paid OOP by the individual and the portion paid by the insurer, aggregated at the annual level (in 2019 dollars). The measure of days of supply is the sum across all prescribed opioid and non-opioid painkiller purchases at the individual-year level. Finally, outcome (4) counts the number of painkiller prescriptions filled at the individual-year level.

The first four columns of Table 4 report the estimated λ_p coefficients from Equation (2) for these four outcomes. The estimates indicate that painkiller purchases decrease significantly as health insurance generosity declines. For instance, individuals with the highest cost-sharing are 9.8%-points (37.4%) less likely to purchase painkillers relative to individuals with full insurance. They also spend \$11.7 (49.7%) less on painkillers in a given year, have 4.2 (49.4%) fewer annual days of supply, and make 0.44 (49.7%) fewer purchases.

Our focus now turns to prescribed opioid painkillers. To evaluate effects at the extensive margin, we consider two measures: (1) a dummy variable for any opioid painkiller purchase in the year, and (2) a dummy variable for any high-dose opioid painkiller purchase in the year. At the intensive margin, we consider four outcomes: (1) annual spending on opioid painkillers, (2) annual days of supply, (3) MME per day, and (4) the number of opioid prescriptions filled in the year. The measure of MME per day is the average across all opioid painkiller purchases at the individual-year level, and is equal to zero for individuals without opioid purchases in a given year. The remaining measures are defined analogously to overall painkiller use.

The results are reported in columns 5 to 10 of Table 4. The estimates provide clear evidence that all six outcomes decrease significantly as health insurance generosity declines. On the extensive margin, individuals with the highest cost-sharing are 6.9%-points (37.5%) and 1.7%-points (47.2%) less likely to purchase opioid and high-dose opioid painkillers, respectively, relative to individuals with full insurance. On the intensive margin, the estimates indicate that individuals in the least generous plan spend \$5.7 (53.7%) less on opioid painkillers, have 1.2 (46.5%) fewer days of supply, consume 2.9 (36.2%) fewer MME per day, and fill 0.28 (54.1%) fewer prescriptions, compared to individuals with full insurance.

We now examine prescribed non-opioid painkillers. At the extensive margin, we consider one measure: a dummy variable for any non-opioid painkiller purchase in the year. At the intensive margin, we analyze three outcomes: (1) annual spending on non-opioid painkillers, (2) annual days of supply, and (3) the number of non-opioid prescriptions filled in the year. All measures are defined analogously to the opioid painkiller measures.

The results for non-opioid painkillers are reported in Table 5. As was the case for opioid painkillers, the estimates indicate that all four outcomes decrease significantly as health insurance generosity declines. For instance, individuals with the highest cost-sharing are 5.1%-points (38.3%) less likely to purchase non-opioid painkillers relative to individuals with full insurance. They also spend \$5.97 (46.5%) less on non-opioid painkillers in a given year, have 3.0 (50.7%) fewer days of supply, and fill 0.16 (43.5%) fewer prescriptions. All point estimates show a consistent pattern of fewer opioid and non-opioid purchases, at all margins, in higher cost-sharing plans.[31]

[31] Appendices OA.4 and OA.5 show that our analyses are robust to including painkiller purchases prescribed by non-dentists or dentists only, respectively.

Table 4: Plans' Effects on Prescribed Painkiller Purchases

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any	Spending in $	Annual Days of Supply	Number of Rx Purchased	Share with Any	Share with Any High-Dose	Spending in $	Annual Days of Supply	MME per Day	Number of Rx Purchased
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Const. (Free Care)	0.262	23.483	8.534	0.880	0.184	0.036	10.637	2.586	7.974	0.519
	(0.008)	(2.050)	(0.810)	(0.064)	(0.007)	(0.003)	(1.123)	(0.303)	(0.367)	(0.047)
25% Coinsurance	-0.061	-10.330	-3.922	-0.370	-0.046	-0.018	-5.813	-1.457	-2.576	-0.260
	(0.012)	(2.316)	(0.984)	(0.071)	(0.009)	(0.004)	(1.121)	(0.308)	(0.471)	(0.050)
Mixed Coinsurance	-0.055	-7.586	-3.234	-0.329	-0.045	-0.010	-3.448	-0.674	-2.070	-0.226
	(0.014)	(2.857)	(1.039)	(0.078)	(0.012)	(0.005)	(1.831)	(0.505)	(0.587)	(0.055)
50% Coinsurance	-0.091	-13.772	-5.551	-0.475	-0.063	-0.025	-6.063	-1.531	-3.019	-0.275
	(0.012)	(2.113)	(0.869)	(0.070)	(0.010)	(0.004)	(1.127)	(0.342)	(0.597)	(0.053)
Ind. Deductible	-0.079	-9.673	-3.415	-0.404	-0.058	-0.015	-4.531	-0.993	-2.413	-0.257
	(0.010)	(2.365)	(0.932)	(0.067)	(0.008)	(0.004)	(1.445)	(0.409)	(0.441)	(0.049)
95% Coinsurance	-0.098	-11.681	-4.216	-0.437	-0.069	-0.017	-5.711	-1.202	-2.884	-0.281
	(0.010)	(2.281)	(0.995)	(0.070)	(0.009)	(0.003)	(1.234)	(0.391)	(0.456)	(0.050)
Adjusted R^2	0.09	0.03	0.02	0.04	0.05	0.02	0.02	0.01	0.03	0.03
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table 5: Plans' Effects on Prescribed Non-Opioiod Painkiller Purchases

	Share with Any (1)	Spending in $ (2)	Annual Days of Supply (3)	Number of Rx Purchased (4)
Constant (Free Care)	0.133	12.847	5.948	0.361
	(0.006)	(1.415)	(0.678)	(0.030)
25% Coinsurance	-0.029	-4.518	-2.465	-0.111
	(0.009)	(1.780)	(0.861)	(0.039)
Mixed Coinsurance	-0.024	-4.139	-2.560	-0.103
	(0.009)	(1.778)	(0.788)	(0.040)
50% Coinsurance	-0.057	-7.709	-4.020	-0.200
	(0.009)	(1.545)	(0.733)	(0.038)
Ind. Deductible	-0.040	-5.142	-2.421	-0.147
	(0.007)	(1.533)	(0.752)	(0.033)
95% Coinsurance	-0.051	-5.970	-3.014	-0.157
	(0.007)	(1.657)	(0.782)	(0.036)
Adjusted R^2	0.05	0.02	0.02	0.03
# Families	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922
# Individual-years	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of non-opioid painkillers, (2) annual spending on non-opioid painkillers, (3) annual days of supply of non-opioid painkillers, and (4) annual number of non-opioid prescriptions purchased. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

6 Threats to Validity and Robustness Checks

In this section, we present results from alternative specifications designed to address potential threats to our identification strategy and to illustrate the robustness of our main findings. First, we provide evidence that our identification strategy is valid. Second, we show that our results are robust to controlling for additional covariates, adjusting for underreporting, accounting for the deadline effect, hitting the MDE, or accounting for the participation incentives.

Our estimates from Table 4 rely on random assignment of individuals to health insurance plans from the RAND HIE. One potential concern is that random assignment failed to produce comparable experimental conditions on characteristics measured before the treatment was administered. A related concern is that the sample restrictions described in Section 3 may have affected balance. To address these concerns, we estimate Equation (2) using pre-randomization covariates as the main outcome. Following AEF, we include a broad set of characteristics, encompassing both demographic information and measures of prior healthcare utilization.[32] We fail to reject the null hypothesis that these characteristics are balanced across plans at the 1% significance level, with only one exception: missing data for doctor visits (see Table OA.6.2).

To further validate the credibility of the initial randomization in our analytic sample, we conduct the same analysis on pre-randomization characteristics that were not considered by AEF, and that are pertinent to our analysis of opioid painkiller purchases. We examine variables related to smoking and drinking behavior, which are often correlated with other risky behaviors such as opioid use (Cawley and Ruhm, 2011). Specifically, we use dummy variables for whether the individual is a current smoker, a former smoker, or whether smoking information is missing. In addition, we use dummy variables for whether the individual has a drinking problem, missing information on drinking issues, a continuous variable measuring the average monthly volume of ethanol consumption, and a dummy variable for missing information on alcohol volume. All these variables come from the baseline questionnaire. Table 6 reports the estimated λ_p coefficients from Equation (2) for each outcome. In all cases, we fail to reject the null hypothesis that characteristics related to smoking and drinking are balanced across plans.

[32]The covariates considered in this exercise are all variables listed in Table A4 of AEF.

Table 6: Pre-Randomization Covariates and Plan Assignment

	Former Smoker (1)	Current Smoker (2)	Smoking Missing (3)	Ethanol Vol (4)	Ethanol Missing (5)	Drink Problem (6)	Drink Missing (7)
Constant (Free Care Plan)	0.178	0.441	0.031	21.928	0.026	0.172	0.004
	(0.026)	(0.045)	(0.026)	(3.609)	(0.025)	(0.024)	(0.024)
25% Coinsurance	0.010	-0.009	0.024	0.164	0.021	0.011	0.024
	(0.022)	(0.032)	(0.015)	(1.449)	(0.016)	(0.015)	(0.014)
Mixed Coinsurance	0.008	0.030	-0.018	0.106	-0.021	-0.004	-0.020
	(0.024)	(0.032)	(0.019)	(1.351)	(0.019)	(0.015)	(0.018)
50% Coinsurance	0.004	-0.022	0.025	-0.295	0.042	-0.007	0.033
	(0.027)	(0.041)	(0.021)	(1.788)	(0.021)	(0.017)	(0.020)
Individual Deductible	-0.027	0.013	0.013	0.895	0.008	-0.000	0.012
	(0.017)	(0.026)	(0.013)	(1.336)	(0.012)	(0.012)	(0.012)
95% Coinsurance	0.000	0.000	0.021	2.019	0.009	0.008	0.014
	(0.018)	(0.027)	(0.014)	(1.411)	(0.015)	(0.013)	(0.013)
Adjusted R^2	0.03	0.04	0.61	0.08	0.58	0.06	0.64
P-Value F	0.485	0.882	0.246	0.735	0.191	0.936	0.165
# Families	1869	1869	1916	1874	1916	1894	1916
# Individuals	3616	3616	5542	3584	5542	3681	5542

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes, measured at the baseline survey, are: (1) a dummy variable for whether the individual is a former smoker, (2) a dummy for whether he is a current smoker, (3) a dummy for missing smoking status, (4) average monthly volume of ethanol consumption, (5) a dummy variable for missing ethanol consumption, (6) a dummy variable for whether the individual reports having a drinking problem, and (7) a dummy variable for missing information on drinking issues. All regressions are estimated at the individual level and include de-meaned site-by-start-month dummy variables as well as de-meaned year fixed effects. The number of individuals varies across specifications due to missing data, as noted in columns (3), (5), and (7). Additionally, the number of individuals is smaller than in Table 4 because newborns during the experiment were incorporated after enrollment. Standard errors, clustered on family, are reported in parentheses below the coefficients.

In addition, we present results from an alternative specification of Equation (2) that adds all pre-randomization covariates as controls (i.e., those considered by AEF plus the smoking and drinking variables). The purpose of this exercise is to illustrate the robustness of our core findings regarding sensitivity of opioid painkiller purchases to health insurance generosity. These results for the six measures of opioid painkiller purchases are displayed in Table 7.[33] In all cases, our results are very robust to adding pre-randomization covariates as controls and, consequently, we further validate the credibility of our core findings.

As noted early on by Newhouse et al. (1993), refusal and attrition were higher on the cost-sharing plans, though they seem to be random with respect to the characteristics of the

[33] In Appendix OA.6 we provide analogous results for all painkillers (Table OA.6.4) and non-opioid painkillers (Table OA.6.5). In all cases, our results remain robust to adding all baseline covariates and adjusting for underreporting.

Table 7: Controlling for Pre-Randomization Covariates and Adjustment for Underreporting

	Share with Any	Share with Any High-Dose	Spending in $		Annual Days of Supply	MME per Day	Number of Rx Purchased
	Covs.	Covs.	Covs.	Adj.	Covs.	Covs.	Covs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant (Free Care Plan)	0.155	0.030	8.671	11.133	1.956	6.860	0.426
	(0.009)	(0.004)	(1.021)	(1.227)	(0.272)	(0.525)	(0.042)
25% Coinsurance	-0.044	-0.016	-5.128	-5.813	-1.284	-2.406	-0.235
	(0.009)	(0.003)	(0.999)	(1.121)	(0.279)	(0.458)	(0.044)
Mixed Coinsurance	-0.047	-0.009	-3.490	-3.448	-0.677	-2.125	-0.236
	(0.011)	(0.005)	(1.859)	(1.831)	(0.514)	(0.575)	(0.058)
50% Coinsurance	-0.060	-0.024	-4.931	-6.063	-1.214	-2.827	-0.233
	(0.011)	(0.004)	(1.021)	(1.127)	(0.313)	(0.595)	(0.047)
Individual Deductible	-0.057	-0.014	-4.407	-4.531	-0.981	-2.342	-0.256
	(0.008)	(0.004)	(1.404)	(1.445)	(0.411)	(0.426)	(0.050)
95% Coinsurance	-0.065	-0.015	-4.940	-5.711	-0.992	-2.726	-0.256
	(0.008)	(0.003)	(1.136)	(1.234)	(0.384)	(0.446)	(0.047)
Adjusted R^2	0.07	0.03	0.07	0.02	0.07	0.05	0.08
# Families	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes are: (1) a dummy variable for annual purchase of opioid painkillers, (2) a dummy variable for annual purchase of high-dose opioid painkillers, (3-4) annual spending on opioid painkillers, (5) annual days of supply of opioid painkillers, (6) MME per day for opioid painkillers, and (7) annual number of opioid prescriptions purchased. The regressions include all pre-randomization covariates as controls. The specification in column (4) adjusts the spending outcome for underreporting. All regressions include a dummy variable for women, a dummy variable for individuals under the age of 18, de-meaned site-by-start-month dummy variables, and de-meaned year fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Standard errors, clustered on family, are reported in parentheses below the coefficients.

participants. To mitigate this concern, we present results from an alternative specification that adjusts the spending measure for underreporting of expenditures. Mimicking AEF, we scale up the spending outcome using the plan-specific underreporting percentages identified in Rogers and Newhouse (1985).[34] The results are displayed in column (4) of Table 7. Once again, our estimate remains largely unchanged and, therefore, we confirm the robustness of our findings to underreporting.[35]

[34] Following Rogers and Newhouse (1985), we use a 4% underreporting rate for individuals in free care; 6% for the 25 percent, 50 percent and mixed coinsurance plans; 14% for the individual deductible plan; and 11% for the 95 percent coinsurance plan.

[35] In Appendix OA.6 we provide analogous results for the sample that excludes dentists (Table OA.6.1) and the sample that excludes non-dentists (Table OA.6.3). In all cases, our results remain robust to adding all baseline covariates and adjusting for underreporting.

In Appendix OA.6, we consider the robustness of our results to accounting for several distinctive features of the RAND HIE: the *deadline* effect, hitting the MDE in a given year, and the participation incentive. First, prior studies suggest that families may alter their behavior during the final months of the experiment, in anticipation of changes in insurance coverage (Balesh Abadi, Devereux, and Omran, 2023; Lin and Sacks, 2019). Behavioral adjustments near the end of the experiment could confound the estimated impact of insurance generosity on opioid consumption. To address this concern, we estimate a specification that includes an indicator for the last contract year. As shown in Table OA.6.6, our findings remain robust to this *deadline* effect.

Second, there is a concern that reaching the MDE may affect how health insurance generosity influences outcomes. In particular, individuals in cost-sharing plans who reach the MDE may behave more like those enrolled in the free care plan. To examine this, we estimate a specification that interacts the health insurance plan indicators with a dummy equal to one if the family reaches the MDE in a given year, and zero otherwise. The results, presented in Table OA.6.7, show that opioid purchases are more responsive to health insurance generosity among families that do not reach the MDE, relative to full insurance.

Finally, we explore the sensitivity of our results to controlling for the participation incentive, a lump-sum payment provided to families whose assigned plan offered less coverage than their pre-randomization insurance policy (Newhouse et al., 1993). As reported in Table OA.6.8, the inclusion of this control does not alter our main findings.

7 Mechanisms

In this section, we focus on prescribed opioid painkillers and explore the mechanisms driving the documented responses to changes in patients' health insurance generosity. An increase in insurance generosity can affect opioid purchases via three main mechanisms. First, individuals may respond by seeking additional visits to healthcare providers (i.e., physician or dentist). Secondly, conditional on a visit, providers may respond by writing additional opioid prescriptions. Lastly, conditional on having an opioid prescription, individuals may respond by increasing the probability of filling the prescription. The first and last mechanisms are inherent to the patient, while the second mechanism is within the provider's discretion. Typical claims data do not record unfilled prescriptions. By exploiting the uniqueness of our data, we can tease out the second mechanism from the third.

We begin by examining the role of additional healthcare provider visits. This is the natural first channel to consider when analyzing prescription drug use, as increases in provider contact mechanically increase prescribing opportunities. To do so, we estimate Equation (2) using three outcomes related to outpatient provider visits in any given year: (1) a dummy variable for any visit, (2) annual spending on visits, and (3) number of visits. The results are displayed in the first three columns of Table 8. The estimates provide clear evidence that outpatient provider visits decrease significantly as patients' health insurance generosity declines, at both extensive and intensive margins. For instance, individuals with the highest cost-sharing are 17.8%-points (19.5%) less likely to visit a provider office, spend \$665 (36.9%) less on outpatient visits, and have 3.6 (38.2%) fewer visits, relative to individuals with full insurance. Our findings are consistent with a well-established body of causal evidence examining the effects of patient cost-sharing on outpatient care utilization.

We now focus on the providers' response to patient cost-sharing. Conditional on an outpatient provider visit, the provider may be less likely to write an opioid prescription when patients face a less generous insurance plan. This would suggest higher prescription rates per visit for patients in free care. However, any tendency to do so may be offset by the additional visits on the free-care plan that are for less serious reasons, diminishing the likelihood of re-

Table 8: Outpatient Provider Visits, Prescribing Behavior, and Filled Prescriptions

	Outpatient Provider Visits			Share with Any Opioid Painkiller Rx		Share of Filled Opioid Prescriptions		
	Share with Any	Spending in $	Number of Provider Visits	Baseline	Pain and Health Dummies	Baseline	Pain and Health Dummies	Pain and Health Dummies, + Prescriber FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. (Free Care Plan)	0.911	1802.259	9.434	0.235	0.229	0.831	0.832	0.817
	(0.007)	(50.723)	(0.255)	(0.008)	(0.008)	(0.014)	(0.014)	(0.023)
25% Coinsurance	-0.086	-457.735	-2.352	-0.033	-0.033	-0.091	-0.089	-0.060
	(0.015)	(72.011)	(0.437)	(0.011)	(0.011)	(0.027)	(0.027)	(0.051)
Mixed Coinsurance	-0.071	-412.870	-2.287	-0.036	-0.039	-0.069	-0.076	-0.059
	(0.016)	(82.269)	(0.429)	(0.013)	(0.014)	(0.030)	(0.030)	(0.048)
50% Coinsurance	-0.104	-590.212	-3.146	-0.061	-0.058	-0.032	-0.030	-0.091
	(0.020)	(93.430)	(0.395)	(0.013)	(0.012)	(0.033)	(0.033)	(0.061)
Ind. Deductible	-0.140	-476.828	-2.765	-0.041	-0.041	-0.084	-0.089	-0.064
	(0.013)	(60.984)	(0.337)	(0.010)	(0.010)	(0.024)	(0.024)	(0.041)
95% Coinsurance	-0.178	-664.805	-3.601	-0.056	-0.057	-0.064	-0.066	-0.065
	(0.016)	(59.372)	(0.343)	(0.011)	(0.010)	(0.026)	(0.025)	(0.044)
Some Pain					-0.104		-0.046	-0.000
					(0.026)		(0.025)	(0.044)
A Little Pain					-0.145		-0.088	-0.053
					(0.025)		(0.024)	(0.046)
No Pain at All					-0.160		-0.107	-0.077
					(0.025)		(0.027)	(0.049)
Fair Health					-0.031		0.007	-0.022
					(0.041)		(0.034)	(0.066)
Good Health					-0.048		0.023	0.034
					(0.040)		(0.033)	(0.062)
Excellent Health					-0.068		0.033	0.047
					(0.040)		(0.036)	(0.071)
Adjusted R^2	0.09	0.07	0.07	0.06	0.07	0.03	0.04	0.24
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2936	2936	1398	1398	1398
# Individuals	5922	5922	5922	5575	5575	1714	1714	1714
# Individual-Years	20004	20004	20004	16809	16809	2525	2525	2525

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: a dummy variable for any outpatient visit to an individual provider (column 1), annual spending on visits (column 2), number of visits (column 3), a dummy variable for any opioid painkiller prescription (columns 4 and 5), and the share of filled opioid prescriptions (columns 6 to 8). Regressions in columns (4) and (5) are conducted on a subsample of individuals who visited a healthcare provider in a given year. Regressions in columns (6) to (8) are conducted on a subsample of individuals who visited a provider in a given year and obtained an opioid prescription. All regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. Regressions in columns (5), (7), and (8) add dummies for self-reported pain and health at the baseline survey. The excluded category for pain variables is "A great deal of pain" and the excluded category for health variables is "Poor health." Column (8) further adds prescriber fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month, year, pain, and health dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" variables mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

ceiving a prescription. A simple theoretical model *à la* Grossman (1972) featuring health capital and visits to healthcare providers would suggest that, given exogenous variation in the price of visits, patients' decision to visit the healthcare provider would be a function of their health and pain. One would expect that, as patient cost-sharing increases, the pain or health threshold above which the patient decides to consult a healthcare provider also increases. In such sense, among individuals who choose to visit the healthcare provider, those in the least generous plan should be sicker and suffer more pain relative to those in free care, on average, and therefore more likely to get a prescription. The overall impact of plan generosity on prescription rates is a priori unknown due to the conflicting effects from prescription likelihood and the selection on health and pain across plans.

In columns (4) and (5) of Table 8, we provide evidence regarding this second mechanism. For individual-year pairs with at least one outpatient provider visit, we estimate Equation (2) using as outcome a dummy variable for having an opioid prescription. The estimates in column (4) indicate that the aforementioned combined effect is negative. We find a negative correlation between patient cost-sharing and opioid prescriptions. In this sense, the first channel (i.e., healthcare providers being less likely to prescribe as generosity declines) seems to dominate, yielding, for example, 5.6%-points (23.8%) lower opioid prescription rates for patients in the 95 percent coinsurance plan, relative to full insurance.

To control for the patient selection on pain and health previously mentioned, in column (5), we include demeaned dummy variables for self-reported pain and health at baseline as covariates.[36] As expected, individuals in higher pain are more likely to receive an opioid prescription, conditional on visiting the healthcare provider.[37] However, overall health sta-

[36]For the first mechanism, using the entire sample with random assignment to plans eliminates the need to control for health and pain. However, controls are required for the second mechanism, assessed in a non-random sample of healthcare provider visitors.

[37]The excluded category for pain variables is "A Great Deal of Pain."

tus does not significantly impact the likelihood of receiving an opioid prescription.[38] The estimates suggest that patients on less-generous plans are 5.7%-points (24.9%) less likely to receive an opioid script, even after controlling for patients' selection on pain and health.[39] Taken together, these results offer the first direct causal evidence linking providers' opioid prescribing behavior to patient insurance generosity, independent of patient adherence.

Lastly, we turn to our third mechanism. Conditional on having an opioid prescription, the patient chooses whether to fill it or not. Individuals may be more likely to fill the prescription as coverage increases.[40] Once again, this higher propensity may also be offset by the differential patient selection on health and pain across plans. In addition, some healthcare providers may be more prone to write a prescription, other things equal (see, e.g., Barnett, Olenski, and Jena (2017); Eichmeyer and Zhang (2022, 2023)). To provide evidence of this third mechanism, we estimate Equation (2) using as outcome the share of filled opioid prescriptions at the individual-year level, conditional on having one. The estimates in column 6 of Table 8 suggest that the first channel dominates (i.e., individuals being more less to fill a prescription as generosity declines), in that, for example, patients in the 95% coinsurance group have a share of filled opioid prescriptions 6.4%-points (7.7%) smaller relative to those in full insurance. To account for the potential patient's selection on health and

[38] The excluded category for health variables is "Poor health."

[39] In Appendix Table OA.7.1, we show that these results are robust to addressing selection using, as an alternative, the two-stage estimator proposed by Heckman (1979). We employ three measures as exclusion restrictions in the first stage to instrument for the decision to visit a healthcare provider: (1) number of primary care physicians (PCP) per 100,000 population by experimental site in 1972 (Newhouse et al. (1993), Table 2.1, column 4), (2) average number of days spent waiting for an appointment with a PCP for a new patient by experimental site (Newhouse et al. (1993), Table 2.1, column 5), and (3) average fee for initial office visit to a General Practice physician in 1975 by geographic division (U.S. Department of Health, Education, and Welfare (1978), Table 182, column 2).

[40] This mechanism may be somewhat attenuated for opioids given their potential for addiction and dependence.

pain and the healthcare provider's prescribing propensity, we add as covariates demeaned dummy variables for self-reported health and pain measured at baseline (column (7)) and healthcare provider fixed effects (column (8)), respectively.[41] We find that, even though one in five opioid prescriptions to adult males are not filled, the filling probability does not vary significantly by plan generosity.

In all, we find that the price response of opioid purchases is mostly driven by the first two mechanisms: the decision of patients to visit a healthcare provider and the decision of healthcare providers to prescribe opioids.[42] We find no evidence linking responses to the share of filled prescriptions, once we control for selection based on health, pain, and healthcare providers' characteristics. This last result is consistent with the finding related to all (painkiller and non-painkiller) prescription drugs in Newhouse et al. (1993). Furthermore, the flat fill probability once a prescription is written hints that physicians may screen well and that the main margin of adjustment is whether to prescribe opioid painkillers.

Our findings contribute to the understanding of the opioid epidemic's origins, largely driven by physician-prescribed opioids (Alpert et al., 2022). Conditional on having an opioid prescription, we find no effect of health insurance generosity on the share of filled prescriptions, underscoring the key role of physicians. Our results also highlight the distinct responsiveness of physicians' opioid prescribing to changes in patients' insurance generosity—

[41] Note that more than one healthcare provider fixed effect can be turned on simultaneously for a given individual-year pair.

[42] In Tables OA.7.2, we show that our results are robust to excluding opioid painkiller purchases prescribed by dentists. However, excluding opioid prescriptions written by non-dentists substantially weakens the results (see Table OA.7.3), and we find no evidence of the second mechanism under this specification. This sensitivity suggests that the second mechanism may operate primarily through medical prescribing. Additionally, in Table OA.7.4 we show that our results are robust to excluding purchases that do not match with any recorded prescription by patient and provider IDs, which probably come from prescriptions obtained in inpatient settings and/or before the experiment.

a pattern not observed among dental providers. Nonetheless, patients also play a role, as they must first select into healthcare providers to obtain a prescription.

8 Discussion and Concluding Remarks

Overdose deaths involving opioids remain the primary driver of the ongoing drug overdose epidemic, which has devastated communities across the United States. Although the literature has offered several explanations for the origins of the opioid crisis, it remains mostly silent regarding the context that preceded the epidemic.

In this paper, we exploit the uniqueness of the RAND Health Insurance Experiment (1974-1982) to fill two gaps in our understanding of the prelude to the U.S. opioid epidemic. First, we provide novel evidence of the widespread use of prescribed opioid painkillers during this period. We also show that specialists were the primary prescribers, with dentists playing a non-negligible role. Although the dominant opioid drugs differed from those in the modern epidemic, prescribing was similarly concentrated, with propoxyphene accounting for 59% of opioid prescriptions. Finally, we show that opioids were already being widely used to treat chronic non-cancer pain, a practice that would later intensify during the first wave of the crisis.

Second, we leverage the experiment's random assignment of families to health insurance plans to estimate the causal effects of insurance generosity on prescription opioid use. Our rich data allow us to explore the mechanisms underlying these effects. Taken together, our findings highlight two key behavioral channels through which insurance generosity influences opioid consumption. First, more generous insurance increases patients' likelihood of seeking care. Second, conditional on a visit, physicians are more likely to prescribe opioids when patients face lower out-of-pocket costs. In contrast, we find no evidence that insurance generosity affects the likelihood that patients fill opioid prescriptions once written. By separately identifying each step in the treatment chain—seeking care, receiving a prescription, and filling it—we isolate the distinct roles of patients and providers. This decomposition clarifies the mechanisms at work and reveals that, for opioids, the primary effects of insurance operate upstream of the pharmacy, at the points of care-seeking and prescribing. We also uncover a heterogeneous prescribing response to patient cost-sharing by provider type: dentists do not adjust their prescribing margin to changes in insurance generosity.

Our findings shed new light on the early roots of the opioid epidemic and complement existing work that has emphasized the role of physician-prescribed opioids for chronic non-cancer pain during the epidemic's first wave. By tracing the origins of the crisis two decades before its recognized onset, our study contributes to a deeper understanding of how systemic factors shaped its emergence. These insights offer important lessons for the design of policies aimed at preventing, mitigating, and responding to future public health crises involving addictive substances. More broadly, our study contributes a historical perspective to the ongoing debate over the appropriate level of opioid prescribing in society by offering a benchmark from a formative period, situated between two extremes: under-prescribing shaped by growing anti-opioid sentiment and over-prescribing driven by aggressive pharmaceutical marketing.

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Online Appendix

OA.1 Details about the RAND HIE Data

In this section, we provide further details about the RAND Health Insurance Experiment.[43] The experiment excluded individuals age 62 and over at enrollment, as well as those eligible for Medicaid; those with family incomes greater than $25,000 (in 1973 dollars); those who were institutionalized; those in the military and their dependents; and veterans with service-connected disabilities. To further limit participants' financial exposure, the Maximum Dollar Expenditure (MDE) was capped at $1,000 in 1973 dollars, corresponding to $6,000 in 2020 dollars, based on the U.S. Consumer Price Index (CPI-U).

OA.1.1 Self-Reported Measures of Pain

The RAND HIE collected information about the participants' pain levels at three different instances: baseline, enrollment, and exit. Some of the questions differ between the Dayton and non-Dayton questionnaires, partly because they were administered to the former two years earlier than to the latter. The measure of self-reported pain level at baseline comes from the Baseline Questionnaire or the EVF new person supplement (for persons not present at baseline).

OA.1.2 Sample Construction

The initial RAND HIE participant sample consists of 26,148 persons, of which 7,700 were ultimately enrolled. An additional 554 persons were enrolled later, all but a few of them newborns or adopted children under one year of age. Those 8,254 insured enrollees were assigned to an experimental insurance treatment.

We start from these 8,254 enrollees and make four restrictions to construct our sample.

[43] The RAND HIE data can be downloaded from https://www.icpsr.umich.edu/web/ICPSR/studies/6439.

Table OA.1.1 below presents the remaining observations after applying each exclusion criterion. First, we drop individuals enrolled in the Health Maintenance Organization plan (i.e., a prepaid group practice) because the method of care delivery is substantially different from the fee-for-service (FFS) plans. Second, we exclude the years in which individuals do not participate fully and all subsequent years, except for the first year of newborns. Third, we drop the year in which individuals move, and all years thereafter, because relocation may trigger a switch in plans. Finally, we drop a few cases with missing age at baseline. Following these restrictions, our sample comprises 20,004 individual-year observations, with 5,922 unique individuals and 3,100 unique families.

Table OA.1.1: Analysis Sample Derivation

Dropping Condition	Remaining Obs. (Individual-Year)	Unique Individuals	Unique Families
Initial RAND HIE sample		26,148	
Drop never insured	30,725	8,254	4,640
Drop HMO experimental and control groups	21,999	6,223	3,308
Drop incomplete years of participation	20,547	6,031	3,213
Drop relocation year and the years after	20,007	5,923	3,100
Drop if missing age at baseline	20,004	5,922	3,100
Analysis Sample	20,004	5,922	3,100

OA.1.3 Steps to Identify Painkillers in the RAND HIE

This section describes how we identify opioid and non-opioid painkillers sold by prescription only in the RAND HIE data.

Step 1: We start by identifying painkillers. To that end, we use the drug therapeutic codes reported in the claims files.[44] We define painkillers as those drug purchases or pre-

[44]Drug therapeutic codes used in the RAND HIE claims files were taken from American Medical Association (1973).

scriptions falling under three therapeutic codes: (a) strong analgesics, (b) mild analgesics, and (c) anti-rheumatic agents. It is important to stress that drug therapeutic codes may vary within generic drug codes. This is particularly important since some drugs that are usually used to treat pain may be serving a different purpose (e.g., antitussive).[45] The full list of drug therapeutic codes used in the RAND HIE claims files can be found in Codebook 211 of the publicly available data.[46]

Step 2: Next, we identify opioid painkillers. To this end, we use data from the CDC Oral MME Conversion file, containing all opioid analgesics that are normally prescribed in outpatient settings, dispensed by retail pharmacies, and controlled by the Drug Enforcement Administration (DEA).[47,48,49] We match the generic drugs listed in the CDC file to the generic components listed in the HIE claims files. For each drug purchase or prescription, we have detailed information on up to ten generic drug components.[50]

Step 3: Since the CDC Opioid NDC and Oral MME Conversion File excludes most opioid medications that are normally used in inpatient settings and some injectable opioids,

[45]For instance, codeine phosphate, typically used to treat pain, is prescribed as an antitussive agent in 28% of RAND HIE pharmacy claims involving it.

[46]The share of missing drug therapeutic codes is less than 0.1% for the file containing drug purchases and 0.3% for the file containing drug prescriptions/suggestions.

[47]The CDC stopped updating this file, and it is no longer available online. For details, visit https://www.cdc.gov/opioids/data-resources/index.html.

[48]The CDC Oral MME Conversion file excludes most opioid medications that are normally used in inpatient settings (e.g., medications administered by an injection route), among others. We address this issue in Step 3.

[49]An alternative is to use the NDC Directory to identify opioids. For each product listed in the NDC Directory, it identifies the underlying generic drugs and their pharma-class category (e.g., full opioid agonist), which can be later matched to the generic codes in the HIE claims files.

[50]The share of missing all generic components is 0.02% in prescriptions/suggestions of painkillers and 0.04% in purchases of painkillers.

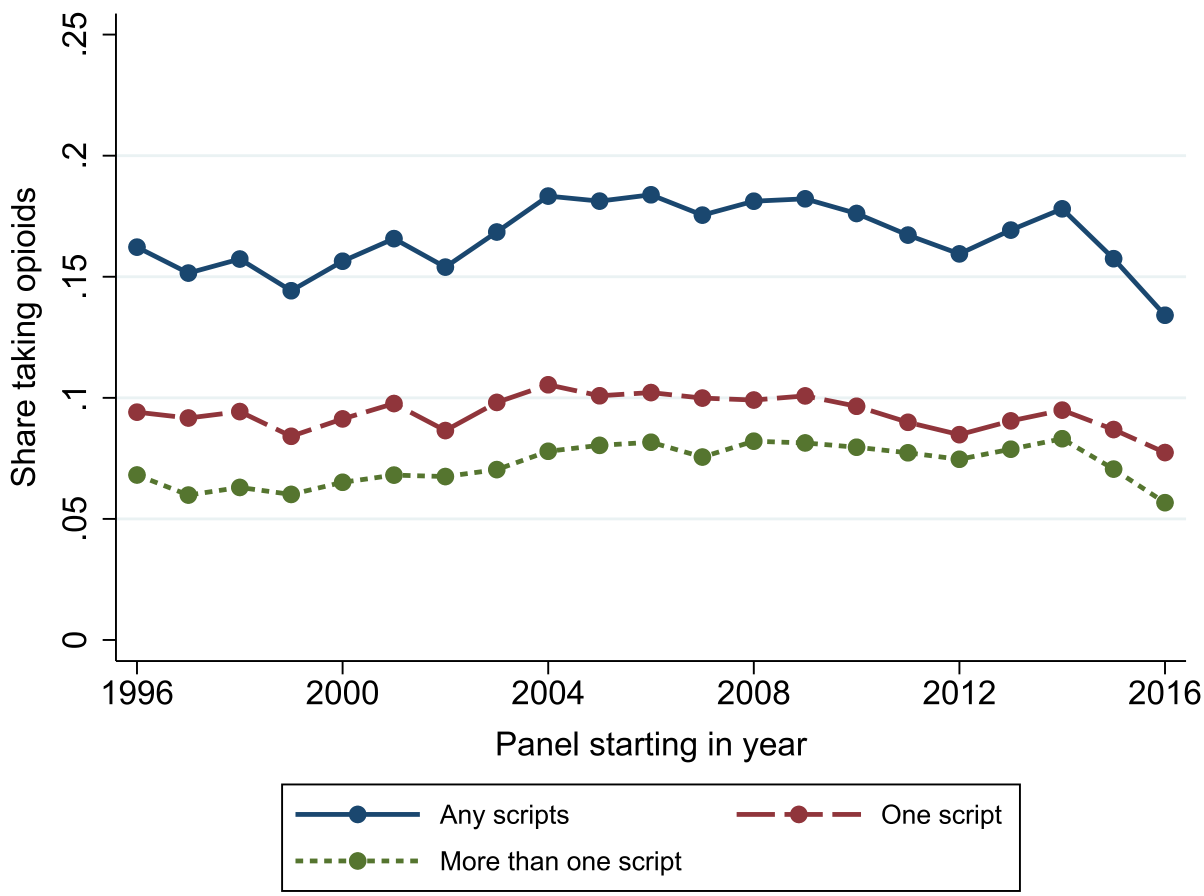
we browse through all the observations identified as non-opioids and identify one additional generic component that was miss-classified as non-opioid: pentazocine lactate.

Step 4: We exclude painkillers available over the counter.

OA.2 Additional Figures: The Stage for Modern Opioid Crisis

OA.2.1 Additional Figures: Medical Expenditure Panel Survey, 1996 - 2016

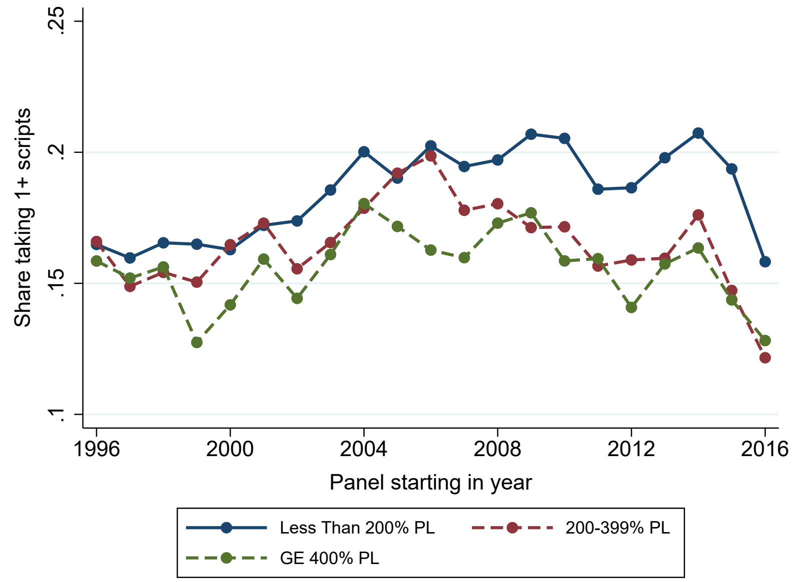
Figure OA.2.1: Prescribed Opioid Painkiller Utilization, 1996 - 2016



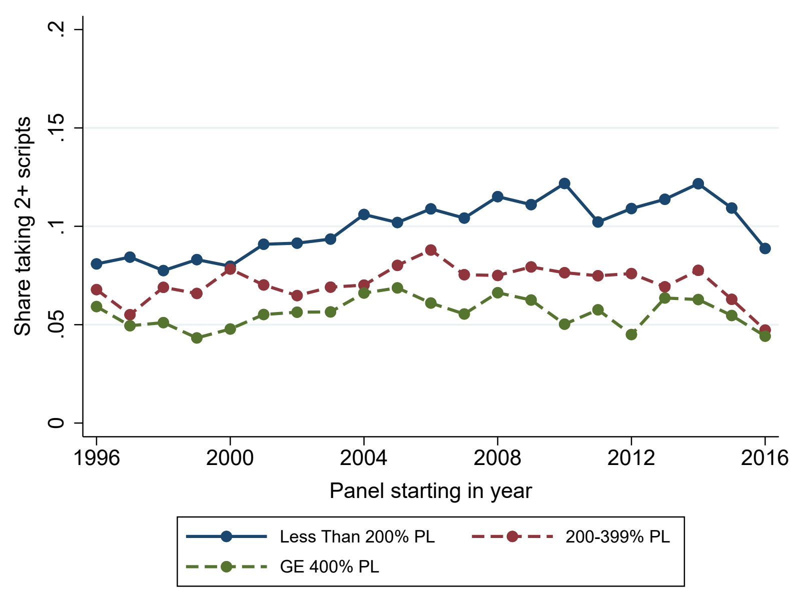
Notes: Figures are based on the authors' calculations using data from the Medical Expenditure Panel Survey (MEPS), covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The analysis is restricted to individuals under the age of 65. All percentages are weighted using survey weights and adjusted for age and sex to match the demographic structure of the U.S. population in the year 2000. Opioid use is defined as having at least one recorded purchase of a prescribed opioid during any of the five rounds of data collection.

Figure OA.2.2: Prescribed Painkiller Utilization in MEPS by Poverty Status

(a) Share with at least one recorded purchase of a prescribed opioid

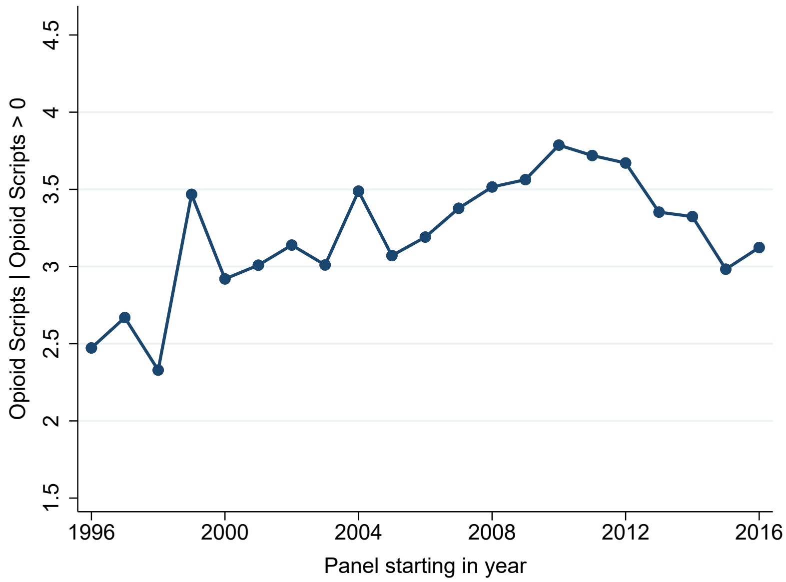


(b) Share with two or more recorded purchases of a prescribed opioid



Notes: Figures are based on the authors' calculations using data from the Medical Expenditure Panel Survey (MEPS), covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The analysis is restricted to individuals under the age of 65. All percentages are weighted using survey weights and adjusted for age and sex to match the demographic structure of the U.S. population in the year 2000. Both panels display shares across three income groups: below 200% of the federal poverty line, between 200% and 399%, and 400% or above. Panel A reports the share of individuals with at least one recorded purchase of a prescribed opioid; Panel B shows the share of individuals with two or more such purchases.

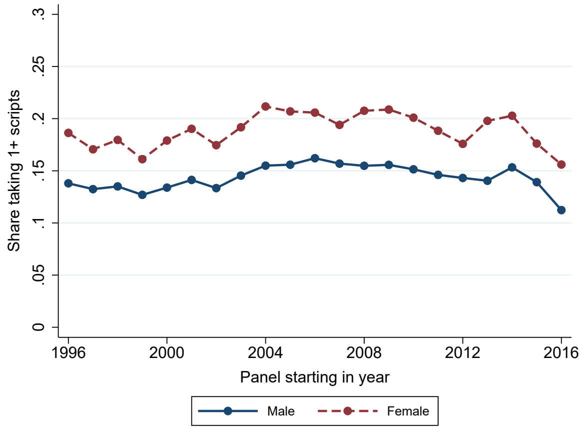
Figure OA.2.3: Average Number of Purchased Opioid Prescriptions in MEPS (Conditional on a Purchase)



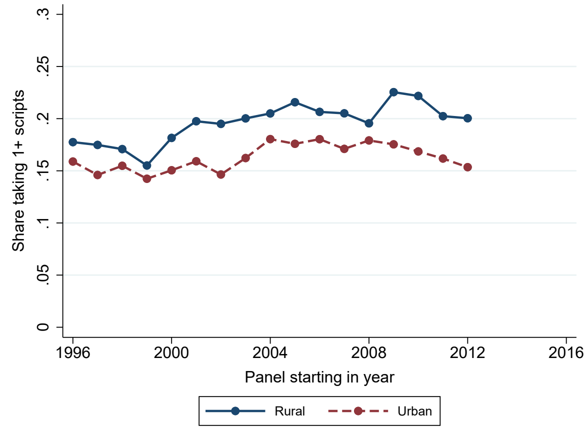
Notes: This figure shows the average number of purchased opioid prescriptions and is based on the authors' calculations using data from the Medical Expenditure Panel Survey (MEPS), covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The analysis is restricted to individuals under the age of 65. All reported figures are weighted using survey weights and adjusted for age and sex to match the demographic structure of the U.S. population in the year 2000. We restrict the sample to individuals with at least one recorded purchase of a prescribed opioid during any of the five rounds of data collection.

Figure OA.2.4: Prescribed Painkiller Utilization in MEPS by Demographics

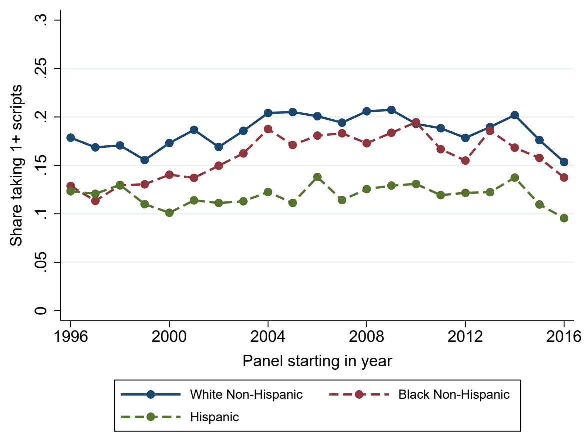
(a) By Gender



(b) By Geographic Location



(c) By Ethnicity

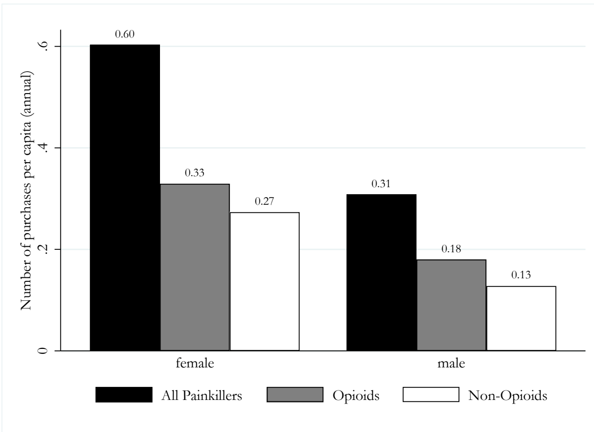


Notes: Figures are based on the authors' calculations using data from the Medical Expenditure Panel Survey (MEPS), covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The analysis is restricted to individuals under the age of 65. All percentages are weighted using survey weights and adjusted for age and sex to match the demographic structure of the U.S. population in the year 2000. The outcome in all panels is the share of individuals with at least one recorded purchase of a prescribed opioid. Panel A reports shares across gender groups (male vs. female), Panel B reports shares by geographic Location (rural vs. urban), and Panel C reports shares by Ethnicity (white non-Hispanic, Black non-Hispanic, and Hispanic).

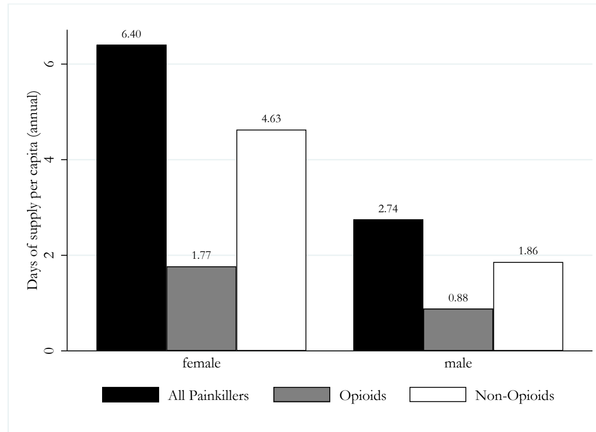
OA.2.2 Additional Figures and Tables: RAND HIE

Figure OA.2.5: Prescribed Painkiller Utilization by Gender (Including Zeros)

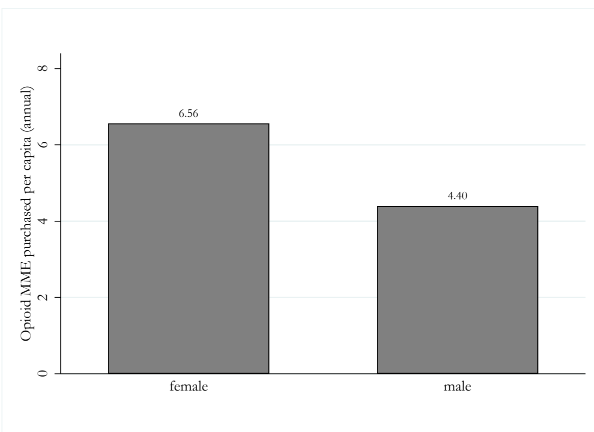
(a) Average Number of Purchases Per Capita



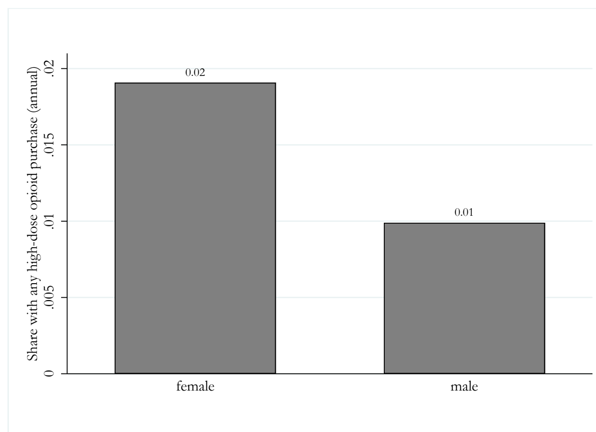
(b) Average Annual Days of Supply Per Capita



(c) Average MME Per Day Per Capita



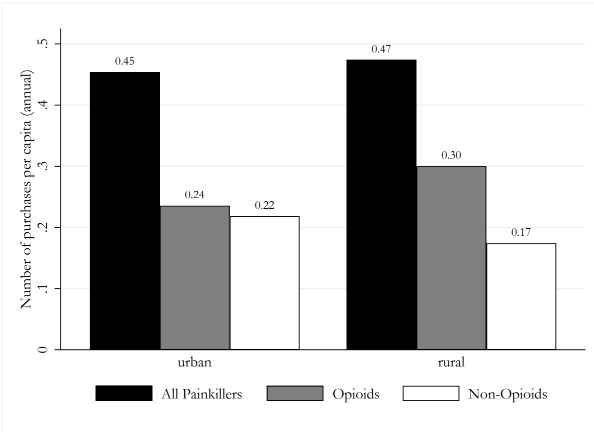
(d) Share with Any High-Dose Opioid



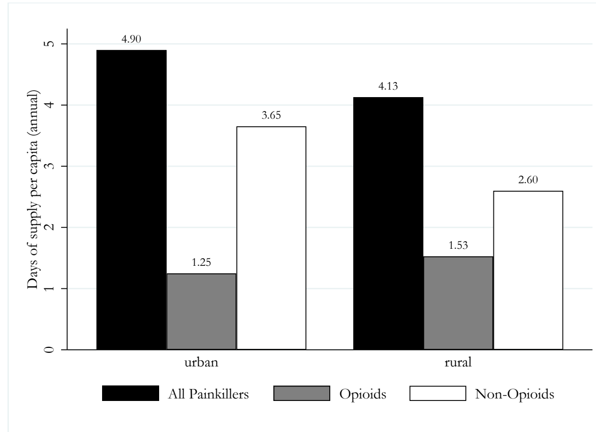
Notes: Figures are based on the authors' calculations using data from the Medical Expenditure Panel Survey (MEPS), covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The analysis is restricted to individuals under the age of 65. All percentages are weighted using survey weights and adjusted for age and sex to match the demographic structure of the U.S. population in the year 2000. The outcome in all panels is the proportion of individuals with at least one recorded opioid purchase. Each panel displays results for different demographic groups. Panel A reports shares by gender, Panel B by educational attainment, Panel C by geographic location, and Panel D by labor force status. Panels B and C restrict the analysis to individuals aged 25 to 54.

Figure OA.2.6: Opioid Utilization by Location (Including Zeros)

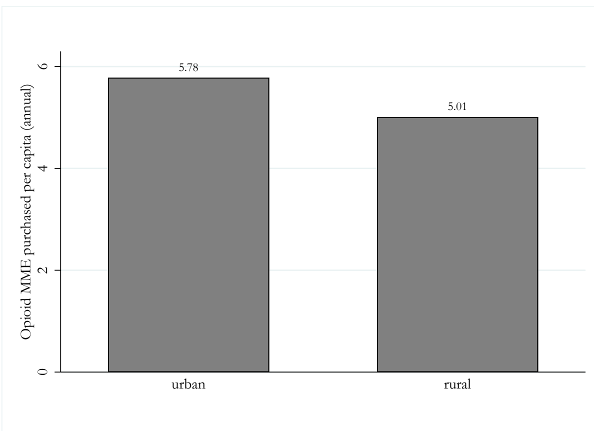
(a) Average Number of Purchases Per Capita



(b) Average Annual Days of Supply Per Capita



(c) Average MME Per Day Per Capita



(d) Share with Any High-Dose Opioid

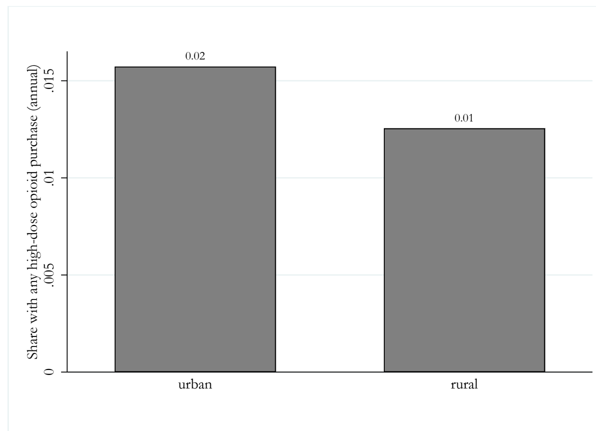


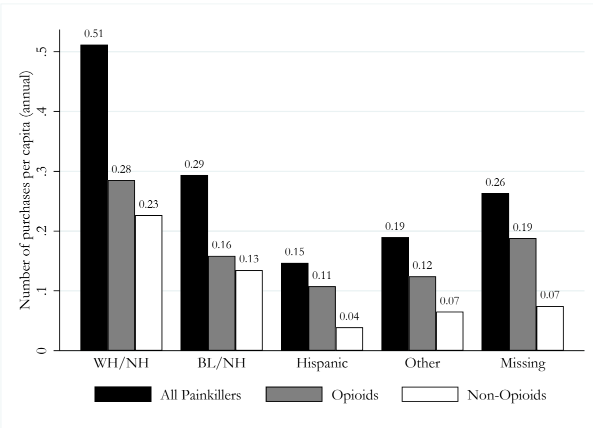
Table OA.2.1: Summary Statistics

	MEAN	SD	N
Opioids			
1. Number of prescriptions filled			5149
2. Days of supply per prescription filled	5.217	5.631	5149
3. MME per day per prescription filled	52.591	40.268	5149
4. Share of high-dose among prescriptions filled	0.140	0.347	5149
Non-Opioids			
5. Number of prescriptions filled			4065
6. Days of supply per prescription filled	16.218	24.315	4065

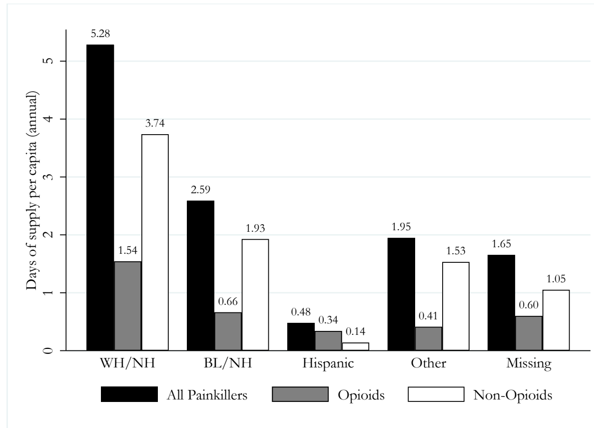
Notes: This table presents summary statistics for our RAND HIE analysis sample regarding opioid and non-opioid prescriptions filled. Each row reports raw means, standard deviations, and number of observations at the filled-prescription level.

Figure OA.2.7: Opioid Utilization by Ethnicity (Including Zeros)

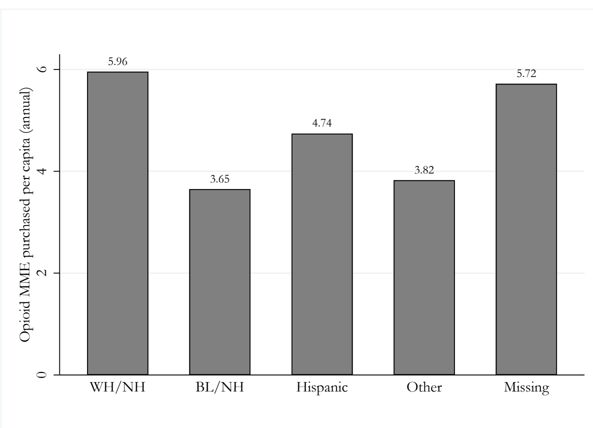
(a) Average Number of Purchases Per Capita



(b) Average Annual Days of Supply Per Capita



(c) Average MME Per Day Per Capita



(d) Share with Any High-Dose Opioid

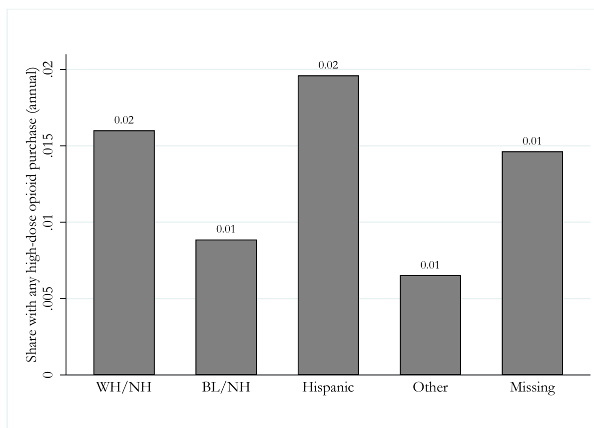
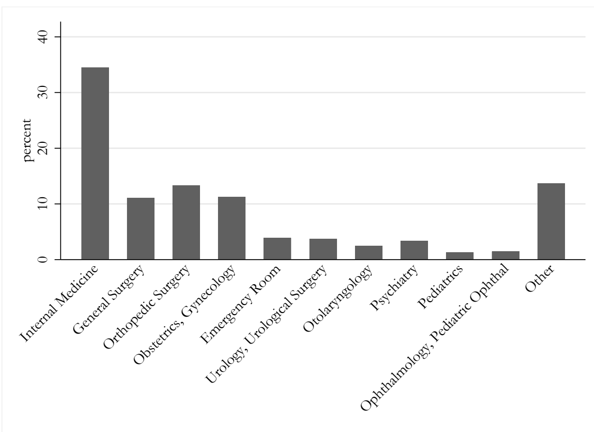
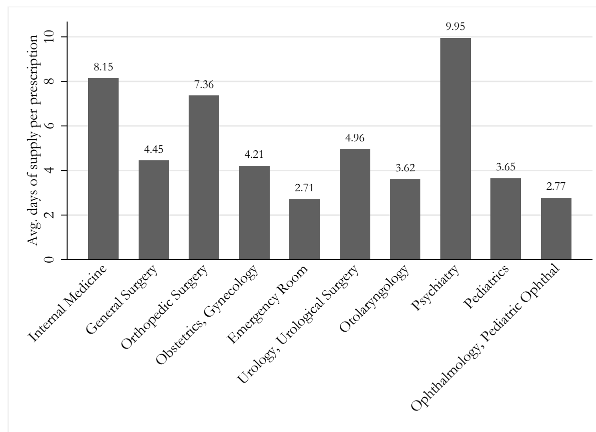


Figure OA.2.8: Characteristics of Opioid Prescribers: Specialists

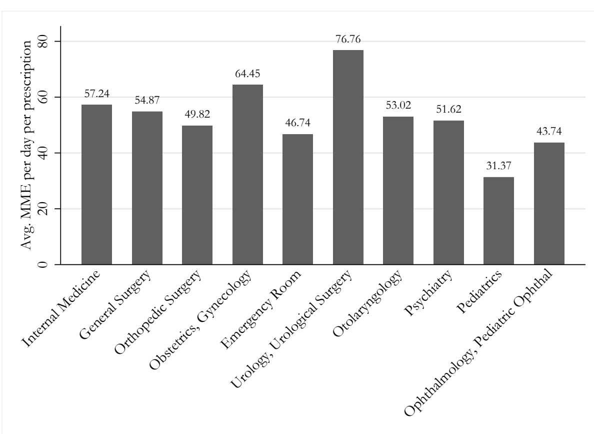
(a) Distribution of Prescribers



(b) Average Days of Supply per Prescription



(c) Average MME per Day per Prescription



(d) Share of High-Dose Prescriptions

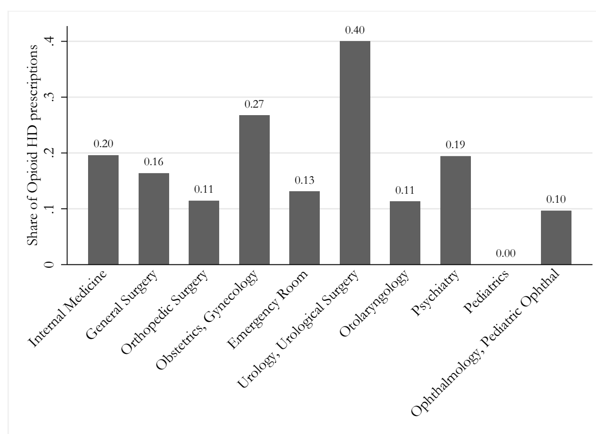
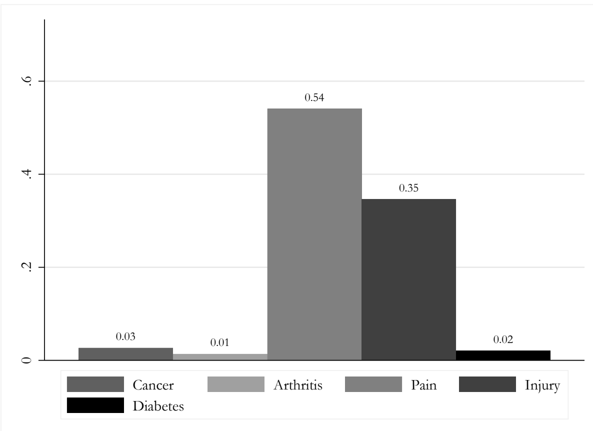
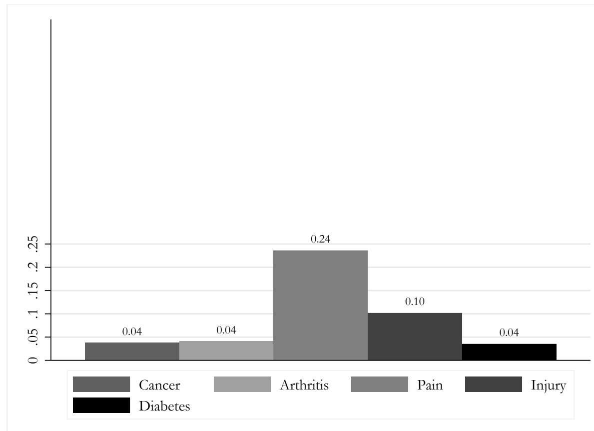


Figure OA.2.9: Common Diagnosis Codes and Reasons for Healthcare Visits Underlying Painkiller Prescriptions - 90 Days

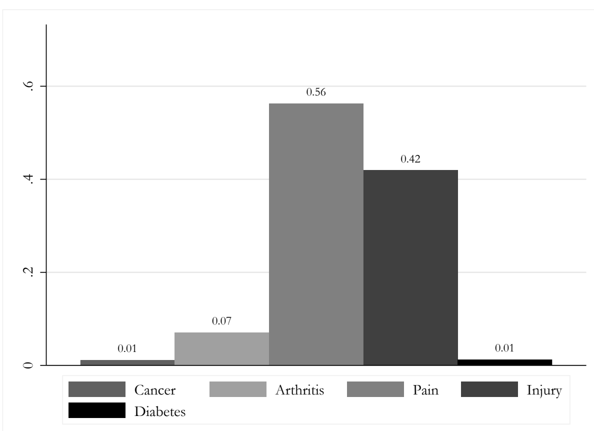
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



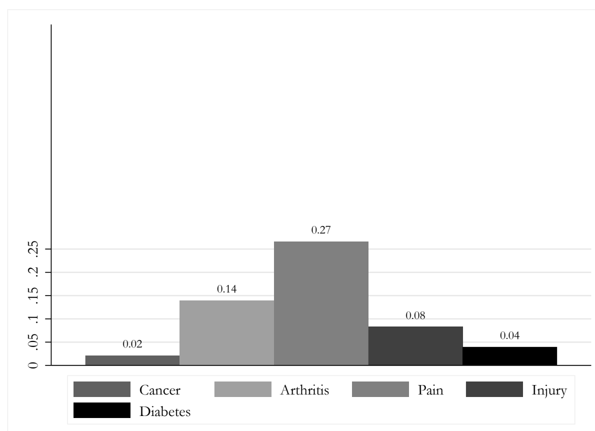
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



(c) Share of Non-Opioid Prescriptions Involving Selected Reasons for Visiting Provider



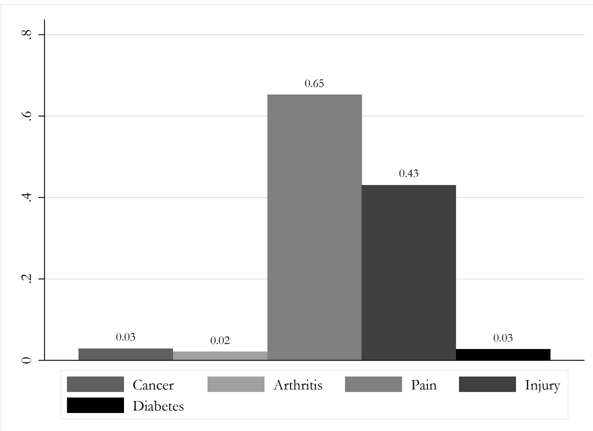
(d) Share of Non-Opioid Prescriptions Involving Selected Diagnosis Codes



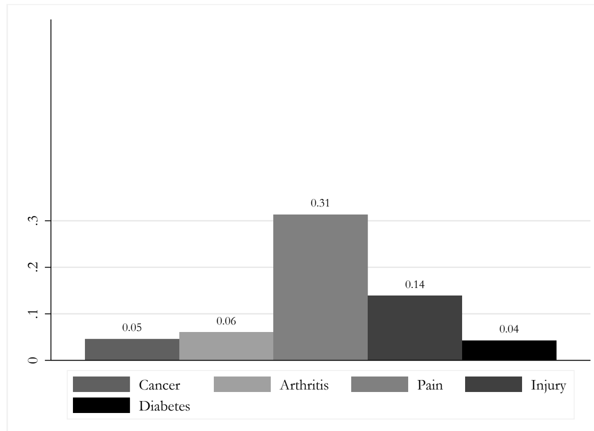
Notes: Figures OA.2.10b and OA.2.10d display, for opioid and non-opioid prescriptions respectively, the average of four indicator variables capturing whether any outpatient visit within the 90 days preceding the prescription involved: (1) at least one diagnosis related to cancer, (2) at least one diagnosis related to arthritis, (3) at least one diagnosis related to pain, (4) at least one diagnosis related to injury, or (5) at least one diagnosis related to diabetes. Figures OA.2.10a and OA.2.10c present analogous measures but focus instead on the reported reasons and symptoms for the visits.

Figure OA.2.10: Common Diagnosis Codes and Reasons for Healthcare Visits Underlying Painkiller Prescriptions - 180 Days

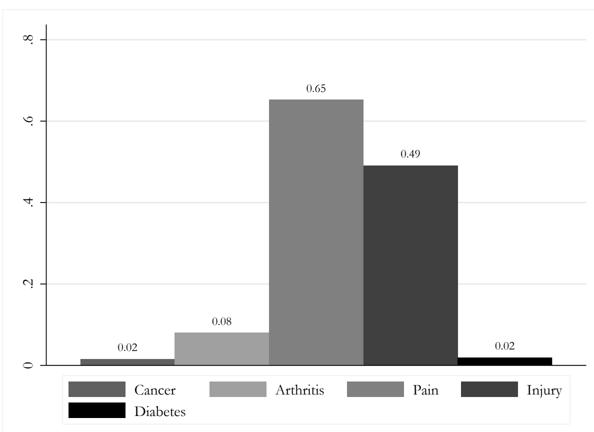
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



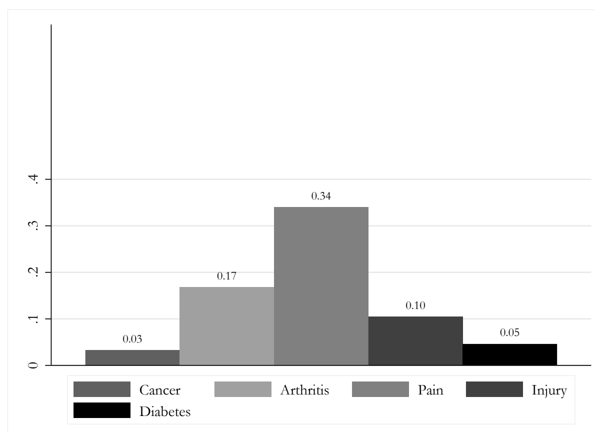
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



(c) Share of Non-Opioid Prescriptions Involving Selected Reasons for Visiting Provider



(d) Share of Non-Opioid Prescriptions Involving Selected Diagnosis Codes



Notes: Figures OA.2.10b and OA.2.10d display, for opioid and non-opioid prescriptions respectively, the average of four indicator variables capturing whether any outpatient visit within the 180 days preceding the prescription involved: (1) at least one diagnosis related to cancer, (2) at least one diagnosis related to arthritis, (3) at least one diagnosis related to pain, (4) at least one diagnosis related to injury, or (5) at least one diagnosis related to diabetes. Figures OA.2.10a and OA.2.10c present analogous measures but focus instead on the reported reasons and symptoms for the visits.

OA.3 Opioid Drugs in the 2021 MEPS

This section describes the main steps for cleaning the MEPS data files and compares the opioid painkiller drugs purchased in the 2021 MEPS data versus the 1974-1982 RAND HIE data.

OA.3.1 Steps to Identify Opioid Painkillers in the 2021 MEPS Data

1. We use the 2021 MEPS Full-Year Consolidated Data File (HC-233) and the 2021 Prescribed Medicines File (HC-229A). The MEPS Full-Year Consolidated Data File for 2021 includes 28,336 individuals. The MEPS Prescribed Medicines File for 2021 contains 303,394 observations from 16,534 unique individuals.

2. To make the MEPS and the RAND HIE sample comparable in age, we drop 6,541 unique individuals aged 65 or more and keep 21,795 unique individuals younger than 65.

3. We classify as painkillers those observations with Therapeutic Class equal to "analgesics", "miscellaneous analgesics", or "analgesic combinations." We identify 11,292 painkiller purchases, which represent 6.55% of all prescribed medicines purchased weighted for national representation.

4. Following (Moriya and Fang, 2023), we classify as opioid painkillers those observations with Therapeutic Sub-Class equal to "narcotic analgesics" or "narcotic analgesic combinations" in the Multum Lexicon database from Cerner Multum, Inc. We exclude respiratory agents, antitussives, and drugs commonly used in medication-assisted treatment, as these opioids are not primarily indicated for pain management. We identify 5,249 opioid painkiller purchases, which represent 45.22% of all painkillers weighted for national representation.

5. In 2021, a total of 13.7 million individuals under age 65, or 5% of this population, filled at least one opioid prescription. During the same period, 3.8 million or 1.4% of individuals under age 65 obtained four or more opioid prescription fills or refills.

6. Of the 5,249 opioid painkiller observations, 890 are missing both NDCs and drug names. We rename the opioid drug names to "Unknown Opioids" for these observations.

7. We incorporate additional information on MME units by merging this file with the CDC Oral MME file from 2020 using the NDC identifiers. The CDC file successfully matches 96.26% of the opioid painkiller observations with non-missing NDCs.

Table OA.3.1 presents a comparison between the opioid drugs purchased in the 2021 MEPS versus the 1974-1982 RAND HIE data. The columns show the results using alternative measures to weight the observations. We find that between 84% and 93% of the opioid painkiller drugs in the MEPS data were also in the RAND HIE data.

Table OA.3.1: Comparison of Opioid Painkiller Drugs in MEPS versus RAND HIE Data

Opioids in MEPS 2021	Raw Frequency (1)	Percent MEPS adjusted (2)	Percent MEPS adjusted and MME weighted (3)	Percent MEPS adjusted and days-supplied weighted (4)
Only in MEPS	737	16.45	7.12	12.80
Both in MEPS and RAND HIE	3622	83.55	92.88	87.20
Total	4359	100.00	100.00	100.00

Notes: The reported statistics are derived from the MEPS Prescribed Medicines File for 2021. We restrict the sample to opioid painkillers with non-missing drug names purchased by individuals aged 64 or less. We classify these opioid painkiller purchases into two mutually exclusive groups: (a) opioid drugs present only in MEPS and (b) opioid drugs present both in MEPS and RAND HIE. Drugs in group (a) include only Tramadol, approved by the U.S. Federal Drug Administration in 1995. Drugs in group (b) include codeine, hydrocodone, hydromorphone, morphine, and oxycodone. Column (1) shows the raw frequencies of each group. Column (2) shows the group percentages adjusted by MEPS survey weights for national representation. Column (3) displays percentages weighted by Morphine Milligram Equivalents (MMEs) and adjusted by MEPS survey weights for national representation. Column (4) displays percentages weighted by days supplied and adjusted by MEPS survey weights for national representation.

OA.4 Analyses of Opioid Painkillers Prescribed by Non-Dentists Only

In this section, we replicate our main analysis in section 5 including only painkiller purchases prescribed by non-dentists.

Table OA.4.1 describes the summary statistics by plan group for this sample inclusion criteria. Each of the six columns presents raw means and standard deviations at the person-year level by plan. Each row presents a measure related to the utilization of prescribed painkillers or the use of outpatient provider services. On the extensive margin, we find that individuals with the highest cost-sharing are 4.9%-points (45%) less likely to purchase opioid painkillers relative to individuals with full insurance. On the intensive margin, the estimates indicate that individuals in the least generous plan spend $5.1 (65.6%) less on opioid painkillers, have 1.1 (56.0%) fewer annual days of supply, and consume 1.9 (40.3%) fewer MME per day, compared to individuals with full insurance.

Tables OA.4.2 and OA.4.3 present the treatment effects based on painkiller purchases prescribed exclusively by non-dentists. Overall, our main conclusions remain robust after excluding opioid and non-opioid purchases prescribed by dentists.

Table OA.4.1: Summary Statistics - All Painkillers (Medical Only)

	(1) Free Care		(2) 25% Coinsurance		(3) Mixed Coinsurance		(4) 50% Coinsurance		(5) Individual Deductible		(6) 95% Coinsurance	
	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD
All Prescribed Painkillers:												
1. Any prescription filled	0.173	(0.38)	0.123	(0.33)	0.125	(0.33)	0.102	(0.30)	0.108	(0.31)	0.096	(0.29)
2. Annual spending (2019 $)	18.302	(103.19)	8.063	(46.43)	10.779	(73.15)	4.850	(26.70)	9.161	(63.16)	7.468	(46.50)
3. Annual days of supply	6.984	(40.65)	3.204	(21.09)	3.634	(23.17)	1.851	(10.74)	3.719	(26.98)	3.099	(23.74)
4. Number of Rx Purchased	0.651	(3.15)	0.305	(1.33)	0.348	(1.54)	0.215	(1.00)	0.287	(1.34)	0.267	(1.41)
Opioids:												
5. Any prescription filled	0.109	(0.31)	0.070	(0.25)	0.077	(0.27)	0.061	(0.24)	0.068	(0.25)	0.060	(0.24)
6. Any high-dose Rx filled	0.027	(0.16)	0.010	(0.10)	0.022	(0.15)	0.005	(0.07)	0.016	(0.13)	0.013	(0.11)
7. Annual spending (2019 $)	7.725	(64.09)	2.279	(13.51)	4.538	(56.29)	1.806	(11.85)	3.625	(39.08)	2.660	(21.73)
8. Annual days of supply	1.920	(16.22)	0.569	(3.71)	1.249	(15.13)	0.505	(4.31)	1.006	(11.65)	0.844	(9.24)
9. Average MME per day	4.750	(18.45)	2.678	(12.80)	3.436	(15.96)	2.704	(14.18)	3.075	(14.92)	2.835	(14.54)
10. Number of Rx Purchased	0.358	(2.46)	0.122	(0.73)	0.165	(1.03)	0.109	(0.67)	0.135	(0.84)	0.123	(0.79)
11. Share filled Rx | Rx	0.833	(0.32)	0.707	(0.42)	0.777	(0.38)	0.824	(0.34)	0.743	(0.39)	0.781	(0.38)
Non-Opioids:												
12. Any prescription filled	0.103	(0.30)	0.078	(0.27)	0.075	(0.26)	0.053	(0.22)	0.063	(0.24)	0.056	(0.23)
13. Annual spending (2019 $)	10.578	(67.27)	5.783	(41.30)	6.241	(39.76)	3.044	(23.30)	5.536	(45.05)	4.807	(37.10)
14. Annual days of supply	5.064	(34.28)	2.635	(19.85)	2.385	(15.52)	1.345	(9.72)	2.712	(23.06)	2.255	(18.01)
15. Number of Rx Purchased	0.293	(1.42)	0.183	(0.96)	0.183	(0.93)	0.105	(0.70)	0.152	(0.88)	0.144	(0.90)
Outpatient Provider Visits:												
16. Any visit	0.841	(0.37)	0.754	(0.43)	0.748	(0.43)	0.745	(0.44)	0.690	(0.46)	0.644	(0.48)
17. Number of visits	6.764	(11.04)	5.087	(10.65)	5.025	(9.65)	4.432	(7.48)	4.745	(8.44)	4.115	(8.25)
18. Annual spending (2019 K$)	0.204	(0.44)	0.150	(0.37)	0.172	(0.46)	0.123	(0.30)	0.157	(0.37)	0.128	(0.37)
19. Any opioid Rx | any visit	0.140	(0.35)	0.112	(0.32)	0.112	(0.31)	0.087	(0.28)	0.111	(0.31)	0.100	(0.30)
# Families	1040		327		285		208		668		572	
# Individuals	1964		663		507		393		1261		1134	
# Individual-years	6724		2333		1704		1417		4087		3739	

Notes: This table reports summary statistics from our RAND HIE analysis sample, by health insurance plan. Each of the six columns presents raw means and standard deviations at the individual-year level by plan. Standard deviations are reported in parentheses beside the mean.

Table OA.4.2: Plans' Effects on Prescribed Painkiller Purchases (Medical Only)

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any	Spending in $	Annual Days of Supply	Number of Rx Purchased	Share with Any	Share with Any High-Dose	Spending in $	Annual Days of Supply	MME per Day	Number of Rx Purchased
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Const. (Free Care)	0.219	21.939	8.270	0.783	0.138	0.032	9.181	2.351	5.971	0.426
	(0.008)	(2.032)	(0.808)	(0.063)	(0.006)	(0.003)	(1.098)	(0.300)	(0.330)	(0.046)
25% Coinsurance	-0.052	-9.764	-3.826	-0.340	-0.037	-0.016	-5.311	-1.386	-2.050	-0.232
	(0.011)	(2.292)	(0.980)	(0.068)	(0.008)	(0.003)	(1.085)	(0.302)	(0.415)	(0.046)
Mixed Coinsurance	-0.045	-6.924	-3.126	-0.291	-0.033	-0.007	-2.813	-0.581	-1.392	-0.189
	(0.012)	(2.844)	(1.037)	(0.076)	(0.010)	(0.005)	(1.818)	(0.503)	(0.533)	(0.053)
50% Coinsurance	-0.077	-13.188	-5.441	-0.440	-0.050	-0.023	-5.479	-1.437	-2.344	-0.240
	(0.011)	(2.097)	(0.866)	(0.069)	(0.009)	(0.003)	(1.105)	(0.339)	(0.500)	(0.051)
Ind. Deductible	-0.068	-9.123	-3.315	-0.375	-0.045	-0.011	-4.023	-0.909	-1.787	-0.229
	(0.009)	(2.351)	(0.931)	(0.066)	(0.007)	(0.003)	(1.428)	(0.407)	(0.406)	(0.047)
95% Coinsurance	-0.080	-10.869	-4.076	-0.388	-0.050	-0.014	-4.969	-1.084	-2.015	-0.234
	(0.010)	(2.263)	(0.992)	(0.069)	(0.008)	(0.003)	(1.212)	(0.388)	(0.415)	(0.049)
Adjusted R^2	0.08	0.03	0.02	0.04	0.04	0.02	0.01	0.01	0.03	0.02
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by non-dentists only. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.4.3: Plans' Effects on Prescribed Non-Opioid Painkiller Purchases (Medical Only)

	Share with Any (1)	Spending in $ (2)	Annual Days of Supply (3)	Number of Rx Purchased (4)
Constant (Free Care)	0.130	12.758	5.919	0.356
	(0.006)	(1.414)	(0.677)	(0.030)
25% Coinsurance	-0.029	-4.453	-2.440	-0.109
	(0.009)	(1.776)	(0.859)	(0.039)
Mixed Coinsurance	-0.023	-4.111	-2.545	-0.102
	(0.009)	(1.777)	(0.787)	(0.040)
50% Coinsurance	-0.055	-7.709	-4.004	-0.199
	(0.009)	(1.541)	(0.731)	(0.038)
Ind. Deductible	-0.040	-5.100	-2.406	-0.145
	(0.007)	(1.532)	(0.751)	(0.033)
95% Coinsurance	-0.050	-5.900	-2.992	-0.154
	(0.007)	(1.655)	(0.781)	(0.036)
Adjusted R^2	0.05	0.02	0.02	0.03
# Families	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922
# Individual-years	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of non-opioid painkillers, (2) annual spending on non-opioid painkillers, (3) annual days of supply of non-opioid painkillers, and (4) annual number of non-opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by non-dentists only. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

OA.5 Analyses of Opioid Painkillers Prescribed by Dentists Only

In this section, we replicate our main analysis in section 5 including only painkiller purchases prescribed by dentists.

Table OA.5.1 describes the summary statistics by plan group for this sample inclusion criteria. Each of the six columns presents raw means and standard deviations at the person-year level by plan. Each row presents a measure related to the utilization of prescribed painkillers or the use of outpatient provider services. On the extensive margin, we find that individuals with the highest cost-sharing are 2.6%-points (54.2%) less likely to purchase opioid painkillers relative to individuals with full insurance. On the intensive margin, the estimates indicate that individuals in the least generous plan spend $0.7 (65.4%) less on opioid painkillers, have 0.11 (61.6%) fewer annual days of supply, and consume 0.8 (53.6%) fewer MME per day, compared to individuals with full insurance.

Tables OA.5.2 and OA.5.3 present the treatment effects based on painkiller purchases prescribed exclusively by dentists. Overall, our main conclusions remain robust after excluding opioid and non-opioid purchases prescribed by non-dentists.

Table OA.5.1: Summary Statistics - All Painkillers (Dental Only)

	(1)		(2)		(3)		(4)		(5)		(6)	
	Free Care		25% Coinsurance		Mixed Coinsurance		50% Coinsurance		Individual Deductible		95% Coinsurance	
	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD	MEAN	SD
All Prescribed Painkillers:												
1. Any prescription filled	0.049	(0.22)	0.034	(0.18)	0.031	(0.17)	0.027	(0.16)	0.030	(0.17)	0.022	(0.15)
2. Annual spending (2019 $)	1.207	(7.03)	0.695	(5.68)	0.516	(3.25)	0.570	(4.49)	0.686	(4.94)	0.404	(3.31)
3. Annual days of supply	0.208	(1.40)	0.131	(1.40)	0.093	(0.63)	0.100	(0.88)	0.113	(0.84)	0.075	(0.68)
4. Number of Rx Purchased	0.076	(0.41)	0.050	(0.46)	0.038	(0.23)	0.040	(0.28)	0.049	(0.35)	0.028	(0.21)
Opioids:												
5. Any prescription filled	0.048	(0.21)	0.033	(0.18)	0.030	(0.17)	0.025	(0.16)	0.029	(0.17)	0.022	(0.15)
6. Any high-dose Rx filled	0.004	(0.06)	0.002	(0.05)	0.001	(0.02)	0.002	(0.05)	0.001	(0.03)	0.001	(0.04)
7. Annual spending (2019 $)	1.135	(6.72)	0.659	(5.57)	0.492	(3.17)	0.469	(3.44)	0.664	(4.81)	0.393	(3.26)
8. Annual days of supply	0.185	(1.10)	0.123	(1.38)	0.091	(0.63)	0.083	(0.71)	0.108	(0.81)	0.071	(0.63)
9. Average MME per day	1.577	(8.85)	1.134	(7.81)	0.871	(5.74)	0.919	(7.74)	1.002	(6.76)	0.732	(6.27)
10. Number of Rx Purchased	0.073	(0.40)	0.048	(0.45)	0.036	(0.22)	0.035	(0.26)	0.048	(0.33)	0.027	(0.21)
11. Share filled Rx | Rx	0.865	(0.31)	0.839	(0.36)	0.718	(0.44)	0.754	(0.42)	0.780	(0.39)	0.781	(0.38)
Non-Opioids:												
12. Any prescription filled	0.003	(0.05)	0.003	(0.05)	0.001	(0.03)	0.002	(0.05)	0.002	(0.04)	0.001	(0.03)
13. Annual spending (2019 $)	0.072	(1.67)	0.036	(0.75)	0.024	(0.71)	0.101	(2.70)	0.022	(0.61)	0.011	(0.38)
14. Annual days of supply	0.024	(0.80)	0.008	(0.18)	0.002	(0.07)	0.017	(0.51)	0.005	(0.16)	0.004	(0.21)
15. Number of Rx Purchased	0.003	(0.06)	0.003	(0.05)	0.001	(0.03)	0.004	(0.10)	0.002	(0.04)	0.001	(0.03)
Outpatient Provider Visits:												
16. Any visit	0.666	(0.47)	0.539	(0.50)	0.518	(0.50)	0.528	(0.50)	0.478	(0.50)	0.475	(0.50)
17. Number of visits	2.292	(2.82)	1.691	(2.55)	1.705	(2.62)	1.601	(2.35)	1.621	(2.75)	1.457	(2.30)
18. Annual spending (2019 K$)	0.185	(0.52)	0.108	(0.35)	0.122	(0.43)	0.091	(0.34)	0.121	(0.42)	0.090	(0.33)
19. Any opioid Rx | any visit	0.057	(0.23)	0.045	(0.21)	0.046	(0.21)	0.040	(0.20)	0.045	(0.21)	0.034	(0.18)
# Families	1040		327		285		208		668		572	
# Individuals	1964		663		507		393		1261		1134	
# Individual-years	6724		2333		1704		1417		4087		3739	

Notes: This table reports summary statistics from our RAND HIE analysis sample, by health insurance plan. Each of the six columns presents raw means and standard deviations at the individual-year level by plan. Standard deviations are reported in parentheses beside the mean.

Table OA.5.2: Plans' Effects on Prescribed Painkiller Purchases (Dental Only)

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any	Spending in $	Annual Days of Supply	Number of Rx Purchased	Share with Any	Share with Any High-Dose	Spending in $	Annual Days of Supply	MME per Day	Number of Rx Purchased
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Const. (Free Care)	0.061	1.544	0.264	0.098	0.060	0.004	1.455	0.235	2.003	0.093
	(0.004)	(0.120)	(0.024)	(0.007)	(0.004)	(0.001)	(0.115)	(0.018)	(0.155)	(0.007)
25% Coinsurance	-0.015	-0.567	-0.096	-0.030	-0.015	-0.002	-0.502	-0.071	-0.525	-0.028
	(0.005)	(0.163)	(0.040)	(0.012)	(0.005)	(0.001)	(0.155)	(0.035)	(0.216)	(0.012)
Mixed Coinsurance	-0.018	-0.662	-0.108	-0.038	-0.019	-0.003	-0.634	-0.094	-0.678	-0.037
	(0.005)	(0.123)	(0.025)	(0.008)	(0.005)	(0.001)	(0.120)	(0.022)	(0.192)	(0.008)
50% Coinsurance	-0.020	-0.585	-0.110	-0.035	-0.020	-0.002	-0.584	-0.094	-0.675	-0.035
	(0.006)	(0.163)	(0.036)	(0.010)	(0.005)	(0.002)	(0.129)	(0.025)	(0.232)	(0.009)
Ind. Deductible	-0.020	-0.550	-0.100	-0.029	-0.021	-0.003	-0.508	-0.084	-0.627	-0.028
	(0.004)	(0.127)	(0.025)	(0.008)	(0.004)	(0.001)	(0.122)	(0.021)	(0.169)	(0.008)
95% Coinsurance	-0.027	-0.812	-0.139	-0.050	-0.026	-0.003	-0.742	-0.117	-0.868	-0.047
	(0.004)	(0.112)	(0.025)	(0.007)	(0.004)	(0.001)	(0.105)	(0.019)	(0.159)	(0.006)
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by non-dentists only. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.5.3: Plans' Effects on Prescribed Non-Opioiod Painkiller Purchases (Dental Only)

	Share with Any (1)	Spending in $ (2)	Annual Days of Supply (3)	Number of Rx Purchased (4)
Constant (Free Care)	0.004	0.089	0.029	0.004
	(0.001)	(0.025)	(0.013)	(0.001)
25% Coinsurance	-0.001	-0.065	-0.025	-0.002
	(0.001)	(0.038)	(0.017)	(0.002)
Mixed Coinsurance	-0.001	-0.028	-0.014	-0.001
	(0.001)	(0.025)	(0.009)	(0.001)
50% Coinsurance	-0.002	-0.000	-0.016	-0.000
	(0.002)	(0.076)	(0.022)	(0.003)
Ind. Deductible	-0.001	-0.042	-0.015	-0.001
	(0.001)	(0.023)	(0.011)	(0.001)
95% Coinsurance	-0.002	-0.069	-0.022	-0.003
	(0.001)	(0.028)	(0.014)	(0.001)
Adjusted R^2	0.00	0.00	0.00	0.00
# Families	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922
# Individual-years	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of non-opioid painkillers, (2) annual spending on non-opioid painkillers, (3) annual days of supply of non-opioid painkillers, and (4) annual number of non-opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by non-dentists only. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site by start month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

OA.6 Empirical Analyses - Additional Robustness Checks

Table OA.6.1: Controlling for Pre-Randomization Covariates and Adjustment for Underreporting (Medical Only)

	Share with Any	Share with Any High-Dose	Spending in $		Annual Days of Supply	MME per Day	Number of Rx Purchased
	Covs.	Covs.	Covs.	Adj.	Covs.	Covs.	Covs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant (Free Care Plan)	0.110	0.025	6.922	9.181	1.645	4.806	0.326
	(0.008)	(0.004)	(0.919)	(1.098)	(0.250)	(0.451)	(0.037)
25% Coinsurance	-0.035	-0.014	-4.634	-5.311	-1.214	-1.923	-0.207
	(0.008)	(0.003)	(0.961)	(1.085)	(0.272)	(0.401)	(0.040)
Mixed Coinsurance	-0.034	-0.006	-2.838	-2.813	-0.580	-1.410	-0.198
	(0.010)	(0.004)	(1.848)	(1.818)	(0.512)	(0.523)	(0.057)
50% Coinsurance	-0.046	-0.022	-4.378	-5.479	-1.124	-2.183	-0.199
	(0.009)	(0.003)	(1.001)	(1.105)	(0.310)	(0.501)	(0.045)
Individual Deductible	-0.044	-0.011	-3.924	-4.023	-0.901	-1.755	-0.230
	(0.007)	(0.003)	(1.390)	(1.428)	(0.409)	(0.392)	(0.049)
95% Coinsurance	-0.047	-0.013	-4.215	-4.969	-0.878	-1.886	-0.211
	(0.007)	(0.003)	(1.118)	(1.212)	(0.383)	(0.406)	(0.046)
Adjusted R^2	0.07	0.03	0.06	0.01	0.07	0.04	0.07
# Families	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes are: (1) a dummy variable for annual purchase of opioid painkillers, (2) a dummy variable for annual purchase of high-dose opioid painkillers, (3) annual spending on opioid painkillers, (4) annual days of supply of opioid painkillers, (5) MME per day for opioid painkillers, and (6) annual number of opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by non-dentists. The regressions include all pre-randomization covariates as controls. The specification in column (4) adjusts the spending outcome for underreporting. All regressions include a dummy variable for women, a dummy variable for individuals under the age of 18, de-meaned site by start month dummy variables, and de-meaned year fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.2: Pre-Randomization Covariates and Plan Assignment - Additional Covariates

	Free Care	25% Coins	Mixed Coins	50% Coins	Individual Deductible	95% Coins	p-value all equal
Panel A: Pre-Experiment Utilization Variables							
hospitalized in year before expt	.103	.097	.099	.08	.106	.101	.815
hospitalization data missing	.029	.015	.01	.022	.018	.016	.102
had a regular doctor	.963	.97	.959	.974	.955	.956	.872
doctor data missing	.195	.193	.208	.182	.192	.187	.001
had a medical exam in year before expt	.505	.524	.453	.524	.431	.485	.017
medical exam data missing	.038	.026	.036	.024	.028	.039	.535
num doc visits in year before expt	5.114	4.533	4.863	4.087	5.378	4.654	.031
doc visits data missing	.195	.179	.158	.166	.197	.192	.468
log medcl expenditures in year before expt	3.473	3.491	3.478	3.375	3.523	3.348	.601
medical expenditures data missing	.386	.406	.333	.33	.384	.403	.11
any routine dental visits in year before expt	.712	.695	.71	.739	.707	.693	.948
routine dental visits data missing	.391	.336	.366	.369	.418	.358	.135
any nonroutine dental visits in year before expt	.536	.499	.575	.59	.532	.535	.484
nonroutine dental visits data missing	.391	.336	.366	.369	.418	.358	.135
Joint F-test	.	.	.	.	.	.	.
Panel B: Non-Utilization-Related Baseline Covariates							
female	.51	.52	.524	.511	.531	.524	.76
age 6 to 17	.29	.282	.333	.284	.25	.299	.039
age 18 to 44	.409	.434	.434	.439	.451	.435	.208
age 45 +	.169	.135	.124	.148	.169	.144	.215
white	.848	.816	.845	.872	.845	.803	.201
race data missing	.479	.456	.464	.448	.424	.465	.054
hs graduate	.645	.734	.707	.659	.7	.677	.043
education beyond hs	.297	.351	.293	.302	.307	.321	.702
education data missing	.411	.423	.421	.397	.377	.417	.201
grew up in a city	.164	.157	.175	.123	.181	.163	.228
grew up in a suburb	.07	.062	.058	.079	.067	.06	.817
grew up in a town	.223	.223	.206	.277	.231	.225	.253
background data missing	.407	.414	.412	.388	.373	.411	.275
log baseline family income	9.247	9.276	9.276	9.317	9.301	9.243	.679
log baseline family income squared	85.91	86.45	86.396	87.151	86.916	85.822	.659
anyone in family working at baseline	.618	.678	.626	.664	.649	.638	.266
work data missing	.421	.421	.419	.394	.378	.419	.157
insured at baseline	.855	.89	.866	.885	.879	.884	.793
insurance data missing	.058	.034	.025	.032	.038	.045	.025
employer-provided insurance	.773	.765	.761	.809	.803	.781	.909
employer-provided insurance data missing	.295	.269	.262	.276	.279	.295	.092
private insurance	.136	.155	.157	.084	.153	.158	.622
private insurance data missing	.296	.269	.264	.267	.281	.293	.038
public insurance	.098	.091	.064	.069	.072	.076	.647
public insurance data missing	.055	.032	.023	.032	.038	.044	.039
excellent health at baseline	.5	.523	.507	.528	.497	.5	.97
good health at baseline	.387	.368	.411	.359	.402	.404	.789
health status data missing	.056	.034	.023	.04	.042	.045	.097
experienced pain at baseline	.529	.511	.525	.491	.538	.554	.669
pain data missing	.056	.039	.025	.04	.041	.045	.213
worried about health at baseline	.426	.429	.412	.391	.384	.403	.591
worry data missing	.056	.034	.023	.04	.041	.045	.094
N (number of individuals)	1824	634	478	374	1180	1052	.

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. All regressions are estimated at the individual level and include de-meaned site by start month dummy variables as well as de-meaned year fixed effects. Standard errors are clustered on family. The number of individuals is smaller than in Table 4 because newborns during the experiment were incorporated after enrollment.

Table OA.6.3: Controlling for Pre-Randomization Covariates and Adjustment for Underreporting (Dental Only)

	Share with Any	Share with Any High-Dose	Spending in $		Annual Days of Supply	MME per Day	Number of Rx Purchased
	Covs.	Covs.	Covs.	Adj.	Covs.	Covs.	Covs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant (Free Care Plan)	0.054	0.005	1.293	1.455	0.198	1.990	0.081
	(0.006)	(0.002)	(0.135)	(0.115)	(0.022)	(0.269)	(0.009)
25% Coinsurance	-0.014	-0.002	-0.493	-0.502	-0.070	-0.483	-0.027
	(0.005)	(0.001)	(0.156)	(0.155)	(0.035)	(0.212)	(0.012)
Mixed Coinsurance	-0.019	-0.003	-0.652	-0.634	-0.098	-0.715	-0.038
	(0.005)	(0.001)	(0.120)	(0.120)	(0.022)	(0.189)	(0.008)
50% Coinsurance	-0.020	-0.002	-0.552	-0.584	-0.090	-0.644	-0.034
	(0.005)	(0.001)	(0.129)	(0.129)	(0.025)	(0.231)	(0.009)
Individual Deductible	-0.020	-0.003	-0.484	-0.508	-0.080	-0.586	-0.027
	(0.004)	(0.001)	(0.120)	(0.122)	(0.021)	(0.164)	(0.008)
95% Coinsurance	-0.025	-0.003	-0.726	-0.742	-0.114	-0.840	-0.046
	(0.004)	(0.001)	(0.103)	(0.105)	(0.019)	(0.157)	(0.006)
Adjusted R^2	0.02	0.00	0.01	0.01	0.01	0.01	0.01
# Families	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes are: (1) a dummy variable for annual purchase of opioid painkillers, (2) a dummy variable for annual purchase of high-dose opioid painkillers, (3) annual spending on opioid painkillers, (4) annual days of supply of opioid painkillers, (5) MME per day for opioid painkillers, and (6) annual number of opioid prescriptions purchased. All outcomes account for opioid purchases prescribed by dentists only. The regressions include all pre-randomization covariates as controls. The specification in column (4) adjusts the spending outcome for underreporting. All regressions include a dummy variable for women, a dummy variable for individuals under the age of 18, de-meaned site by start month dummy variables, and de-meaned year fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.4: Controlling for Pre-Randomization Covariates and Adjustment for Underreporting - All Painkillers

	Share with Any	Spending in $		Annual Days of Supply	Number of Rx Purchased
	Covs.	Covs.	Adj.	Covs.	Covs.
	(1)	(2)	(3)	(4)	(5)
Constant (Free Care Plan)	0.207	16.282	23.483	5.558	0.650
	(0.010)	(1.602)	(2.050)	(0.650)	(0.052)
25% Coinsurance	-0.059	-9.904	-10.330	-3.880	-0.349
	(0.012)	(2.274)	(2.316)	(0.991)	(0.066)
Mixed Coinsurance	-0.060	-8.128	-7.586	-3.379	-0.349
	(0.013)	(2.856)	(2.857)	(1.054)	(0.080)
50% Coinsurance	-0.090	-12.841	-13.772	-5.304	-0.437
	(0.012)	(2.091)	(2.113)	(0.868)	(0.066)
Individual Deductible	-0.079	-9.608	-9.673	-3.354	-0.402
	(0.009)	(2.282)	(2.365)	(0.902)	(0.066)
95% Coinsurance	-0.095	-10.732	-11.681	-3.833	-0.407
	(0.010)	(2.073)	(2.281)	(0.961)	(0.066)
Adjusted R^2	0.12	0.07	0.03	0.06	0.09
# Families	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes are: (1) a dummy variable for annual purchase of opioid and non-opioid painkillers, (2) annual spending on painkillers, (3) annual days of supply of painkillers, and (4) annual number of prescriptions purchased. All outcomes account for purchases prescribed by dentists and non-dentists. The regressions include all pre-randomization covariates as controls. The specification in column (3) adjusts the spending outcome for underreporting. All regressions include a dummy variable for women, a dummy variable for individuals under the age of 18, de-meaned site by start month dummy variables, and de-meaned year fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.5: Controlling for Pre-Randomization Covariates and Adjustment for Underreporting - Non Opioid Painkillers

	Share with Any	Spending in $		Annual Days of Supply	Number of Rx Purchased
	Covs.	Covs.	Adj.	Covs.	Covs.
	(1)	(2)	(3)	(4)	(5)
Constant (Free Care Plan)	0.099	8.066	12.847	3.716	0.243
	(0.007)	(1.073)	(1.415)	(0.542)	(0.025)
25% Coinsurance	-0.029	-4.776	-4.518	-2.597	-0.114
	(0.009)	(1.809)	(1.780)	(0.881)	(0.039)
Mixed Coinsurance	-0.026	-4.639	-4.139	-2.702	-0.113
	(0.009)	(1.808)	(1.778)	(0.802)	(0.040)
50% Coinsurance	-0.058	-7.910	-7.709	-4.090	-0.204
	(0.009)	(1.577)	(1.545)	(0.745)	(0.038)
Individual Deductible	-0.041	-5.200	-5.142	-2.372	-0.146
	(0.007)	(1.515)	(1.533)	(0.730)	(0.032)
95% Coinsurance	-0.049	-5.792	-5.970	-2.841	-0.151
	(0.007)	(1.495)	(1.657)	(0.743)	(0.034)
Adjusted R^2	0.09	0.04	0.02	0.04	0.06
# Families	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004

Notes: The reported coefficients are from an ordinary least squares regression and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan. The outcomes are: (1) a dummy variable for annual purchase of non-opioid painkillers, (2) annual spending on non-opioid painkillers, (3) annual days of supply of non-opioid painkillers, and (4) annual number of non-opioid prescriptions purchased. All outcomes account for purchases prescribed by dentists and non-dentists. The regressions include all pre-randomization covariates as controls. The specification in column (3) adjusts the spending outcome for underreporting. All regressions include a dummy variable for women, a dummy variable for individuals under the age of 18, de-meaned site by start month dummy variables, and de-meaned year fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.6: Plans' Effects on Prescribed Painkiller Purchases - Deadline Effect

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any	Spending in $	Annual Days of Supply	Number of Rx Purchased	Share with Any	Share with Any High-Dose	Spending in $	Annual Days of Supply	MME per Day	Number of Rx Purchased
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Const. (Free Care)	0.259	23.446	8.462	0.874	0.180	0.035	10.580	2.622	7.723	0.515
	(0.009)	(2.119)	(0.839)	(0.067)	(0.007)	(0.003)	(1.168)	(0.319)	(0.390)	(0.049)
25% Coinsurance	-0.061	-10.331	-3.924	-0.370	-0.046	-0.018	-5.814	-1.456	-2.582	-0.260
	(0.012)	(2.316)	(0.984)	(0.071)	(0.009)	(0.004)	(1.120)	(0.308)	(0.470)	(0.050)
Mixed Coinsurance	-0.055	-7.586	-3.234	-0.329	-0.045	-0.010	-3.448	-0.674	-2.070	-0.226
	(0.014)	(2.857)	(1.039)	(0.078)	(0.012)	(0.005)	(1.832)	(0.505)	(0.589)	(0.055)
50% Coinsurance	-0.091	-13.772	-5.550	-0.475	-0.063	-0.025	-6.062	-1.531	-3.016	-0.275
	(0.012)	(2.113)	(0.870)	(0.070)	(0.010)	(0.004)	(1.127)	(0.342)	(0.597)	(0.053)
Ind. Deductible	-0.080	-9.674	-3.418	-0.404	-0.058	-0.015	-4.533	-0.992	-2.423	-0.258
	(0.010)	(2.366)	(0.932)	(0.067)	(0.008)	(0.004)	(1.445)	(0.409)	(0.442)	(0.049)
95% Coinsurance	-0.098	-11.682	-4.218	-0.438	-0.069	-0.017	-5.713	-1.201	-2.891	-0.281
	(0.010)	(2.280)	(0.995)	(0.070)	(0.008)	(0.003)	(1.233)	(0.391)	(0.455)	(0.050)
Adjusted R^2	0.09	0.03	0.02	0.04	0.05	0.02	0.02	0.01	0.03	0.03
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18, as well as a dummy variable equal to one if the observation falls in the last contract year. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.7: Plans' Effects on Prescribed Painkiller Purchases - Hit MDE

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any	Spending in $	Annual Days of Supply	Number of Rx Purchased	Share with Any	Share with Any High-Dose	Spending in $	Annual Days of Supply	MME per Day	Number of Rx Purchased
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Const. (Free Care)	0.261	23.460	8.526	0.880	0.849	0.184	0.036	10.637	2.588	7.971
	(0.008)	(2.052)	(0.810)	(0.064)	(0.063)	(0.007)	(0.003)	(1.125)	(0.303)	(0.366)
25% Coinsurance	-0.073	-11.715	-4.416	-0.433	-0.467	-0.057	-0.019	-6.494	-1.636	-2.962
	(0.012)	(2.192)	(0.946)	(0.067)	(0.081)	(0.009)	(0.004)	(1.082)	(0.292)	(0.483)
Mixed Coinsurance	-0.083	-13.376	-5.201	-0.479	-0.405	-0.066	-0.018	-6.488	-1.582	-3.120
	(0.013)	(2.085)	(0.843)	(0.066)	(0.085)	(0.011)	(0.004)	(1.109)	(0.304)	(0.549)
50% Coinsurance	-0.117	-14.726	-5.859	-0.527	-0.580	-0.087	-0.027	-6.780	-1.725	-4.012
	(0.013)	(2.236)	(0.916)	(0.076)	(0.086)	(0.010)	(0.004)	(1.201)	(0.368)	(0.626)
Ind. Deductible	-0.166	-17.279	-6.315	-0.651	-0.435	-0.124	-0.027	-7.912	-1.861	-5.367
	(0.008)	(1.813)	(0.741)	(0.059)	(0.070)	(0.007)	(0.003)	(1.036)	(0.283)	(0.359)
95% Coinsurance	-0.151	-15.900	-5.884	-0.613	-0.531	-0.114	-0.026	-8.041	-1.885	-4.962
	(0.009)	(2.429)	(0.934)	(0.069)	(0.082)	(0.007)	(0.003)	(1.197)	(0.330)	(0.411)
Adjusted R^2	0.11	0.03	0.03	0.05	0.04	0.07	0.02	0.02	0.02	0.05
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18, as well as interaction terms between a dummy equal to one if the family reaches the MDE in a given year and the health insurance plan indicators. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.6.8: Plans' Effects on Prescribed Painkiller Purchases - Participation Incentive

	Painkiller Purchase				Opioid Painkiller Purchase					
	Share with Any (1)	Spending in $ (2)	Annual Days of Supply (3)	Number of Rx Purchased (4)	Share with Any (5)	Share with Any High-Dose (6)	Spending in $ (7)	Annual Days of Supply (8)	MME per Day (9)	Number of Rx Purchased (10)
Const. (Free Care)	0.255	22.288	8.240	0.849	0.180	0.035	10.239	2.483	7.829	0.503
	(0.008)	(1.970)	(0.826)	(0.063)	(0.007)	(0.003)	(1.091)	(0.292)	(0.374)	(0.046)
25% Coinsurance	-0.082	-14.088	-4.846	-0.467	-0.059	-0.021	-7.063	-1.781	-3.031	-0.311
	(0.013)	(2.844)	(1.114)	(0.081)	(0.011)	(0.004)	(1.475)	(0.443)	(0.536)	(0.057)
Mixed Coinsurance	-0.071	-10.534	-3.959	-0.405	-0.054	-0.012	-4.429	-0.928	-2.427	-0.266
	(0.015)	(3.117)	(1.077)	(0.085)	(0.012)	(0.005)	(1.803)	(0.514)	(0.614)	(0.059)
50% Coinsurance	-0.114	-17.823	-6.546	-0.580	-0.077	-0.029	-7.411	-1.880	-3.510	-0.331
	(0.014)	(2.898)	(1.078)	(0.086)	(0.012)	(0.004)	(1.535)	(0.475)	(0.634)	(0.062)
Ind. Deductible	-0.086	-10.890	-3.714	-0.435	-0.062	-0.016	-4.936	-1.098	-2.561	-0.274
	(0.010)	(2.528)	(0.953)	(0.070)	(0.009)	(0.004)	(1.559)	(0.451)	(0.450)	(0.052)
95% Coinsurance	-0.119	-15.304	-5.106	-0.531	-0.081	-0.020	-6.917	-1.514	-3.322	-0.330
	(0.012)	(2.879)	(1.026)	(0.082)	(0.010)	(0.004)	(1.506)	(0.451)	(0.507)	(0.059)
Adjusted R^2	0.09	0.03	0.02	0.04	0.05	0.02	0.02	0.01	0.03	0.03
# Families	3100	3100	3100	3100	3100	3100	3100	3100	3100	3100
# Individuals	5922	5922	5922	5922	5922	5922	5922	5922	5922	5922
# Individual-Years	20004	20004	20004	20004	20004	20004	20004	20004	20004	20004

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of prescribed painkillers, (2) annual spending on prescribed painkillers, (3) annual days of supply of prescribed painkillers, (4) annual number of painkiller prescriptions purchased, (5) a dummy variable for annual purchase of prescribed opioid painkillers, (6) a dummy variable for annual purchase of high-dose prescribed opioid painkillers, (7) annual spending on prescribed opioid painkillers, (8) annual days of supply of prescribed opioid painkillers, (9) MME per day for prescribed opioid painkillers, and (10) annual number of opioid prescriptions purchased. Because assignment to plans was random only conditional on site and start month (Newhouse et al., 1993), all regressions include site-by-start-month dummy variables, as well as calendar year fixed-effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18, and a continuous variable capturing the participation incentive paid to families by the RAND HIE. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

OA.7 Mechanisms - Robustness Checks and Analysis by Provider Type

Table OA.7.1: Prescribing Behavior - Heckman Selection Model

	Share with Any Opioid Painkiller Prescription	
	Baseline (1)	Pain and Health Dummies (2)
A. Main Estimates		
Constant (Free Care Plan)	0.241	0.244
	(0.008)	(0.008)
25% Coinsurance	-0.030	-0.028
	(0.011)	(0.011)
Mixed Coinsurance	-0.034	-0.032
	(0.013)	(0.013)
50% Coinsurance	-0.058	-0.056
	(0.012)	(0.012)
Ind. Deductible	-0.037	-0.033
	(0.010)	(0.010)
95% Coinsurance	-0.051	-0.046
	(0.010)	(0.011)
B. First Stage: Provider Visit		
Constant (Free Care Plan)	1.705	1.845
	(0.293)	(0.293)
25% Coinsurance	-0.435	-0.438
	(0.072)	(0.071)
Mixed Coinsurance	-0.457	-0.465
	(0.078)	(0.078)
50% Coinsurance	-0.506	-0.509
	(0.093)	(0.094)
Ind. Deductible	-0.704	-0.710
	(0.059)	(0.058)
95% Coinsurance	-0.821	-0.833
	(0.065)	(0.065)
PCP per Capita	0.070	0.068
	(0.006)	(0.005)
Av. Days to App.	0.048	0.046
	(0.004)	(0.004)
Av. Fee GPs	-0.275	-0.277
	(0.031)	(0.031)
Health & Pain FE	No	Yes
# Families	3100	3100
# Individuals	5922	5922
# Individual-Years	20004	20004

Notes: The reported coefficients are from the two-stage estimator proposed by Heckman (1979). The first panel reports our main results, indicating the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The main outcome is a dummy variable for having an opioid painkiller prescription. The second panel reports results from the first stage, where the dependent variable is a dummy variable for having at least one healthcare provider visit in a given year. We employ three measures as exclusion restrictions in the first stage to instrument for the decision to visit a healthcare provider: (1) number of primary care physicians (PCP) per 100,000 population by experimental site in 1972 (Newhouse et al. (1993), Table 2.1, column 4), (2) average number of days spent waiting for an appointment with a PCP for a new patient by experimental site (Newhouse et al. (1993), Table 2.1, column 5), and (3) average fee for initial office visit to a General Practice physician in 1975 by geographic division (U.S. Department of Health, Education, and Welfare (1978), Table 182, column 2). All regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. The regression in column (2) add dummies for self-reported pain and health at the baseline survey both in the first and second stage. The excluded category for pain variables is “A great deal of pain” and the excluded category for health variables is “Poor health”. Site by start month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the “average” site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.7.2: Outpatient Provider Visits, Prescribing Behavior, and Filled Prescriptions (Medical Only)

	Outpatient Provider Visits			Share with Any Opioid Painkiller Rx		Share of Filled Opioid Prescriptions		
	Share with Any	Spending in $	Number of Provider Visits	Baseline	Pain and Health Dummies	Baseline	Pain and Health Dummies	Pain and Health Dummies, + Prescriber FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. (Free Care Plan)	0.819	878.709	7.009	0.199	0.193	0.817	0.818	0.814
	(0.009)	(33.800)	(0.244)	(0.008)	(0.008)	(0.017)	(0.017)	(0.025)
25% Coinsurance	-0.099	-201.300	-1.826	-0.029	-0.029	-0.097	-0.093	-0.072
	(0.017)	(52.311)	(0.414)	(0.011)	(0.011)	(0.034)	(0.034)	(0.066)
Mixed Coinsurance	-0.082	-137.706	-1.678	-0.028	-0.029	-0.042	-0.047	-0.030
	(0.019)	(59.892)	(0.405)	(0.013)	(0.013)	(0.031)	(0.031)	(0.054)
50% Coinsurance	-0.122	-286.302	-2.458	-0.060	-0.056	0.019	0.022	-0.066
	(0.021)	(51.112)	(0.356)	(0.012)	(0.012)	(0.038)	(0.038)	(0.067)
Ind. Deductible	-0.143	-196.160	-2.059	-0.032	-0.033	-0.088	-0.094	-0.073
	(0.014)	(42.643)	(0.316)	(0.010)	(0.010)	(0.028)	(0.027)	(0.042)
95% Coinsurance	-0.208	-308.859	-2.786	-0.039	-0.040	-0.036	-0.038	-0.016
	(0.017)	(40.866)	(0.314)	(0.011)	(0.010)	(0.028)	(0.028)	(0.044)
Some Pain					-0.082		-0.060	-0.020
					(0.027)		(0.027)	(0.040)
A Little Pain					-0.125		-0.081	-0.049
					(0.026)		(0.027)	(0.042)
No Pain at All					-0.142		-0.106	-0.081
					(0.026)		(0.030)	(0.050)
Fair Health					-0.030		0.025	-0.044
					(0.042)		(0.033)	(0.056)
Good Health					-0.062		0.025	-0.008
					(0.041)		(0.031)	(0.058)
Excellent Health					-0.085		0.029	-0.006
					(0.042)		(0.036)	(0.070)
Adjusted R^2	0.08	0.05	0.05	0.05	0.07	0.06	0.07	0.35
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2856	2856	1133	1133	1133
# Individuals	5922	5922	5922	5379	5379	1319	1319	1319
# Individual-Years	20004	20004	20004	14973	14973	1894	1894	1894

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: a dummy variable for any visit (column 1), annual spending on visits (column 2), number of visits (column 3), a dummy variable for any opioid painkiller prescription (columns 4 and 5), and the share of filled opioid prescriptions (columns 6 to 8). All regressions exclude opioid painkillers prescribed by dentists. Regressions in columns (4) and (5) are conducted on a subsample of individuals who visited a non-dentist provider in a given year. Regressions in columns (6) to (8) are conducted on a subsample of individuals who visited a non-dentist provider in a given year and obtained an opioid prescription. All regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. Regressions in columns (5), (7), and (8) add dummies for self-reported pain and health at the baseline survey. The excluded category for pain variables is "A great deal of pain" and the excluded category for health variables is "Poor health." Column (8) further adds prescriber fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month, year, pain, and health dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" variables mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.7.3: Outpatient Provider Visits, Prescribing Behavior, and Filled Prescriptions (Dental Only)

	Outpatient Provider Visits			Share with Any Opioid Painkiller Rx		Share of Filled Opioid Prescriptions		
	Share with Any	Spending in $	Number of Provider Visits	Baseline	Pain and Health Dummies	Baseline	Pain and Health Dummies	Pain and Health Dummies, + Prescriber FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. (Free Care Plan)	0.652	923.550	2.425	0.101	0.100	0.864	0.868	0.860
	(0.012)	(37.686)	(0.061)	(0.006)	(0.006)	(0.022)	(0.022)	(0.038)
25% Coinsurance	-0.124	-256.436	-0.527	-0.001	-0.000	-0.109	-0.114	-0.135
	(0.024)	(46.268)	(0.096)	(0.009)	(0.009)	(0.041)	(0.040)	(0.084)
Mixed Coinsurance	-0.135	-275.164	-0.609	-0.005	-0.005	-0.123	-0.140	-0.144
	(0.023)	(53.453)	(0.109)	(0.010)	(0.010)	(0.055)	(0.055)	(0.084)
50% Coinsurance	-0.150	-303.910	-0.688	-0.002	-0.001	-0.145	-0.159	-0.195
	(0.029)	(75.946)	(0.124)	(0.010)	(0.010)	(0.061)	(0.059)	(0.107)
Ind. Deductible	-0.182	-280.668	-0.706	-0.007	-0.007	-0.075	-0.078	-0.098
	(0.018)	(41.627)	(0.084)	(0.008)	(0.008)	(0.040)	(0.039)	(0.069)
95% Coinsurance	-0.189	-355.945	-0.815	-0.019	-0.018	-0.125	-0.133	-0.128
	(0.020)	(38.877)	(0.082)	(0.008)	(0.007)	(0.041)	(0.041)	(0.083)
Some Pain					-0.035		-0.018	0.008
					(0.024)		(0.056)	(0.095)
A Little Pain					-0.047		-0.150	-0.099
					(0.022)		(0.054)	(0.090)
No Pain at All					-0.038		-0.136	-0.088
					(0.022)		(0.057)	(0.094)
Fair Health					-0.056		-0.131	-0.049
					(0.043)		(0.094)	(0.172)
Good Health					-0.053		-0.024	0.058
					(0.042)		(0.087)	(0.159)
Excellent Health					-0.060		-0.009	0.110
					(0.042)		(0.088)	(0.159)
Adjusted R^2	0.08	0.03	0.06	0.03	0.04	0.14	0.15	0.06
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2410	2410	630	630	630
# Individuals	5922	5922	5922	4372	4372	704	704	704
# Individual-Years	20004	20004	20004	11092	11092	800	800	800

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). The outcomes are: a dummy variable for any visit (column 1), annual spending on visits (column 2), number of visits (column 3), a dummy variable for any opioid painkiller prescription (columns 4 and 5), and the share of filled opioid prescriptions (columns 6 to 8). All regressions exclude opioid painkillers prescribed by non-dentists. Regressions in columns (4) and (5) are conducted on a subsample of individuals who visited a dentist in a given year. Regressions in columns (6) to (8) are conducted on a subsample of individuals who visited a dentist in a given year and obtained an opioid prescription. All regressions include site-by-start-month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. Regressions in columns (5), (7), and (8) add dummies for self-reported pain and health at the baseline survey. The excluded category for pain variables is "A great deal of pain" and the excluded category for health variables is "Poor health." Column (8) further adds prescriber fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site-by-start-month, year, pain, and health dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" variables mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table OA.7.4: Prescribing Behavior and Filled Prescriptions - Robustness Check

	Share with Any Opioid Painkiller Prescription		Share of Filled Opioid Prescriptions		
	Baseline	Pain and Health Dummies	Baseline	Pain and Health Dummies	Pain and Health Dummies, + Prescriber FE
	(1)	(2)	(3)	(4)	(5)
Const. (Free Care Plan)	0.195	0.189	0.753	0.752	0.757
	(0.007)	(0.007)	(0.018)	(0.018)	(0.028)
25% Coinsurance	-0.027	-0.027	-0.109	-0.103	-0.076
	(0.011)	(0.010)	(0.033)	(0.033)	(0.060)
Mixed Coinsurance	-0.028	-0.029	-0.067	-0.072	-0.083
	(0.012)	(0.013)	(0.037)	(0.037)	(0.061)
50% Coinsurance	-0.055	-0.052	-0.071	-0.067	-0.177
	(0.012)	(0.011)	(0.043)	(0.043)	(0.067)
Ind. Deductible	-0.025	-0.026	-0.093	-0.098	-0.077
	(0.010)	(0.009)	(0.029)	(0.029)	(0.046)
95% Coinsurance	-0.041	-0.041	-0.063	-0.064	-0.081
	(0.010)	(0.010)	(0.032)	(0.031)	(0.055)
Some Pain		-0.099		-0.078	-0.037
		(0.026)		(0.034)	(0.052)
A Little Pain		-0.132		-0.121	-0.080
		(0.025)		(0.031)	(0.056)
No Pain at All		-0.147		-0.137	-0.075
		(0.025)		(0.035)	(0.060)
Fair Health		-0.039		0.021	-0.040
		(0.040)		(0.046)	(0.074)
Good Health		-0.058		0.041	0.035
		(0.039)		(0.045)	(0.071)
Excellent Health		-0.079		0.042	0.031
		(0.039)		(0.048)	(0.081)
Adjusted R^2	0.05	0.07	0.04	0.05	0.32
Prescriber FE	No	No	No	No	Yes
# Families	2936	2936	1233	1233	1233
# Individuals	5575	5575	1478	1478	1478
# Individual-Years	16809	16809	2128	2128	2128

Notes: The reported coefficients are from ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the column relative to the free-care plan (whose mean is given by the constant term). All regressions exclude purchases that do not match with any recorded prescription by patient and provider IDs. The outcomes are: a dummy variable for any opioid painkiller prescription (columns 1 and 2), and the share of filled opioid prescriptions (columns 3 to 5). Regressions in columns (1) and (2) are conducted on a subsample of individuals who visited a healthcare provider on a given year. Regressions in columns (3) to (5) are conducted on a subsample of individuals who visited a provider on a given year and obtained an opioid prescription. All regressions include site by start month dummy variables, as well as year fixed effects. Regressions also include a dummy variable for women and a dummy variable for individuals under the age of 18. Regressions in columns (5), (7) and (8) add dummies for self-reported pain and health at the baseline survey. The excluded category for pain variables is "A great deal of pain" and the excluded category for health variables is "Poor health". Column (8) further adds prescriber fixed effects. All spending variables are inflation-adjusted to 2019 dollars (adjusted using the CPI-U). Site by start month and year dummy variables are de-meaned so that the coefficients reflect estimates for adult males at the "average" site-month-year mix. Standard errors, clustered on family, are reported in parentheses below the coefficients.