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

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Abstract

This article studies the period preceding the current opioid epidemic 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 what we refer to as *Wave Zero*. Additionally, we exploit random assignment to health insurance plans to estimate how opioid use responds to differences in insurance generosity. We find that more generous plans increase use by raising outpatient visits and providers' likelihood of prescribing opioids, without changes in filling rates.

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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-Hispanics since 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 2013, saw a surge in heroin use; and the third is marked by the prevalent 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; Hollingsworth et al., 2017; Pierce and Schott, 2020; Ruhm, 2019), increased production and marketing campaigns for opioids (Alpert et al., 2022; Arteaga and Barone, 2022; Van Zee, 2009), and a change in physicians' prescribing practices (Case and Deaton, 2020; Quinones, 2015). Although the opioid epidemic is a key contributor to the first sustained decline in life expectancy since World War I and the 1918 influenza pandemic (Dyer, 2018), 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. First, we 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 identify as the start of the opioid epidemic. Second, we provide causal estimates of how prescription opioid use responds to differences in patient health insurance generosity, decomposing these effects into patient- and provider-driven channels. Our analyses provide the first account of the period between the post–Civil War culture of "opia-phobia" (Maclean et al., 2020; Macy, 2018) and the technological innovation marked by the introduction of OxyContin in 1996 (Cutler and Glaeser, 2021), offering new insights into how opioid use gradually evolved into abuse and ultimately

gave rise to one of the largest public health crises in U.S. history.

Our empirical work begins with the facts essential to understanding the opioid landscape before 1990. The RAND HIE data, never used before 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. We find that 10.8% of individuals under age 65 had at least one opioid prescription filled in a given year, 3.9% filled two or more, and 55.9% of painkiller prescriptions filled were for opioids. Despite the RAND HIE being conducted before the first wave of the opioid epidemic, opioid use was already prevalent in the 1970s and early 1980s. To put these numbers into perspective, in 1996, 16.2% of the non-elderly U.S. population filled at least one opioid prescription and 6.8% filled two or more.[1]

Given the central role of prescribers in shaping access to opioids at the onset of the crisis, we examine which types of providers were primarily responsible for early opioid prescribing. Studies suggest that opioids were initially prescribed primarily by specialists, and that pharmaceutical marketing campaigns in the 1990s, targeting general practitioners (GPs), played a pivotal role in shifting prescribing patterns (Alpert et al., 2022; Arteaga and Barone, 2022; GAO, 2003; Van Zee, 2009). By the late 2000s, GPs positioned themselves as the primary opioid prescribers (Schnell, 2025). Our findings show that opioids were primarily prescribed by specialists (42%), followed by general practitioners (34%). An overlooked dimension we document is 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 initially prescribed opioids more conservatively than specialists (i.e., fewer days of supply and lower morphine milligram equivalents (MME) per day), leaving room for increased prescribing. The 1996 OxyContin marketing campaign targeted this prescribing gap by promoting opioids for noncancer chronic pain, thereby lowering

[1] Authors' calculations based on the 1996 Medical Expenditure Panel Survey.

prescribing thresholds for GPs (Van Zee, 2009).

We then leverage the 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 (Arteaga and Barone, 2022). We find that 19% of opioid prescriptions were associated with pain-related diagnoses while 9% were cancer-related. These findings suggest that prescribing opioids for chronic non-cancer pain was already common before the epidemic, anticipating trends seen in later decades.

Our second contribution is to provide the first experimental evidence on how prescription opioid use responds to differences in patients' health insurance generosity in a general, non-elderly 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. Individuals with the highest cost-sharing are 6.9%-points (37.5%) less likely to purchase opioid painkillers than those with full insurance. They also 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 per year. These results add 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 et al., 2018; Soni, 2019; Powell et al., 2020) or the 2008 expansion of Oregon's Medicaid program (see, e.g., Baicker et al., 2017).

We then decompose the opioid response to decreased plan generosity into three channels. The first channel is provider access: increased provider contact mechanically increases prescribing opportunities. The second channel reflects providers' role along the *prescribing* margin: whether to write an opioid prescription. 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 (Barnett et al., 2017), who are seen as passively receiving and filling prescriptions, the literature pro-

vides 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 the role of providers.

We find that the causal decline in opioid painkiller use under less generous insurance is partly driven by reduced outpatient utilization (i.e., patient-initiated behavior). Individuals with the highest cost-sharing are 18.7%-points (21.0%) less likely to visit a provider office, spend $551 (40.3%) less on outpatient visits, and have 2.8 (38.9%) fewer visits compared to individuals with full insurance. These results align with the findings of the original RAND investigators, who document that higher cost-sharing reduces outpatient utilization (Manning et al., 1987). More recent evidence from the Oregon Health Insurance Experiment shows that gaining Medicaid coverage increases outpatient care among previously uninsured adults (Finkelstein et al., 2012). Similarly, Card et al. (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 et al. (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]

Far less is known about how *providers* adjust their treatment decisions in response to patients' cost-sharing, especially regarding prescribing behavior. We provide the first causal evidence that opioid prescribing responds to differences in patient cost-sharing. After controlling for patient selection on pain and health, we find that providers are 24.1% less likely to write an opioid prescription as plan generosity decreases from full insurance to a high-deductible plan. Heterogeneity analyses by provider type uncover that this response is entirely driven by prescriptions written by physicians as opposed to by dentists. If clinical need were the sole determinant of prescribing, differences in insurance generosity would

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

be inconsequential. Instead, the gradient observed in our results suggests that physicians respond to patients' out-of-pocket costs.

These findings inform a broader empirical literature showing how physicians consider factors beyond clinical need when making treatment decisions.[3] Of particular relevance are the studies showing that cost considerations causally influence clinical behavior.[4] For example, Carrera et al. (2018) find that physicians recognize patients' responsiveness to cost-sharing and adjust their prescribing patterns in response to broad and significant changes in drug prices. We extend this literature by showing that insurance generosity influences the initial opioid 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 compliance, 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 compliance 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

[3] A growing body of influential work shows that physicians' treatment decisions are 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 et al. (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.

[4] A few descriptive studies document widespread physician awareness of patients' financial burdens and suggest that cost considerations influence clinical decisions. For example, evidence from the nationally representative 2004-2005 Community Tracking Study Physician Survey finds that 78% of physicians reported routinely considering out-of-pocket costs when prescribing medications (Pham et al., 2007).

characteristics. This suggests that, for highly salient conditions such as acute pain, insurance design primarily affects the supply side (i.e., whether a prescription is written) rather than patient demand conditional on having received a prescription. These findings underscore the importance of distinguishing between prescribing and compliance margins, particularly for therapeutic classes where the costs of non-compliance are less immediate or salient.

Beyond the contributions outlined above, our paper offers several additional insights into 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; Case and Deaton, 2020; Cutler and Glaeser, 2021; Powell et al., 2020).[5] While most existing research begins its analysis with the introduction of OxyContin in 1996, most epidemics of this deadly 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 adds to the broader literature on the origins and evolution of health epidemics more generally (see, e.g., Adda, 2016; Anderson, 2018; Beach et al., 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 informs the literature on the role of healthcare supply, and specifically the role of physicians, during the opioid crisis (see, e.g., Barnett et al., 2017; Currie et al., 2023; Eichmeyer and Zhang, 2022, 2023; Schnell and Currie, 2018; Schnell, 2025). A related strand of research explores policies aimed at reducing opioid prescribing, such as the implementation of prescription drug monitoring programs (see, e.g., Alpert et al., 2024; Buchmueller and Carey, 2018; Kim, 2021; Nguyen et al., 2023), changes to national prescribing guidelines (see, e.g., Allen et al., 2024; Sacks et al., 2021; Stein et al., 2022), and increased enforcement of the Controlled Substances Act of 1970 to curtail inappropriate supply (see, e.g., Donahoe, 2024; Kennedy-Hendricks et al., 2016; Meinhofer, 2016; Soliman,

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

2025). We expand this 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 prescribing 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 for prescription drugs (see, e.g., Aron-Dine et al., 2015; Einav et al., 2015; Leibowitz et al., 1985; Newhouse et al., 1993), and addictive substances other than prescribed opioid drugs (see, e.g., Chaloupka and Pacula, 2000; Dave, 2006; Grossman and Chaloupka, 1998; Nisbet and Vakil, 1972; Olmstead et al., 2015; Saffer and Chaloupka, 1999; Van Ours, 1995). Lastly, our paper relates to recent studies underscoring the continued relevance of the RAND HIE to address current policy questions (see, e.g., Aron-Dine et al., 2013; Diaz-Campo, 2023; Hodor, 2021; Lin and Sacks, 2019; 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 unexplored facts regarding the prelude to the U.S. opioid crisis. Section 5 examines the response of prescribed painkiller consumption to differences 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 differences 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 to 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 reg-

ulate 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.[6]

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 undertreatment of pain surged, partly influenced by the introduction of the gate control theory of pain (Melzack and Wall, 1965) and the McGill Pain Questionnaire (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.

[6]One decade later, during the 1980s and early 1990s, the United States experienced a surge in crack cocaine use (a non-opioid stimulant drug), which also led to increased crime, violence, and a spike in incarceration rates (Agar, 2003).

3 Data

Our analysis relies on rich itemized claim-level data from the RAND HIE, a large-scale Randomized Controlled Trial (RCT) 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 out-of-pocket (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 files: (1) services rendered in outpatient settings by individual providers, (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 individuals assigned to the prepaid group practice because the method of care delivery is substantially different from the FFS plans. Second, we drop the years in which the individuals do not participate in full and all years thereafter, except for newborns. Third, we drop the year in which individuals move and therefore switch plans, and all years thereafter. After these restrictions,

our sample has 20,004 individual-year observations with 5,922 unique individuals and 3,100 unique families.[7]

Panel A of Table I presents descriptive statistics for the sample used in the analysis, including demographic characteristics and self-reported measures of pain, health, diabetes, and cancer prevalence. 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.[8] At enrollment, most individuals report experiencing no or minimal pain (74.6%) and rate their health as good or excellent (80.1%).[9] In addition, 3.2% and 1.9% of individuals reported ever having been diagnosed with diabetes and cancer, respectively.[10]

3.1 Outpatient Visits Claims

We start by combining all line-item claims for services rendered by physicians and dentists.[11] Each line-item record includes provider and patient identifiers, place and date of service, up to three reasons/symptoms for the visit, and up to four diagnosis codes, among other variables. We follow two main steps to obtain observations for outpatient services at the provider-patient-visit level. First, we only keep line-items whose place of service is "doctor's office." Second, we combine line-items sharing the same provider, patient, and service date into one

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

[8] 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.

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

[10] The variable diabetes/pre-diabetes (cancer) is a dummy variable recording whether the participant answered *yes* to the question "Has a doctor ever told you that you had diabetes or pre-diabetes (cancer)?" at enrollment or exit questionnaires. Diabetes/pre-diabetes questions were only asked to Adults (13+). Cancer questions were only asked to non-Dayton participants at enrollment and all participants at exit. We assign a value of zero to missing responses. These measures are used in our analysis of diagnosis codes in Section 4.

[11] These data correspond to the RAND HIE data files 06 and 12, respectively.

unique observation, regardless of claim number. After these steps, we are left with 110,503 outpatient visits to individual providers: 67.7% for physicians and 32.3% for dentists.

Panel B of Table I presents descriptive statistics on outpatient office visits to healthcare providers. These visits are frequent, with more than 80% of individual-year observations including at least one. Physician visits are more prevalent than dental visits (71.1% vs. 55.3%). These measures are used in our discussion of the mechanisms underlying responses to changes in healthcare coverage in Section 7.

3.2 Prescription Files

The RAND HIE collected detailed records on drugs prescribed by physicians and dentists.[12] Each line-item record indicates that a particular drug was prescribed but does not capture whether the prescription was ultimately filled. There was no charge associated with the prescribing: prescriptions are considered as part of the physician's charge for the visit, which are found in the line-item records for provider visits described in Section 3.1. A prescription record contains prescriber and patient identifiers, the prescribed drug identified by its National Drug Code (NDC), up to five generic drug codes, and the drug therapeutic code.

We use these data in our discussion of the mechanisms underlying responses to differences in insurance generosity in Section 7. Two limitations of these data are important for the analysis. First, the records do not report the exact date of prescribing, which prevents precise matching of prescriptions to specific provider visits. Thus, our analysis of prescriptions will be done by aggregating at the individual-year level. Second, the records may not represent the universe of all prescriptions, as they primarily reflect medications prescribed in outpatient settings. We revisit this limitation in Section 7 and conduct robustness checks excluding individual-year observations with no prescription that can be matched to a purchase.

[12] These data correspond to the RAND HIE data files 04 and 13, respectively, which contain drugs prescribed or suggested by providers. Because the analysis focuses on prescription-only medications, drugs that were merely suggested are disregarded.

3.3 Pharmacy Claims

The line-item records related to drugs purchased provide comprehensive information on medication characteristics, including the 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 DEA.[13]

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.[14] Second, we exclude painkillers available over the counter (OTC).[15] Third, we only keep painkillers in tablet or capsule form.[16] Our cleaned pharmacy claims dataset contains 9,214 records of painkillers sold by prescription only: 5,149 opioids and 4,065 non-opioids.[17]

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

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

[14] 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.

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

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

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

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.

4 *Wave Zero*: The Prelude to the Modern Opioid Crisis

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 use at the individual-year level. 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 injuries that led to prescribed opioid use. When relevant, we include comparable measures for non-opioid prescribed painkillers to highlight similarities and differences in prescribing patterns.

4.1 Use of Prescribed Painkillers

Panel C of Table I 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 observations contain at least one opioid painkiller purchase against 7.8% for non-opioids.[18] Additionally, 3.9% of individual-year observations include two or more opioid painkiller purchases, 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 is 2.4, with an average annual supply of 12.4 days, an average MME per day per script of 51.1, and an average share of high-dose prescriptions of 18.9%.

Our results provide the first evidence that opioid consumption was already prevalent in the 1970s and early 1980s, two decades before the introduction of OxyContin 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.[19] Among opioid users, the average number of prescriptions was 2.5.[20] As expected, usage was lower in the 1974-1982 RAND HIE 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 steadily in

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

[19] See Figure OA.2.1 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.

[20] See Figure OA.2.3 for the evolution of the 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).

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 increased to 3.8.[21]

The next step in our analysis is to document relevant patterns in prescribed opioid and non-opioid painkiller use across different demographic and geographic groups. Prescribed opioid painkiller use is 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 Ia) and are more likely to fill multiple opioid prescriptions (5.0% versus 3.0%; Figure Ib). Conditional on at least one purchase within the year, women have a higher annual number of opioid prescriptions filled than men, averaging 2.6 versus 2.0 (Figure Ic), receive more days of supply (14.2 versus 9.8; Figure Id), and have higher average MME per day (52.5 versus 49.0; Figure Ie), which translates to 22% of women (with nonzero opioid purchases) filling at least one high-dose opioid prescription per year (versus 15% for men; Figure If).[22] Prescribed non-opioid painkiller use also shows a higher prevalence among women at both margins.

We document a similar gender pattern in opioid utilization in the 1996 MEPS. For example, Figure OA.2.4a shows that women were more likely than men to fill at least one prescription (18.6% versus 13.8%).[23] However, this gender pattern in opioid use is not reflected in opioid-related mortality. Case and Deaton (2020) show that deaths of despair were more prevalent among men at the onset of the epidemic. 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.

[21] Authors' calculations based on the 2010 MEPS.

[22] 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 figures incorporating individual-year observations with zero use.

[23] 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.

We find no differences in prescribed opioid painkiller use between urban and rural areas at the extensive margin (Figures IIa and IIb). This pattern may reflect the combined influence of two opposing effects. Rural areas had fewer prescribers per capita (Coleman, 1976), which mechanically decreases the prescribing opportunities. However, the prevalence of occupations such as mining and agriculture, which are common in rural areas and associated with occupational injuries, may have contributed to similar levels of opioid use.[24] Our finding is consistent with the 1996 MEPS data, which also show similar levels of opioid use in rural and urban areas (Figure OA.2.4b). However, subsequent increases in opioid use were more pronounced in rural regions. At the intensive margin, individuals in rural areas fill more prescriptions and receive more annual days of supply, conditional on filling at least one opioid script (Figures IIc and IId). 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 annual days of supply.[25]

Focusing on race and ethnicity, we find that prescribed opioid painkiller use is higher among white non-Hispanics than among Blacks or Hispanics (Figures IIIa and IIIb). Conditional on filling at least one opioid prescription in a given year, white non-Hispanics also exhibit a higher annual number of opioid purchases (2.5 versus 2.0 and 1.4; Figure IIIc) and more annual days of supply (13.5 versus 8.4 and 4.3; Figure IIId). Similar racial-ethnic disparities emerge for prescribed non-opioid painkillers use.[26]

These findings are consistent with patterns observed in the 1996 MEPS. Figure OA.2.4c 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

[24]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). For studies documenting that the probability of experiencing pain is higher in rural settings, see e.g., Mansfield et al. (2016) and Zimmer et al. (2022).

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

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

found that deaths of despair were less prevalent among Blacks and remained relatively stable during the early years of the opioid crisis (up to the mid-2000s), while mortality rates among white non-Hispanics increased significantly.

These differences in prescribed opioid use between Whites and Blacks 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. A widely controversial textbook offering guidance on when to administer pain relief to people from different ethnic backgrounds, suggests that Blacks 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 Prescribers of Painkillers

We now use pharmacy claim-level data to examine prescriber characteristics by training (physicians versus dentists) and specialty.[27]

We categorize prescribers into three mutually exclusive groups: general practitioners, specialists, and dentists. *General practitioners* are Doctors of Medicine (MDs) or Doctors of Osteopathy (DOs) whose specialty is family or general practice. *Specialists* are MDs or DOs with any other medical specialty (e.g., oncologists). The third group consists of *dentists*, who are identified separately from physicians.[28]

Figure IV shows various characteristics of filled painkiller prescriptions, broken down by

[27]The analysis of prescribers relies on line-item records for all purchased painkiller prescriptions. These data differ from those used in Section 4.1, which are aggregated to the individual-year level.

[28]Data concerning Doctors of Medicine, Doctors of Osteopathy, or dentists come from the American Medical Association 1976 and 1981 data tapes, the American Osteopathic Association 1976 data tape, and the American Dental Association 1976 data tape, respectively.

prescriber type and painkiller category.[29] Figure IVa shows that, in the 1970s and early 1980s, opioids were primarily prescribed by specialists (42%), followed by GPs (34%). Dentists emerge as unexpectedly important contributors to opioid prescribing, accounting for roughly 20% of all opioid prescriptions in our data. To our knowledge, we are the first to emphasize the role of dentists in opioid prescribing in the prelude to the opioid epidemic.[30]

The dominant role of specialists in opioid prescribing until the 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 Van Zee (2009). The distribution of prescribers for non-opioid painkillers 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.[31] Specialists prescribed opioids with the highest average days of supply (6.33; Figure IVb) and MME per day (57.24; Figure IVc). Consistent with this, 19% of opioid prescriptions by specialists involved high-dose opioids (Figure IVd). Opioid prescribing patterns among GPs were more conservative relative to 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%). Dentists were the most conservative prescribers, with the shortest average days of supply per prescription (2.48), the lowest average MME per day (40.72), and the smallest share of high-dose opioids (5%). Non-opioid painkiller prescriptions followed the same pattern in terms of average days of

[29] A corresponding figure, Figure OA.2.8, presents the same information when prescribers are classified as MDs, DOs, dentists, and others.

[30] Contemporary evidence suggests adolescent prescribing increases following routine dental procedures (Schroeder et al., 2019).

[31] For Figures IVb, IVc, and IVd, the prescriber category "Other" is excluded from the analysis because it captures prescribing in non-outpatient settings.

supply per prescription.[32]

These findings suggest that both GPs and dentists had scope to substitute away from non-opioid to opioid painkillers and/or increase opioid prescription intensive margins (e.g., days of supply) relative to specialists, a factor central to the OxyContin marketing campaign in 1996, which specifically targeted primary-care providers (Alpert et al., 2022; Van Zee, 2009). 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 be willing to prescribe opioids. We further discuss this in Section 4.4.

4.3 Commonly Prescribed Opioid Drugs

We now document the opioid drugs most commonly prescribed in the 1970s and early 1980s, leveraging the pharmacy data on opioid painkiller purchases described in Section 4.2. Figure V shows that codeine was the most commonly prescribed drug, accounting for more than 52% of all opioid purchases. The second most common was propoxyphene (24%), which was discontinued in 2010 due to heart-related risks (U.S. Food and Drug Administration, 2010).[33] Notably, oxycodone accounted for just 11% of opioid purchases during this period, despite later becoming central to the opioid epidemic (Alpert et al., 2022). Propoxyphene prescriptions also had a higher average days of supply (7.52) and more than twice the average MME per day (105.3) compared to other commonly prescribed opioids. For comparison, oxycodone prescriptions averaged 6.68 days of supply and 45.6 MME per day.

[32]Figure OA.2.9 further decomposes filled painkiller prescription patterns among specialists by their respective specialties.

[33]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.

To study how drug distribution changed from the pre-epidemic period to the peak of the prescription-opioid wave, we compare our figures with analogous data from the 2016 MEPS. Table OA.2.1 shows the distribution of opioid purchases by drug name in the MEPS. As shown in the second column, codeine represents only 0.5% of all opioid prescriptions, while propoxyphene has a zero share due to its 2010 discontinuation. Hydrocodone and oxycodone combined account for more than 70% of all opioid prescriptions. These figures reflect the number of prescriptions filled but do not account for differences in drug potency. The last column of Table OA.2.1 adjusts for potency by weighting prescriptions based on their MME. By this measure, oxycodone alone represents 47.1% of all opioid prescriptions, followed by hydrocodone (21.1%) and morphine (7.9%).[34] A similar concentration pattern existed in the 1970s and early 1980s, though with a different dominant drug. Figure Vf shows the MME-weighted distribution of opioids in the RAND data, where propoxyphene accounted for 59% of all opioid painkiller prescriptions, followed by codeine (22%) and oxycodone (11%).

4.4 Common Reasons and Diagnoses in Outpatient Visits

We now examine the main reported reasons and symptoms associated with physician visits that preceded prescribed painkiller purchases, alongside the diagnosis codes linked to these prescriptions. Unlike diagnosis codes, which healthcare providers assign, reasons and symptoms are typically self-reported by patients. This distinction offers a complementary perspective on the factors contributing to opioid prescriptions.

For each filled prescription, we identify the reasons/diagnoses recorded during any physician visit within the 30 days preceding the prescription.[35] We group these reasons/diagnoses into clinically relevant categories and construct five indicator variables measuring whether

[34] 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.

[35] Figures OA.2.10 and OA.2.11 show that the results are similar when we extend the look-back window to 90 or 180 days.

the visit was related to: (1) arthritis, (2) cancer, (3) diabetes, (4) injury, and (5) pain.[36]

Figure VIa presents the share of opioid painkiller purchases involving at least one of these reasons.[37] Approximately 44% of opioid painkiller prescriptions filled have at least one pain-related reason for the office visits within the 30 days before the prescription, whereas only 9% 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 pattern, though somewhat attenuated, when focusing on diagnosis codes. Figure VIb displays the share of opioid prescriptions filled involving at least one of several specified diagnosis codes. We find that 19% of opioid painkiller prescriptions have at least one pain-related diagnosis code within the prior 30 days, whereas only 9% involved 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 VIc and VId). The main distinction is observed in the arthritis category, which accounts for a share at least four times higher of both reasons and diagnosis codes relative to opioid painkillers.

To place our findings in context, we compare them with those of Sherry et al. (2018), who analyze diagnosis codes associated with ambulatory care visits in which opioids were prescribed between 2006 and 2015 using data from the National Ambulatory Medical Care

[36] We classify a prescribed opioid as related to cancer (or diabetes) if the individual either reported having ever been diagnosed with cancer (or diabetes) in the baseline or exit questionnaires, or if a cancer- (or diabetes-) related diagnosis code appears in any physician visit within the 30-day look-back period.

[37] Multiple reasons may be associated with a single opioid purchase. First, individuals may have multiple office visits within the 30 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 to a single opioid purchase. In this case, the RAND HIE data include up to four reasons/symptoms per line-item claim.

Survey (NAMCS).[38] They report that 71.5% of such visits were associated with pain diagnoses, while only 5.1% were linked to cancer-related pain.[39] 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; Van Zee, 2009). The share of prescriptions linked to cancer diagnoses remained relatively stable both before and during the epidemic.

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

In this section, we examine how prescribed painkiller purchases respond to differences 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 II 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)

[38] Their study differs from ours in sampling design, as it is limited to visits by adults aged 18 years or older in which an opioid was prescribed.

[39] Sherry et al. (2018) classify all diabetes-related codes as pain diagnoses.

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 7.7% in the least generous plan to 14.5% in the free-care 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, the prevalence of outpatient provider visits correlates unequivocally with health insurance generosity. Individuals in the highest cost-sharing plan are 18.2%-points (20.0%) less likely to have an outpatient provider visit in a given year, have 2.7 (38.8%) fewer visits on average, and, as a consequence, spend $551 (48.9%) less in visits relative to individuals in free care. Thanks to our unique data, rows 19 and 11 present unique 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 5.6%-points (30.1%) 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 address this issue directly in Section 7, where we attempt to decompose the response to differences in health insurance generosity into provider- versus patient-driven effects.

5.2 Empirical Strategy and 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 et al. (2013),

hereinafter referred to as AEF, our baseline regression for outcome $Y_{i,t}$ is,

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

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 III 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 III. 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. Analogous results for non-opioid painkillers are discussed in Appendix OA.3. All point estimates show a consistent pattern of fewer opioid and non-opioid purchases, at all margins, in higher cost-sharing plans.[40]

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, and accounting for several distinctive features of the experiment.

Our estimates from Table III rely on random assignment of individuals to health insurance plans from the RAND HIE. One potential concern is that the sample restrictions described

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

in Section 3 may have affected balance. To address this concern, 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.[41] 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.6.1).

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 often correlate 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 IV 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.

In addition, we present results from an alternative specification to 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 the sensitivity of opioid painkiller purchases to health insurance generosity. Results for the six measures of opioid use are displayed in Table V.[42] In all cases, our results

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

[42] In Appendix OA.6 we provide analogous results for all prescribed painkillers (Table OA.6.2) and non-opioid painkillers (Table OA.6.3). In all cases, our results remain robust to the addition of all baseline covariates and adjustment for underreporting.

are robust to the addition of pre-randomization covariates as controls, and consequently, we further validate the credibility of our core findings.

Refusal and attrition were higher on the cost-sharing plans relative to the free-care plan, though they seem to be random with respect to the characteristics of the participants (Newhouse et al., 1993). 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 outcomes using the plan-specific underreporting percentages identified in Rogers and Newhouse (1985).[43] The results are displayed in column 4 of Table V. Once again, our estimates remain largely unchanged and, therefore, we confirm the robustness of our findings to underreporting.[44]

We then consider the robustness of our results to accounting for several distinctive features of the RAND HIE: the participation incentive, the deadline effect, and hitting the MDE within the year. First, 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). Table OA.6.6 shows that the inclusion of this control does not alter our main findings.

Second, we explore whether reaching the MDE affects 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. Table OA.6.7 shows that opioid purchases are more responsive to health insurance generosity among individuals in cost-sharing plans in years that do not reach the MDE, relative to full insurance.

[43] 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.

[44] Appendix OA.6 provides analogous results for the sample that excludes opioids prescribed by dentists (Table OA.6.4) and by non-dentist providers (Table OA.6.5). In all cases, our results remain robust to the addition of all baseline covariates and adjustment for underreporting.

Finally, prior studies suggest that families may alter their behavior during the final months of the experiment, anticipating changes in insurance coverage (Balesh Abadi et al., 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. Table OA.6.8 shows that our findings remain robust to accounting for this *deadline* effect.

7 Mechanisms

In this section, we focus on prescribed opioid painkillers and explore the mechanisms driving the documented responses to differences 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., potential prescribers). 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.

7.1 Does Patient Use of Provider Visits Respond to Cost-Sharing?

We begin by examining the role of additional outpatient 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 office 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 VI.

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 18.7%-points (21.0%) less likely to visit a provider office, spend $551 (40.3%) less on outpatient visits, and have 2.8 (38.9%) 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.

7.2 Does Prescribing Behavior Respond to Patient Cost-Sharing?

We now focus on the providers' *prescribing* response to patient cost-sharing.[45] Physicians play a privileged social role by influencing the medical goods and services used by patients (Arrow, 1963). Most relevant to this paper, physicians act as gatekeepers for prescription drugs. Physicians acting in the best interest of their patients may internalize affordability constraints when making treatment decisions, anticipating that high OOP costs could lead to non-compliance or financial distress (Eisenberg, 1986; McGuire, 2000). This suggests lower prescription rates for patients in cost-sharing plans compared to those in free care. However, any tendency to do so may be offset by the additional visits on the free-care plan for less serious reasons, diminishing the likelihood of receiving a prescription.[46] The net impact of insurance generosity on prescription rates is theoretically ambiguous due to the opposite effects from prescription likelihood and patient selection on pain and health across plans.

Columns 4 and 5 of Table VI provide evidence regarding this second mechanism. For individual-year pairs with at least one outpatient provider visit, we estimate Equation (2)

[45] Prescriptions in the RAND HIE were considered part of the services rendered in a provider visit, so they do not bear separate charges that can trigger physicians' financial incentives (Nelsen et al., 1986).

[46] A theoretical model *à la* Grossman (1972) featuring health capital and provider visits would posit that patients' decisions to visit the provider are a function of their pain and health. As patient cost-sharing increases, the pain and health threshold above which the patient consults the provider also increases. Thus, among individuals who choose to visit the provider, those in the least generous plan should be sicker and suffer more pain relative to those in free care, on average, and a model of physician opioid prescribing behavior *à la* Schnell (2025) would make them more likely to get a prescription.

using as outcome a dummy variable for having an opioid prescription. The estimates in column 4 indicate that the aforementioned net effect is negative. We find a negative correlation between patient cost-sharing and opioid prescriptions. In this sense, the first channel (i.e., providers being less likely to prescribe as generosity declines) seems to dominate, yielding, for example, 5.6%-points (23.4%) 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.[47] As expected, individuals in higher pain are more likely to receive an opioid prescription, conditional on visiting the provider.[48] However, overall health status does not significantly impact the likelihood of receiving an opioid prescription.[49] The estimates suggest that patients on the least-generous plan are 5.6%-points (24.1%) less likely to receive an opioid script, even after controlling for patients' selection on pain and health.[50] Tables OA.7.3 and OA.7.4 present results for prescriptions written exclusively by physicians and dentists, respectively. They reveal that dentists' prescribing behavior does not respond to patient cost-sharing, highlighting that our findings operate primarily through physician prescribing. Taken together, these results offer the first causal evidence linking providers' opioid prescribing behavior to patient insurance generosity, regardless of patient compliance.

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

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

[49]The excluded category for health dummy variables is "Poor Health."

[50]Table OA.7.1 shows 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). Additionally, Table OA.7.2 shows 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.

7.3 Does Filling Behavior Respond to Patient Cost-Sharing?

Lastly, we turn to the *filling* margin. 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.[51] Once again, this higher propensity may be offset by the differential patient selection on pain and health across plans. In addition, some providers may be more prone to write a prescription, other things equal (see, e.g., Barnett et al., 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 VI suggest that the first channel dominates (i.e., individuals being less likely to fill a prescription as generosity declines), in that, for example, patients in the 95 percent 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 pain and health and the provider's prescribing propensity, we add as covariates demeaned dummy variables for self-reported pain and health measured at baseline (column 7) and prescriber fixed effects (column 8).[52] 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.

7.4 Taking Stock: The Role of Patients and Providers

Overall, we find that the price response of opioid purchases is mostly driven by the first two mechanisms: the decision of patients to visit a provider and the decision of providers to prescribe opioids. We find no evidence linking responses to the share of filled prescriptions, once we control for selection based on pain, health, and providers' characteristics. This last result is consistent with the finding related to all (painkiller and non-painkiller) prescription

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

[52] More than one provider fixed effect can be simultaneously turned on for a given individual-year pair.

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 decomposition of mechanisms contributes to the understanding of the origins of the opioid epidemic. Our evidence points to a central role for healthcare providers, consistent with their outsized influence in igniting the epidemic (Alpert et al., 2022). We find that medical providers are highly responsive to differences in patient insurance generosity, a pattern not observed among dentists. While patients contribute by initiating contact with the healthcare system, their role appears largely passive once a prescription is offered, further emphasizing the prescriber's influence in shaping early access to opioids.

8 Discussion and Concluding Remarks

Overdose deaths involving opioids remain the primary driver of the ongoing drug epidemic in the United States, with devastating consequences for communities nationwide. While existing studies have offered valuable insights into the origins of the crisis, most begin their analysis with the introduction of OxyContin in 1996 and provide limited attention to the earlier context. Yet, public health crises of this magnitude rarely emerge overnight.

We exploit the unique timing, research design, and richness 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 main prescribers, with dentists playing a non-negligible role. Although the dominant opioid drugs differed from those in the current epidemic, prescribing was similarly concentrated, with propoxyphene accounting for 59% of opioid prescriptions. Finally, we show that opioids were already 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 (i.e., 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 point 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 differences 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 provides 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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Tables

Table I: 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
24. Diabetes or Pre-Diabetes by Exit	0.032	0.176	5922
25. Cancer by Exit	0.019	0.135	5922
Panel B: Provider Outpatient Office Visits			
26. Share with any office visit	0.818	0.386	20004
27. Share with any office visit to physicians	0.711	0.453	20004
28. Share with any office visit to dentists	0.553	0.497	20004
Panel C: Painkiller Prescriptions Filled			
All Painkillers			
29. Share with any prescription filled	0.155	0.362	20004
30. Share with two or more prescriptions filled	0.073	0.261	20004
31. Number of prescriptions filled | any purchase	2.964	4.849	3109
32. Annual days of supply | any purchase	29.844	71.983	3109
Opioids			
33. Share with any prescription filled	0.108	0.310	20004
34. Share with two or more prescriptions filled	0.039	0.195	20004
35. Number of prescriptions filled | any purchase	2.383	4.449	2161
36. Annual days of supply | any purchase	12.429	36.238	2161
37. MME per day per prescription filled | any purchase	51.091	36.330	2161
38. Share with any high-dose prescription filled | any purchase	0.189	0.391	2161
Non-Opioids			
39. Share with any prescription filled	0.078	0.269	20004
40. Share with two or more prescriptions filled	0.036	0.186	20004
41. Number of prescriptions filled | any purchase	2.591	3.040	1569
42. 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 three panels. Panel A reports demographic characteristics and self-reported measures of pain and health from the baseline questionnaire, as well as the prevalence of some health conditions. Panel B presents measures of outpatient office visits to healthcare providers. Panel C provides measures of prescribed painkiller utilization, distinguishing between opioid and non-opioid painkillers. MME stands for Morphine Milligram Equivalent.

Table II: Summary Statistics - All Painkillers

	(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	0.206	(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	0.908	(0.29)	0.824	(0.38)	0.818	(0.39)	0.819	(0.38)	0.751	(0.43)	0.726	(0.45)
17. Number of visits	7.020	(8.44)	5.132	(6.60)	5.050	(6.83)	4.560	(5.13)	4.942	(7.14)	4.296	(6.12)
18. Annual spending (2019 $1K)	1.126	(2.16)	0.725	(1.54)	0.768	(1.83)	0.588	(1.47)	0.761	(1.81)	0.575	(1.41)
19. Any opioid Rx | any visit	0.186	(0.39)	0.152	(0.36)	0.154	(0.36)	0.124	(0.33)	0.154	(0.36)	0.130	(0.34)
# 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 III: Plans' Effects on Prescribed Painkiller Purchases

	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)	0.262	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 IV: 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 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, 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. Additionally, the number of individuals is smaller than in Table III because newborns during the experiment were incorporated after enrollment. Standard errors, clustered on family, are reported in parentheses below the coefficients.

Table V: 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. (1)	Covs. (2)	Covs. (3)	Adj. (4)	Covs. (5)	Covs. (6)	Covs. (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 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 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. All regressions, except for column 4, include the full set of pre-randomization covariates as controls: all outcome variables in Tables IV and OA.6.1. 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 VI: Outpatient Provider Visits, Prescribing Behavior, and Filled Prescriptions

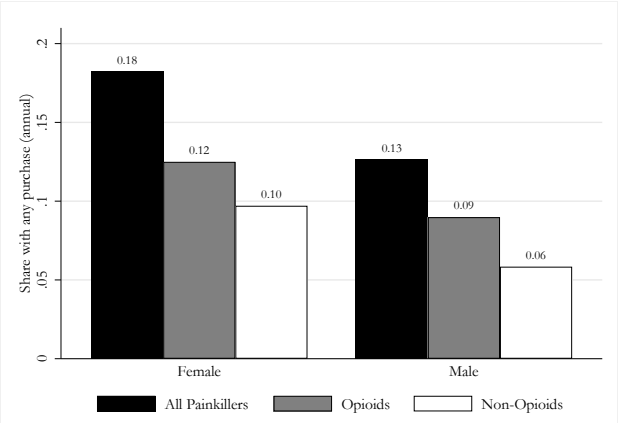
	Outpatient Provider Visits			Share with Any Opioid Painkiller Rx		Share of Filled Opioid Prescriptions		
	Share with Any (1)	Spending in $ (2)	Number of Provider Visits (3)	Baseline (4)	Pain and Health Dummies (5)	Baseline (6)	Pain and Health Dummies (7)	Pain and Health Dummies, + Prescriber FE (8)
Const. (Free Care Plan)	0.890	1364.875	7.205	0.239	0.232	0.831	0.832	0.817
	(0.008)	(41.947)	(0.192)	(0.008)	(0.008)	(0.014)	(0.014)	(0.023)
25% Coinsurance	-0.090	-380.858	-1.981	-0.032	-0.032	-0.091	-0.089	-0.060
	(0.016)	(53.778)	(0.303)	(0.011)	(0.011)	(0.027)	(0.027)	(0.051)
Mixed Coinsurance	-0.080	-372.291	-1.840	-0.037	-0.039	-0.069	-0.076	-0.059
	(0.018)	(64.404)	(0.326)	(0.014)	(0.014)	(0.030)	(0.030)	(0.048)
50% Coinsurance	-0.106	-458.602	-2.453	-0.061	-0.058	-0.032	-0.030	-0.091
	(0.021)	(81.499)	(0.304)	(0.013)	(0.013)	(0.033)	(0.033)	(0.061)
Ind. Deductible	-0.151	-398.107	-2.106	-0.038	-0.038	-0.084	-0.089	-0.064
	(0.014)	(49.962)	(0.273)	(0.010)	(0.010)	(0.024)	(0.024)	(0.041)
95% Coinsurance	-0.187	-550.626	-2.805	-0.056	-0.056	-0.064	-0.066	-0.065
	(0.017)	(45.846)	(0.261)	(0.011)	(0.010)	(0.026)	(0.025)	(0.044)
Some Pain					-0.109		-0.046	-0.000
					(0.027)		(0.025)	(0.044)
A Little Pain					-0.152		-0.088	-0.053
					(0.025)		(0.024)	(0.046)
No Pain at All					-0.166		-0.107	-0.077
					(0.026)		(0.027)	(0.049)
Fair Health					-0.036		0.007	-0.022
					(0.042)		(0.034)	(0.066)
Good Health					-0.055		0.023	0.034
					(0.041)		(0.033)	(0.062)
Excellent Health					-0.077		0.033	0.047
					(0.041)		(0.036)	(0.071)
Adjusted R^2	0.10	0.06	0.08	0.06	0.08	0.03	0.04	0.24
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2890	2890	1398	1398	1398
# Individuals	5922	5922	5922	5496	5496	1714	1714	1714
# Individual-Years	20004	20004	20004	16369	16369	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: (1) a dummy variable for any outpatient visit to an individual provider, (2) annual spending on visits, (3) number of visits, (4-5) a dummy variable for any opioid painkiller prescription, and (6-8) the share of filled opioid prescriptions. 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.

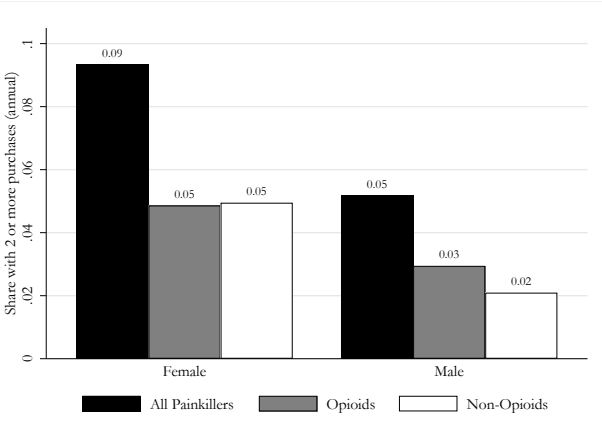
Figures

Figure I: Prescribed Painkiller Utilization by Gender - RAND HIE (1974-1982)

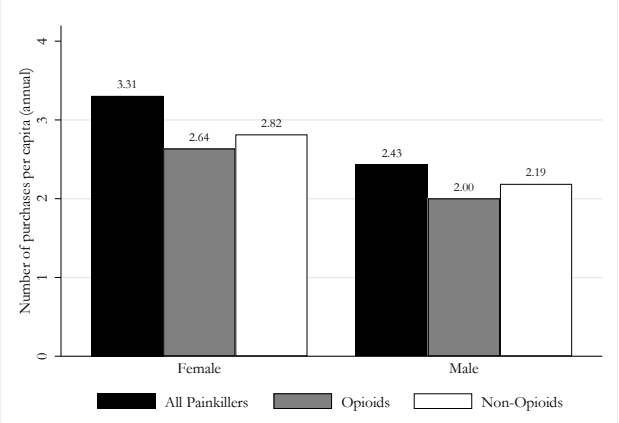
(a) Share with Any Prescription Filled



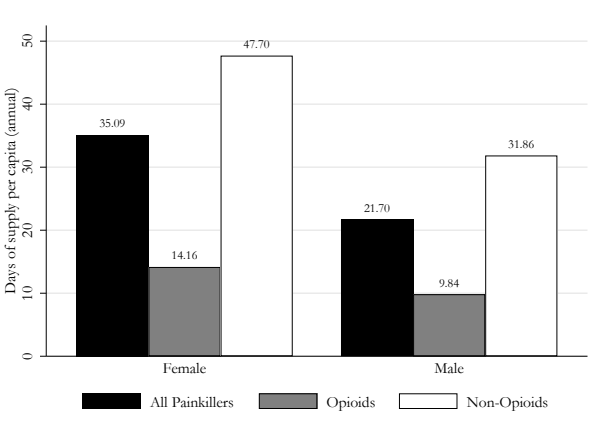
(b) Share with Two or More Prescriptions Filled



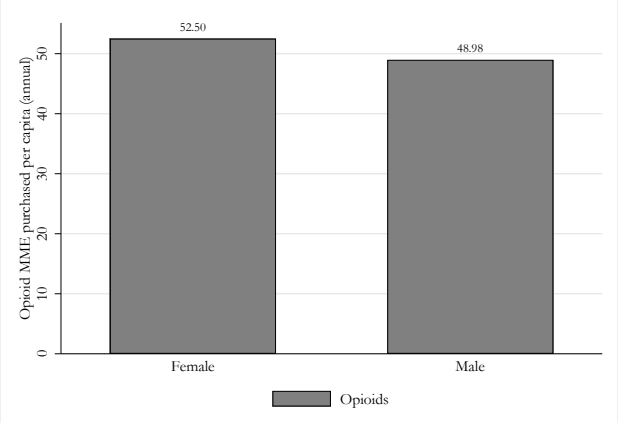
(c) Average Number of Prescriptions Filled



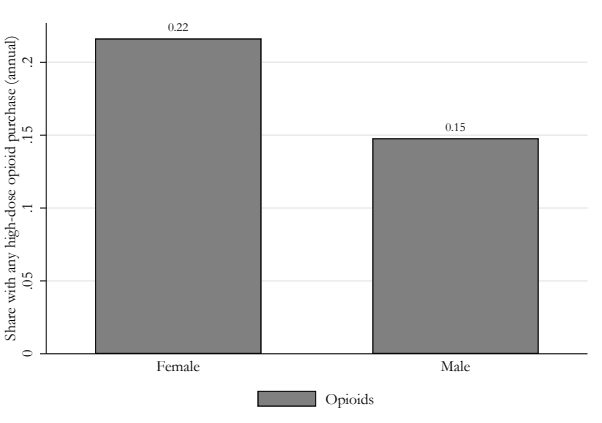
(d) Average Annual Days of Supply



(e) Average MME Per Day Per Prescription



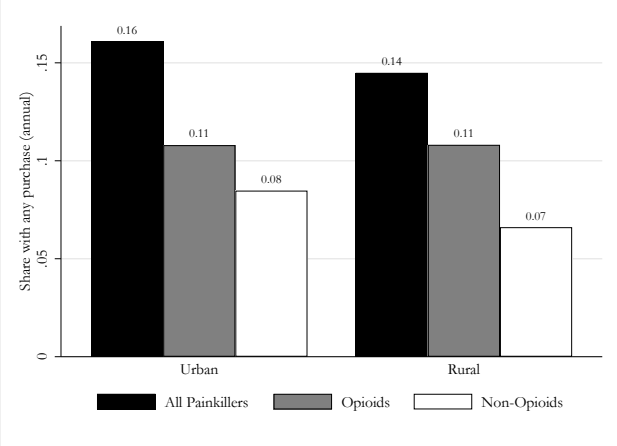
(f) Share with Any High-Dose Opioid



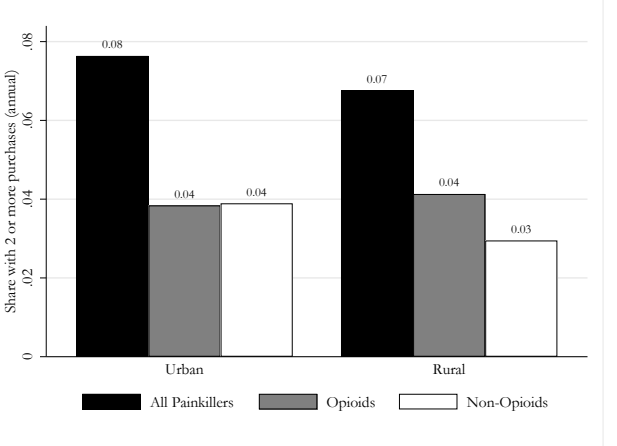
Notes: These figures depict several measures of prescribed painkiller utilization by gender and painkiller type (opioid and non-opioid). Figures Ia and Ib use all individual-year pairs in our RAND HIE analysis sample. Figures Ic, Id, Ie, and If are restricted to individual-year pairs with at least one painkiller prescription filled. Specifically, bars focusing on opioid (non-opioid) painkillers include only individual-year observations with at least one opioid (non-opioid) prescription filled.

Figure II: Opioid Utilization by Location - RAND HIE (1974-1982)

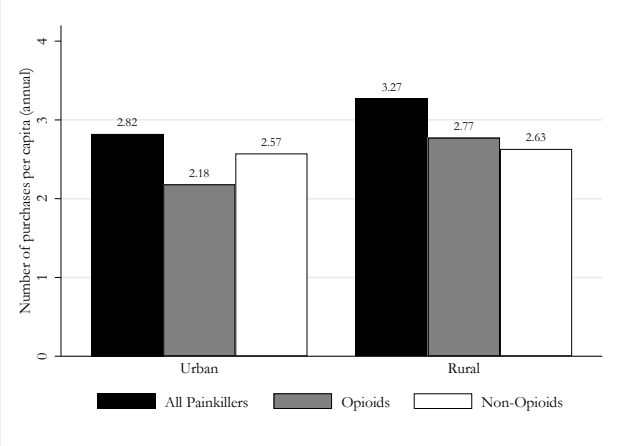
(a) Share with Any Prescription Filled



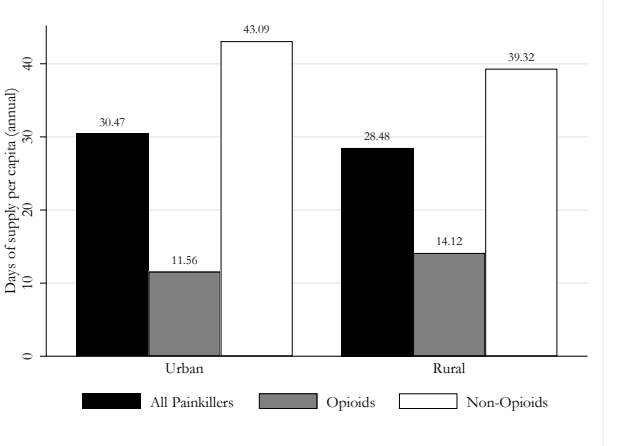
(b) Share with Two or More Prescriptions Filled



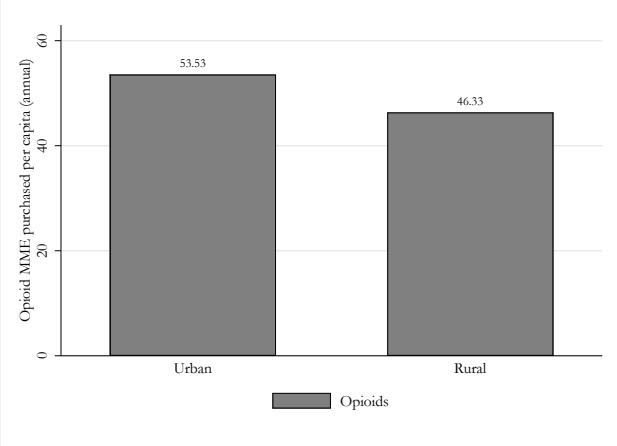
(c) Average Number of Prescriptions Filled



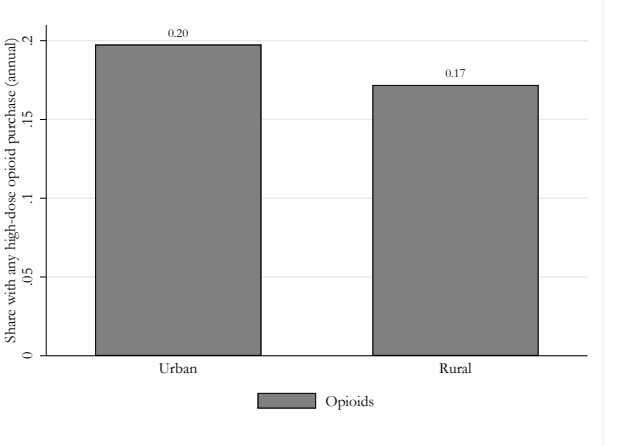
(d) Average Annual Days of Supply



(e) Average MME Per Day Per Prescription



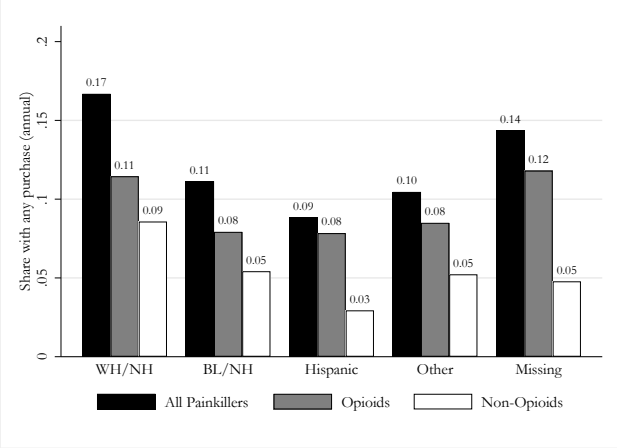
(f) Share with Any High-Dose Opioid



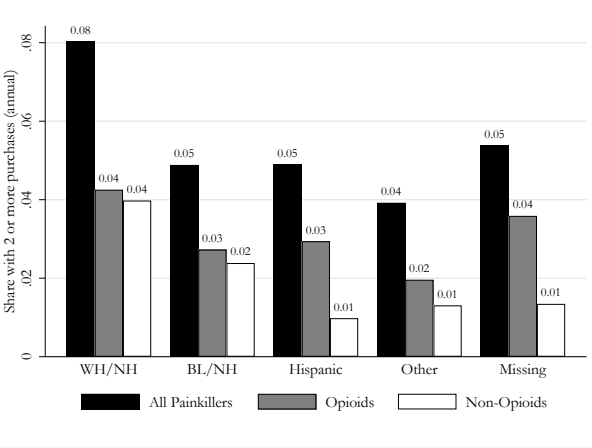
Notes: These figures depict several measures of prescribed painkiller utilization by location (urban, rural) and painkiller type (opioid and non-opioid). Figures IIa and IIb use all individual-year pairs in our RAND HIE analysis sample. Figures IIc, IId, IIe, and IIf are restricted to individual-year pairs with at least one painkiller prescription filled. Specifically, bars focusing on opioid (non-opioid) painkillers include only individual-year observations with at least one opioid (non-opioid) prescription filled.

Figure III: Opioid Utilization by Ethnicity - RAND HIE (1974-1982)

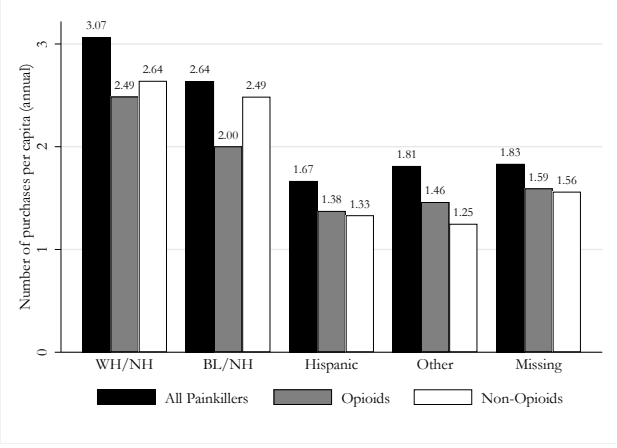
(a) Share with Any Prescription Filled



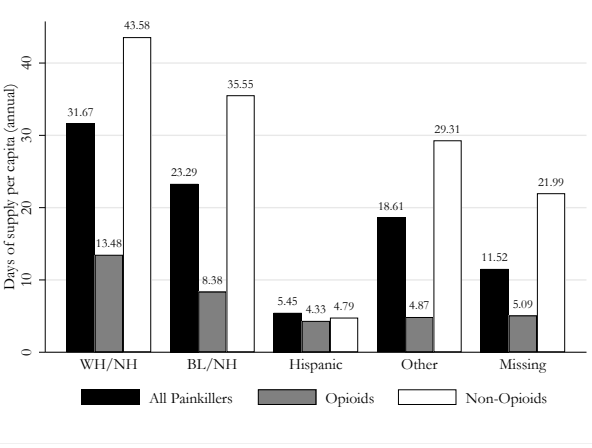
(b) Share with Two or More Prescriptions Filled



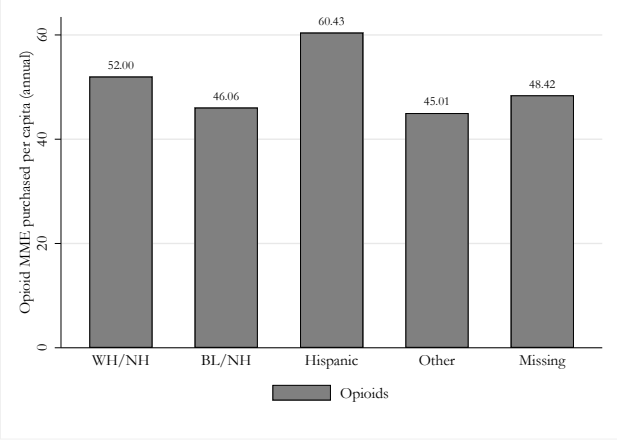
(c) Average Number of Prescriptions Filled



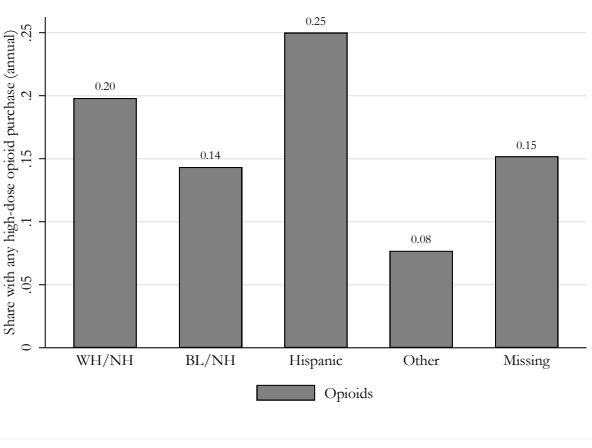
(d) Average Annual Days of Supply



(e) Average MME Per Day Per Prescription



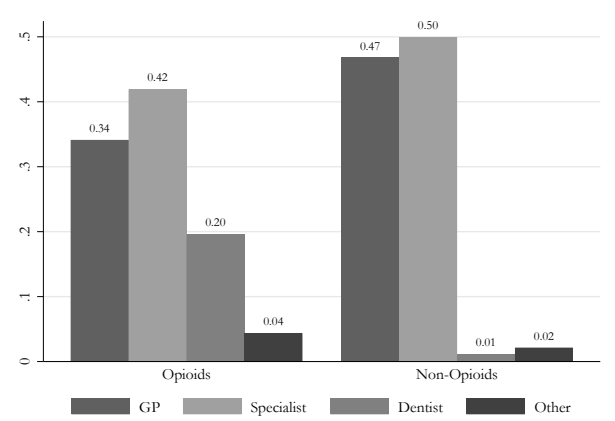
(f) Share with Any High-Dose Opioid



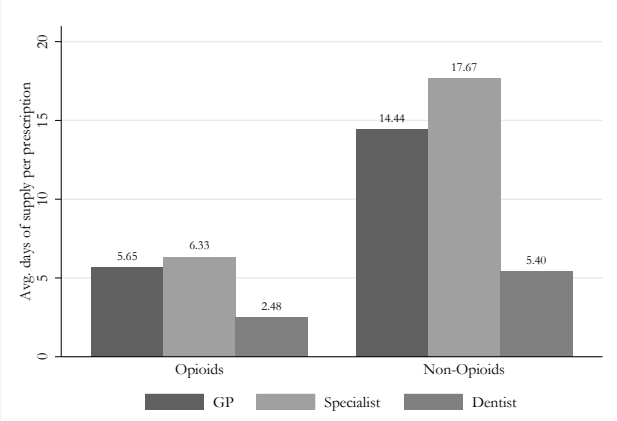
Notes: These figures show measures of prescribed painkiller use by ethnicity (White non-Hispanic (WH/NH), Black non-Hispanic (BL/NH), Hispanic, other, missing) and by painkiller type (opioid and non-opioid). Figures IIIa and IIIb use all individual-year pairs in the RAND HIE sample. The remaining figures are restricted to individual-year pairs with at least one painkiller prescription filled, either opioid, non-opioid, or both.

Figure IV: Characteristics of Painkiller Prescribers in the RAND HIE (1974-1982)

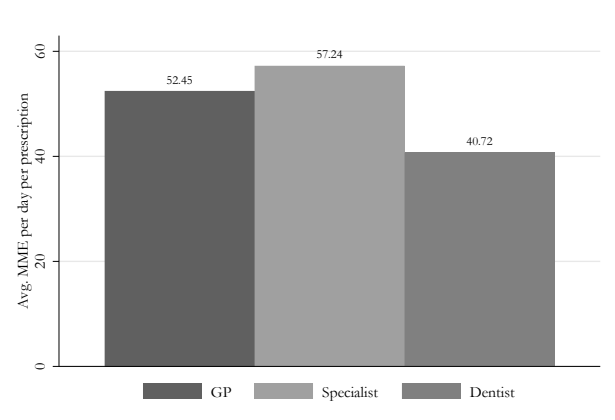
(a) Distribution of Prescribers



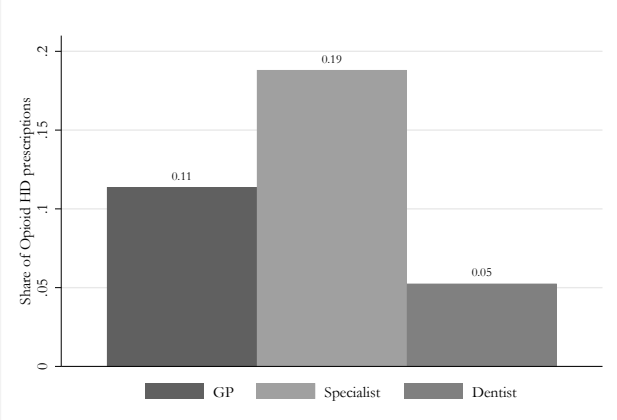
(b) Average Days of Supply per Prescription



(c) Average MME per Day per Prescription



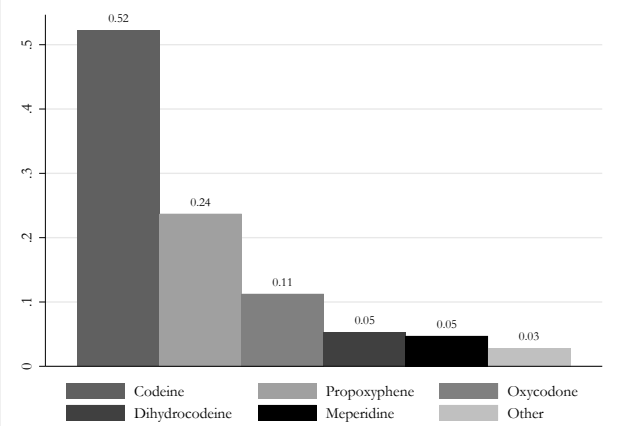
(d) Share of Opioid High-Dose Prescriptions



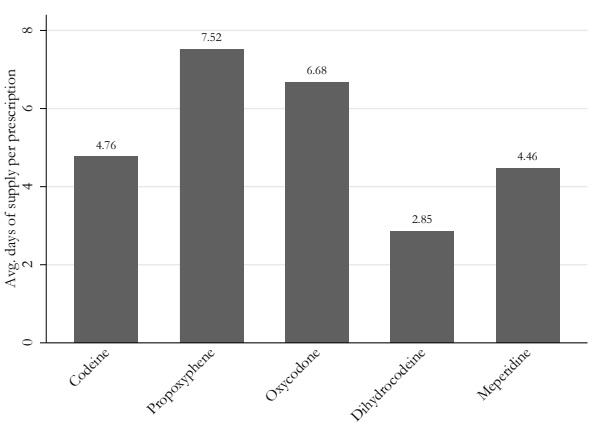
Notes: These figures depict several characteristics of prescribed painkillers filled by type of prescriber (General Practitioner (GP), Specialist, Dentist, and Other) and type of prescribed painkiller (Opioid and Non-Opioid).

Figure V: Most Commonly Prescribed Opioid Drugs in the RAND HIE (1974-1982)

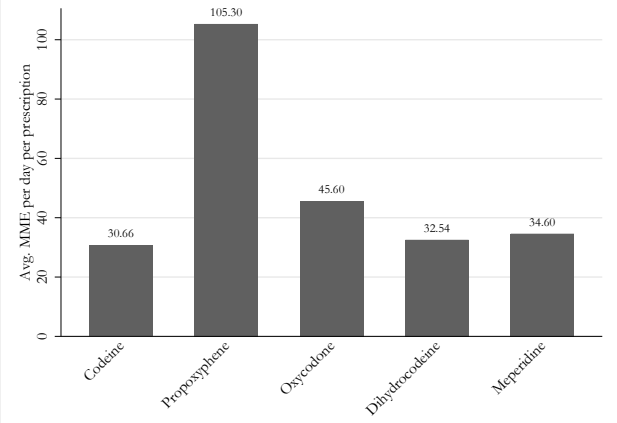
(a) Distribution of Drugs (# of Prescriptions)



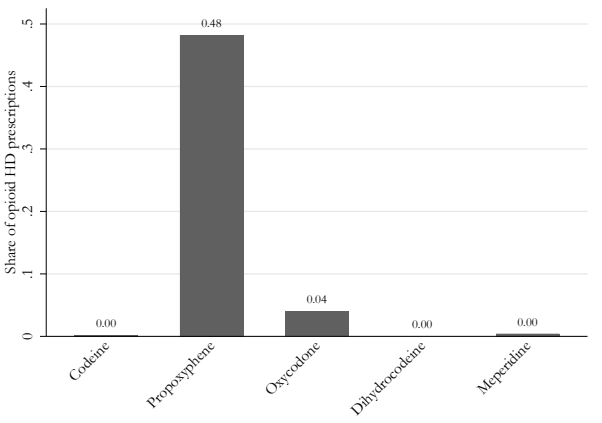
(b) Average Days of Supply per Prescription



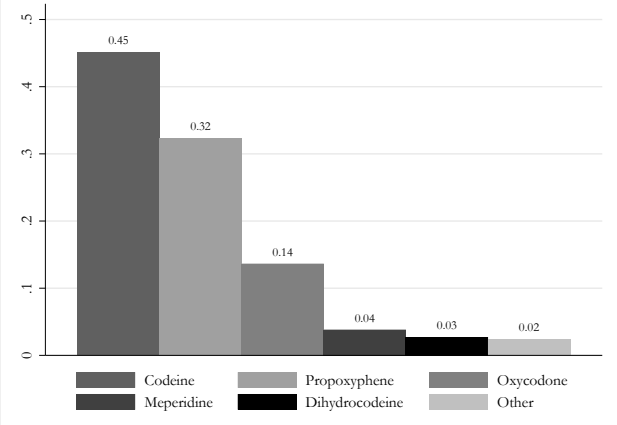
(c) Average MME per Day per Prescription



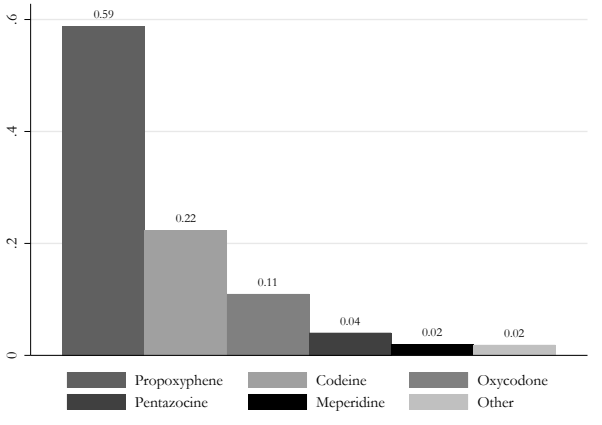
(d) Share of High-Dose Prescriptions



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



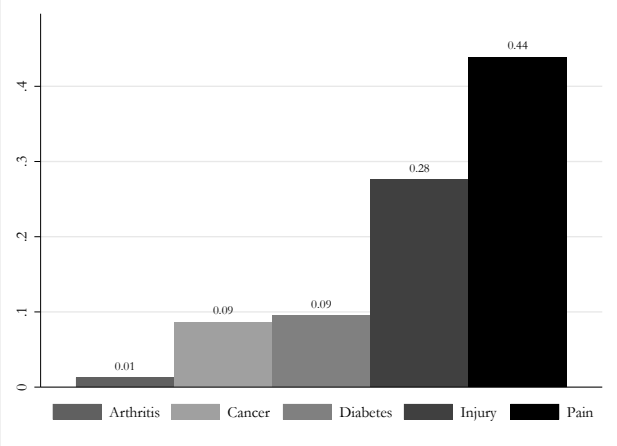
(f) Distribution of Drugs (# of MME)



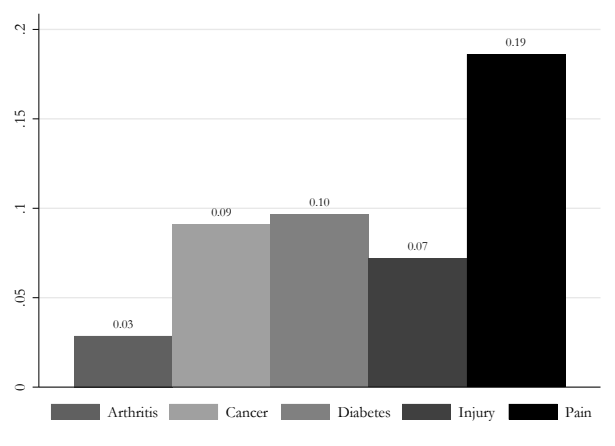
Notes: These figures depict various characteristics of prescribed opioid painkillers by drug type. All figures include opioid prescriptions from our RAND HIE analysis sample.

Figure VI: Common Diagnoses and Reasons for Outpatient Physician Visits Underlying Painkiller Prescriptions in the RAND HIE (1974-1982)

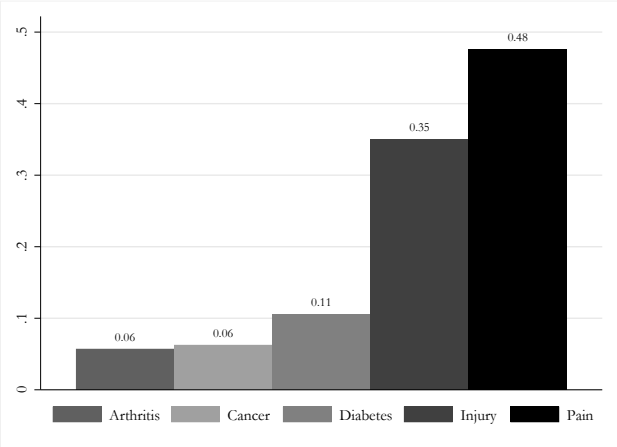
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



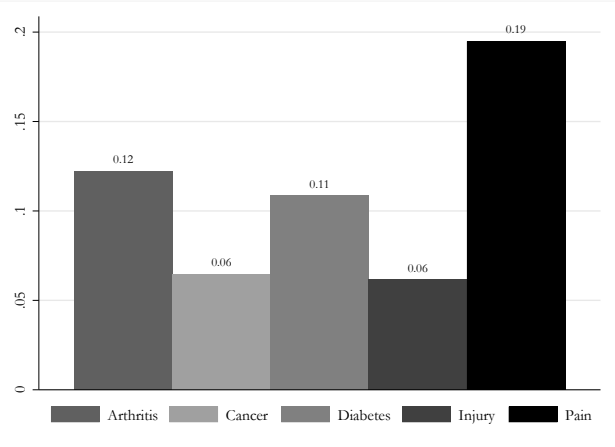
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



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



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



Notes: Figures VIb and VId display, for opioid and non-opioid prescriptions filled respectively, the average of five indicator variables capturing whether any outpatient visit within the 30 days prior to the prescription included a diagnosis related to: (1) cancer, (2) arthritis, (3) pain, (4) injury, or (5) diabetes. For example, the third bar in Figure VIb shows that 20% of opioid prescriptions were preceded within 30 days by an outpatient visit involving a diagnosis related to pain. Figures VIa and VIc present analogous measures, but instead focus on the reported reasons or symptoms for the visit. Percentages within each figure do not sum to 1 because the RAND HIE data allow for multiple entries per visit—up to three diagnoses and up to four reasons/symptoms can be recorded for each line-item claim, and more than one line-item claim can be associated with a single visit.

Online Appendix

OA.1 Details about the RAND HIE Data

In this section, we provide further details about the RAND Health Insurance Experiment.[53] 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 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. 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.,

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

a prepaid group practice) because the method of care delivery is substantially different from the 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.

OA.1.3 Steps to Identify Painkillers in the RAND HIE

Here, we describe 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.[54] We define painkillers as those drug purchases or prescriptions 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).[55] 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.

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

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

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

outpatient settings, dispensed by retail pharmacies, and controlled by the DEA.[56,57,58] 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.

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, 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.

[56]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.

[57]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.

[58]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.

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

Notes: This table shows the number of observations remaining after each sample restriction applied to the RAND HIE sample.

OA.2 *Wave Zero*: The Prelude to the Modern Opioid Crisis - Additional Figures

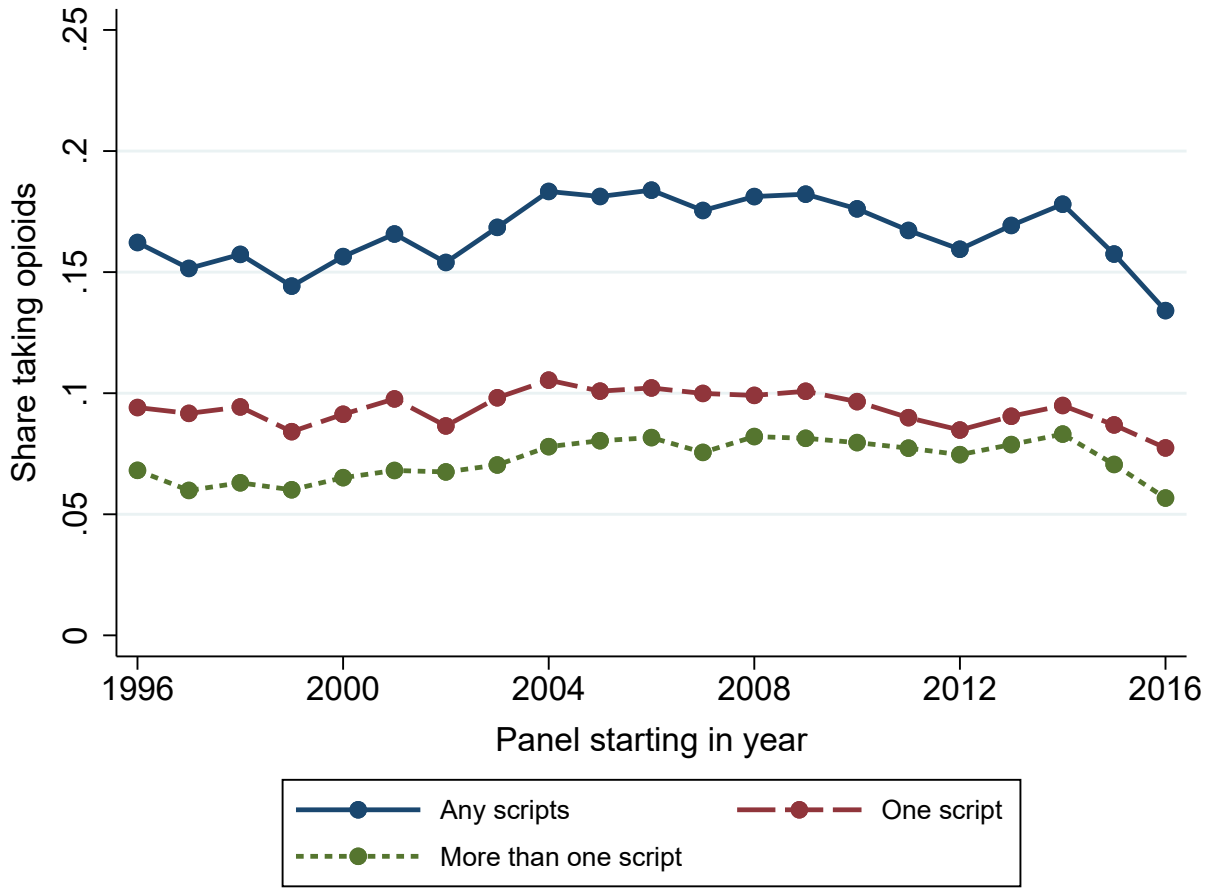
OA.2.1 Medical Expenditure Panel Survey, 1996 - 2016

We employ the Medical Expenditure Panel Survey to examine trends in opioid use in the 1990s and afterward. MEPS is a nationally representative survey of the U.S. civilian, non-institutionalized population, conducted annually by the Agency for Healthcare Research and Quality. It focuses on collecting detailed information about healthcare utilization, expenditures, and health insurance coverage. Since 1996, MEPS has enrolled new cohorts of approximately 30,000 individuals each year. Each participant is surveyed over five rounds spanning about two and a half years. Our analyses use panels from 1996 to 2015. Data are compiled across these survey rounds so that each year's dataset reflects individuals who entered MEPS in that year and were subsequently tracked into the following calendar year.

We follow Cutler and Glaeser (2021) to define our measure of opioid use.[59] This measure is based on self-reported data on medications received over six-month intervals. We exclude cough formulations since our focus is on painkillers. Reported drug names are reviewed for misspellings, and when available, NDCs are validated against a CDC list. Our analysis focuses on individuals under age 65, using MEPS survey weights, age- and sex-adjusted to the 2000 U.S. population.

[59] Replication materials for Cutler and Glaeser (2021) are available at the OpenICPSR repository: https://www.openicpsr.org/openicpsr/project/138262/version/V1/view.

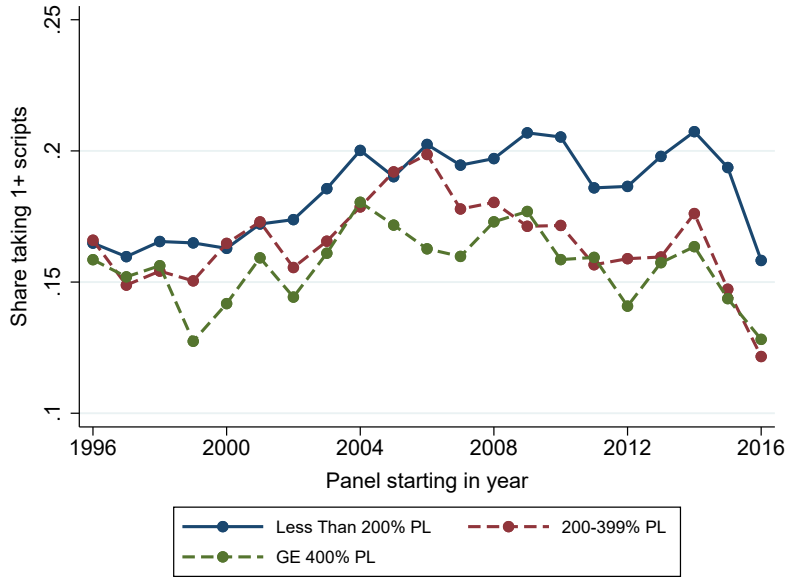
Figure OA.2.1: Prescribed Opioid Painkiller Utilization, 1996 - 2016



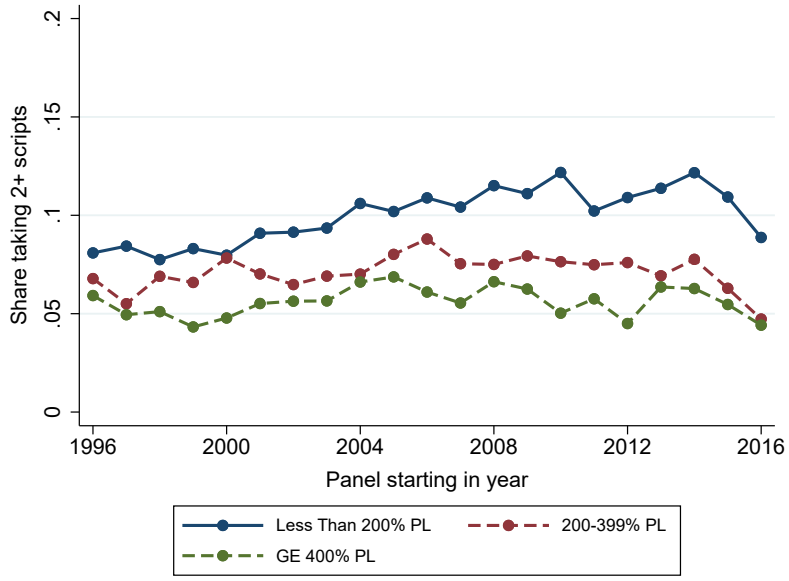
Notes: Figures are based on the authors' calculations using data from the MEPS, covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals who began participation in 1996 and were followed through 1997. The 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. The lower number of observations in columns 3 and 4 is due to missing values in MME data.

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

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

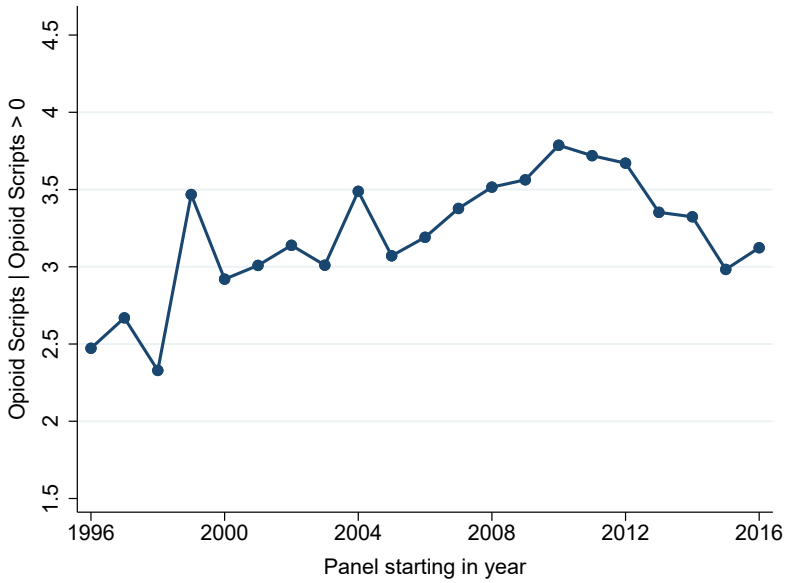


(b) Share with two or more recorded purchases of a prescribed opioid



Notes: Figures are based on the authors' calculations using data from the 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.

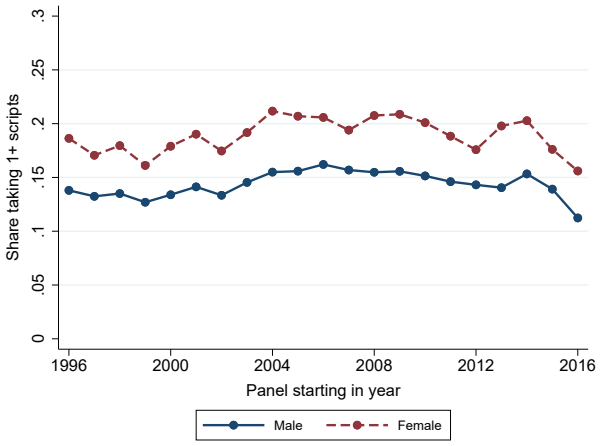
Figure OA.2.3: Average Number of Purchased Opioid Prescriptions in MEPS (Conditional on a Purchase)



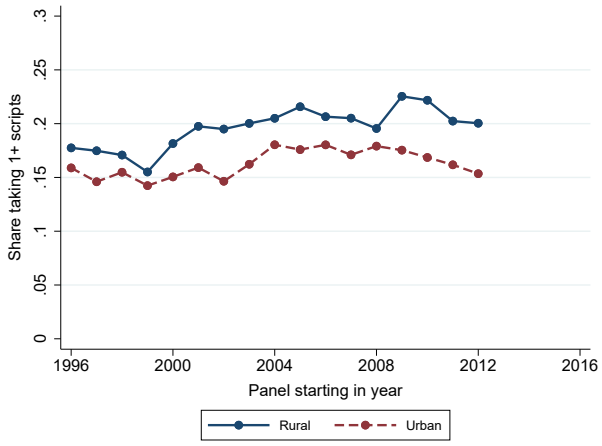
Notes: This figure shows the average number of purchased opioid prescriptions and is based on the authors' calculations using data from the MEPS, covering waves from 1996 to 2016. Each data point corresponds to a cohort entering MEPS in a given year—for instance, the 1996 cohort includes individuals 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

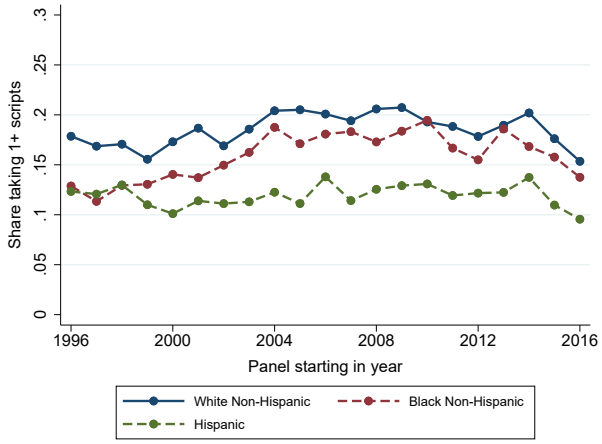
(a) By Gender



(b) By Geographic Location



(c) By Ethnicity



Notes: Figures are based on the authors' calculations using data from the 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).

Table OA.2.1: Opioid Prescriptions Purchased by Drug Name, 2016

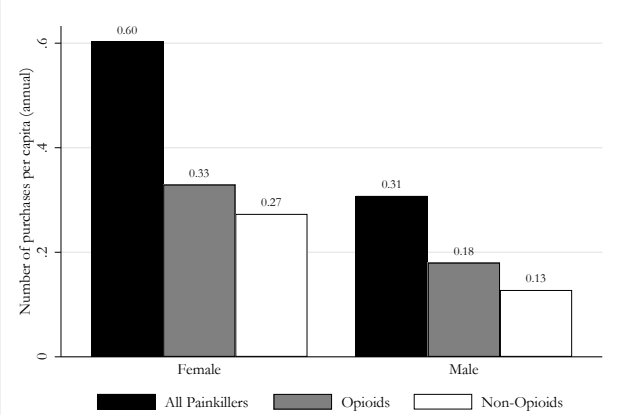
Drug Name	Share (Unweighted)	Share (MEPS Weighted)	Share (MME Weighted)	Share (MEPS & MME Weighted)
Buprenorphine	0.004	0.005	0.027	0.024
Codeine	0.075	0.067	0.018	0.015
Fentanyl	0.013	0.011	0.103	0.099
Hydrocodone	0.423	0.435	0.217	0.211
Hydromorphone	0.034	0.034	0.050	0.051
Morphine	0.035	0.029	0.105	0.079
Oxycodone	0.260	0.279	0.424	0.471
Tramadol	0.156	0.142	0.057	0.051
Observations	7184	7184	3478	3478

Notes: The reported statistics are derived from the MEPS Prescribed Medicine File for 2016. We restrict the sample to opioid painkillers with non-missing drug names purchased by individuals aged 64 or less. Columns show the unadjusted percentages of each opioid drug. Column 2 show the shares adjusted by MEPS survey weights for national representation. Column 3 displays percentages weighted by MMEs only. The last column displays percentages weighted by MMEs and adjusted by MEPS survey weights for national representation.

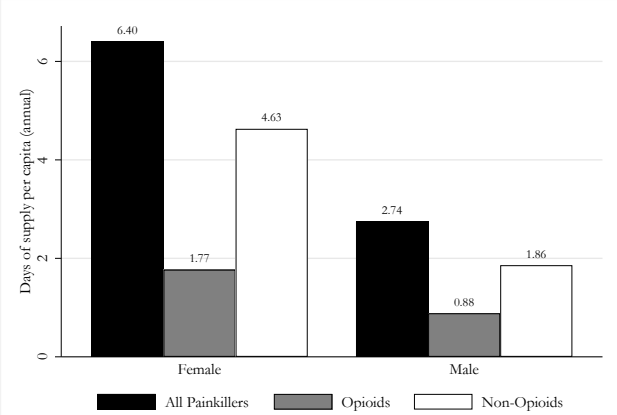
OA.2.2 Additional Figures and Tables: RAND HIE

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

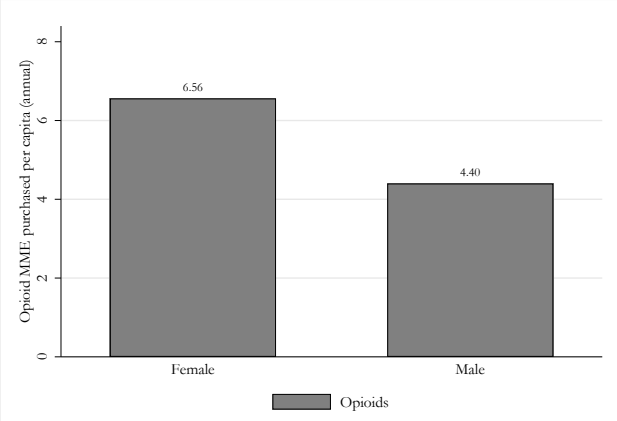
(a) Average Number of Prescriptions Filled



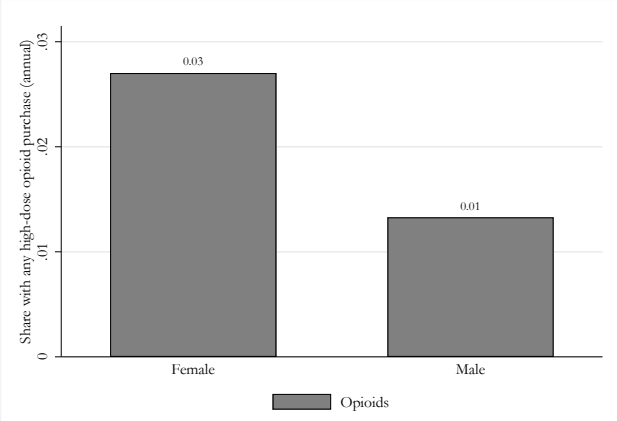
(b) Average Annual Days of Supply



(c) Average MME Per Day Per Prescription



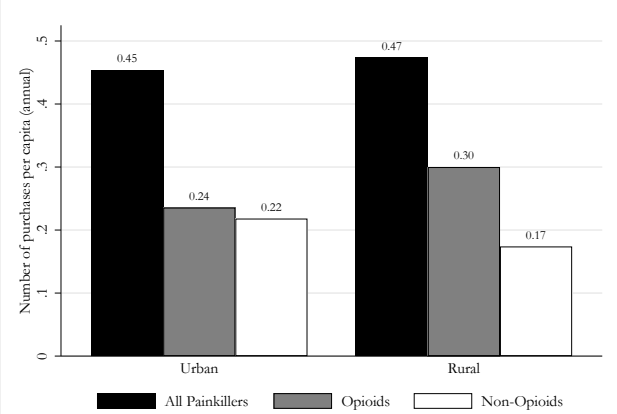
(d) Share with Any High-Dose Opioid



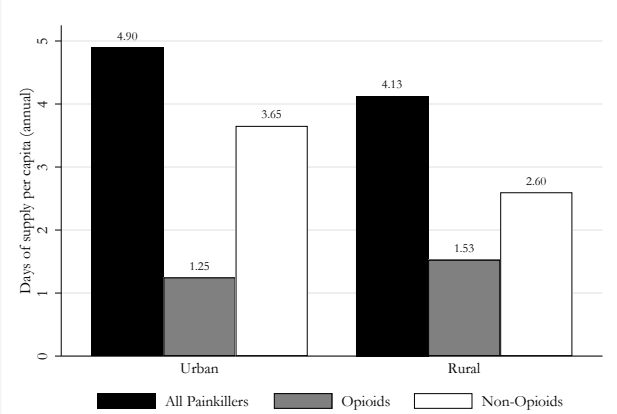
Notes: These figures depict several measures of prescribed painkiller utilization by gender and painkiller type (opioid and non-opioid), based on all individual-year pairs in our RAND HIE analysis sample. Pairs with no filled painkiller prescriptions are assigned a value of zero.

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

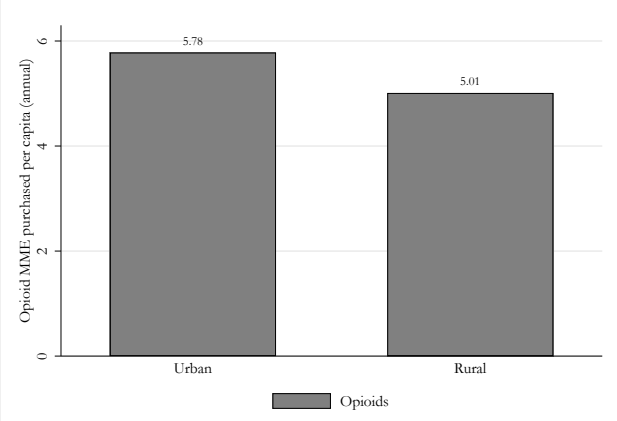
(a) Average Number of Prescriptions Filled



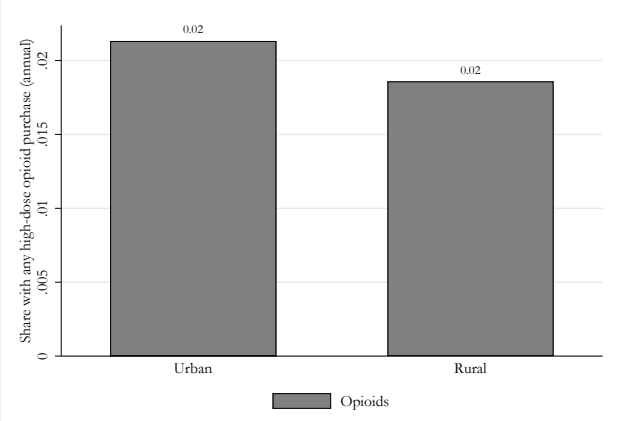
(b) Average Annual Days of Supply



(c) Average MME Per Day Per Prescription



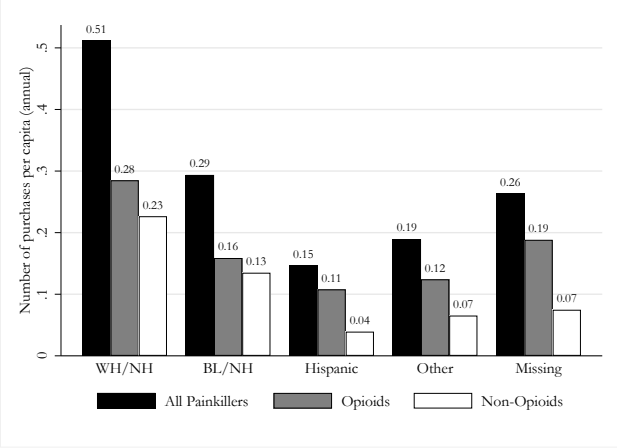
(d) Share with Any High-Dose Opioid



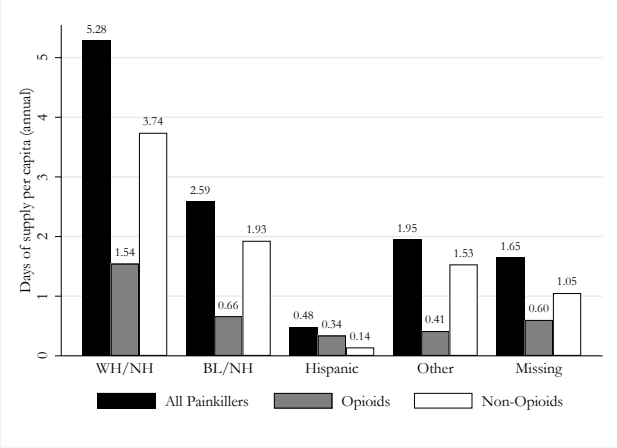
Notes: These figures depict several measures of prescribed painkiller utilization by location (urban, rural) and painkiller type (opioid and non-opioid), based on all individual-year pairs in our RAND HIE analysis sample. Pairs with no filled painkiller prescriptions are assigned a value of zero.

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

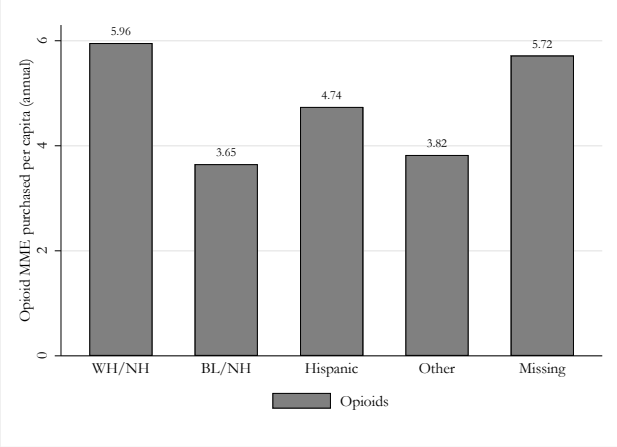
(a) Average Number of Prescriptions Filled



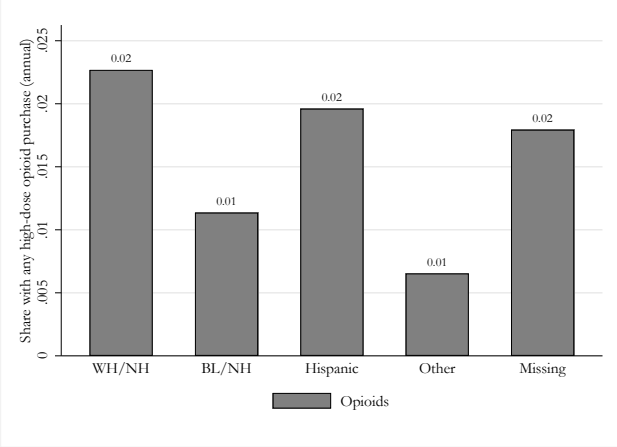
(b) Average Annual Days of Supply



(c) Average MME Per Day Per Prescription



(d) Share with Any High-Dose Opioid



Notes: These figures depict several measures of prescribed painkiller utilization by ethnicity (White non-Hispanic (WH/NH), Black non-Hispanic (BL/NH), Hispanic, other, missing) and painkiller type (opioid and non-opioid), based on all individual-year pairs in our RAND HIE analysis sample. Pairs with no filled painkiller prescriptions are assigned a value of zero.

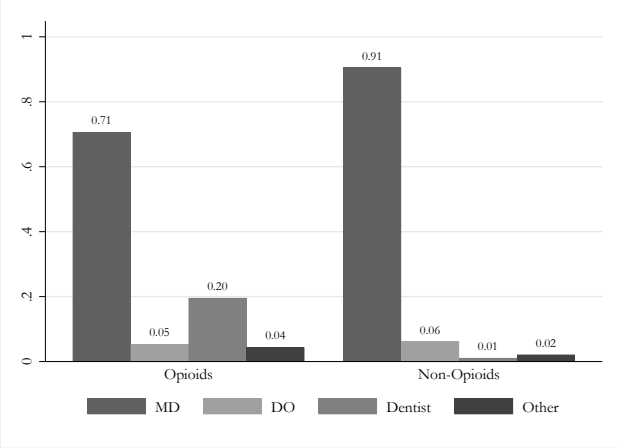
Table OA.2.2: Painkiller Prescriptions Filled

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

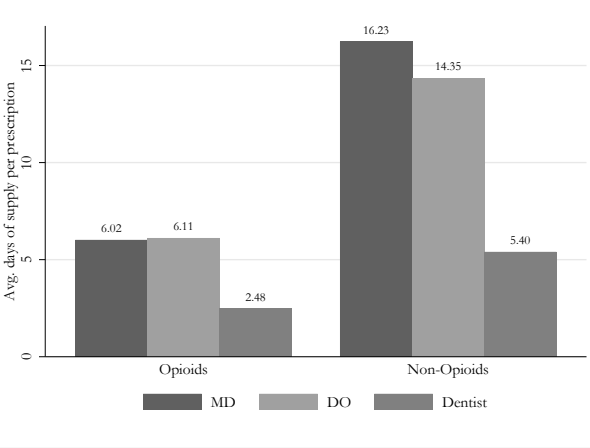
Notes: This table presents summary statistics for our RAND HIE analysis sample regarding opioid and non-opioid painkiller prescriptions filled. Each row reports raw means, standard deviations, and the number of observations at the filled-prescription level.

Figure OA.2.8: Characteristics of Painkiller Prescribers in the RAND HIE (1974-1982)

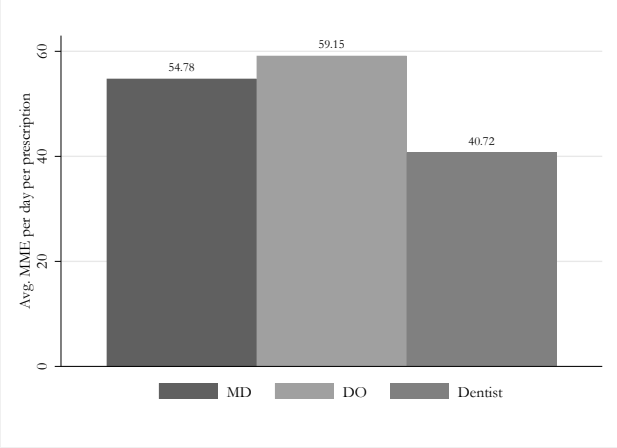
(a) Distribution of Prescribers



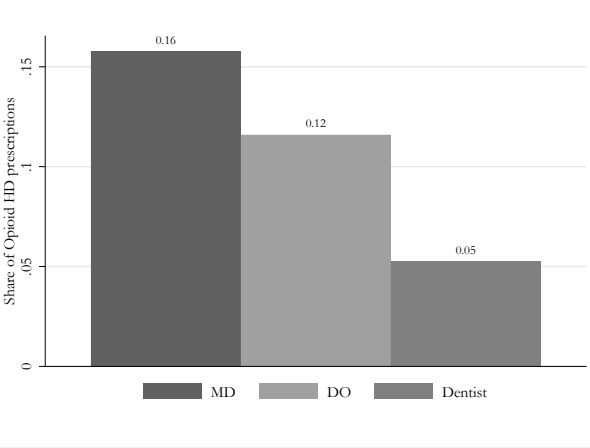
(b) Average Days of Supply per Prescription



(c) Average MME per Day per Prescription



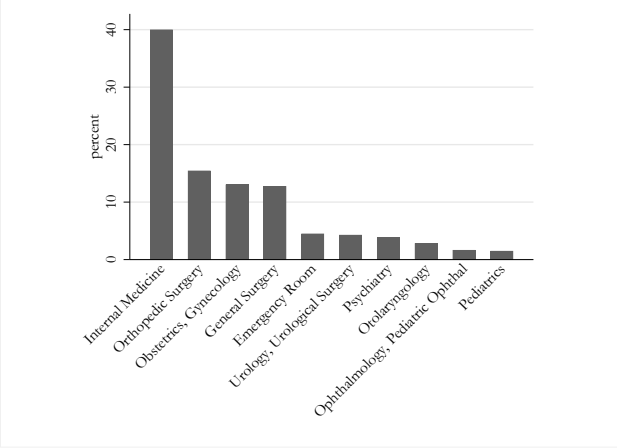
(d) Share of Opioid High-Dose Prescriptions



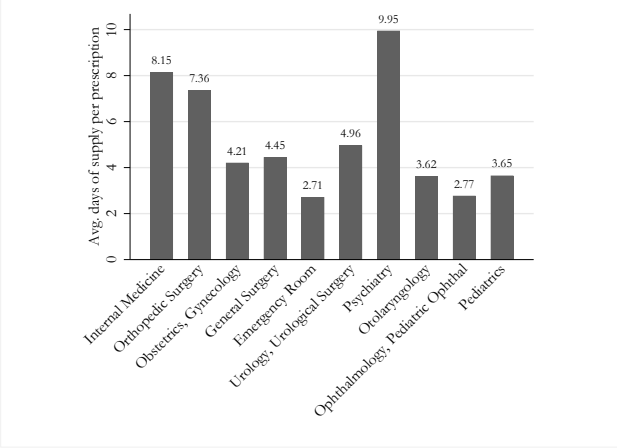
Notes: These figures depict several characteristics of prescribed painkillers filled by type of prescriber (Doctor of Medicine (MD), Doctor of Osteopathy (DO), Dentist, and Other) and type of prescribed painkiller (Opioid and Non-Opioid).

Figure OA.2.9: Characteristics of Opioid Prescribers: Specialists

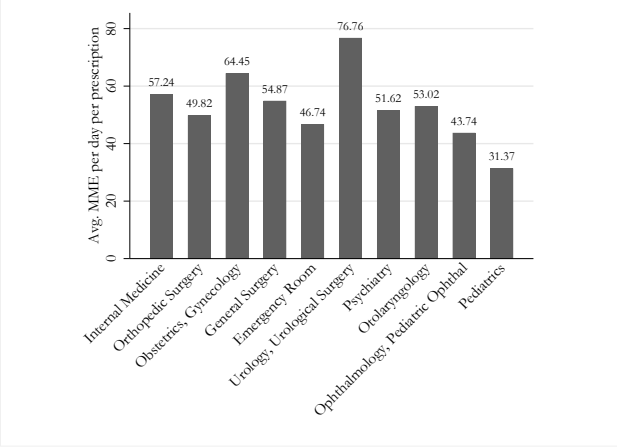
(a) Distribution of Prescribers



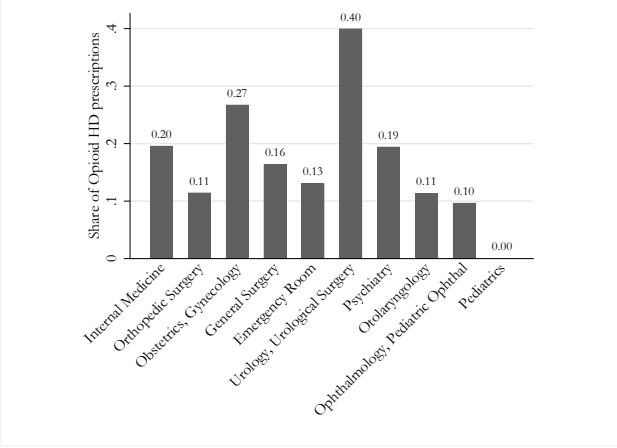
(b) Average Days of Supply per Prescription



(c) Average MME per Day per Prescription



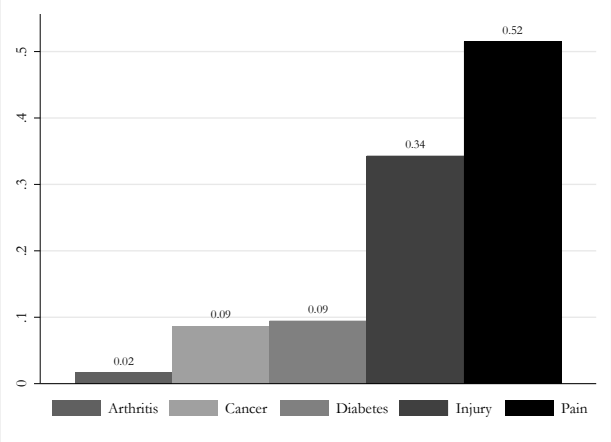
(d) Share of High-Dose Prescriptions



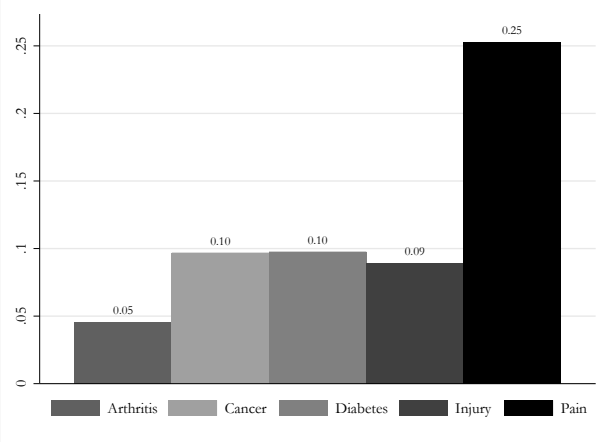
Notes: These figures depict several characteristics of filled opioid painkiller prescriptions, restricted to the ten medical specialties with the highest prescribing volumes.

Figure OA.2.10: Common Diagnosis Codes and Reasons for Outpatient Physician Visits Underlying Painkiller Prescriptions - 90 Days Lookup Window

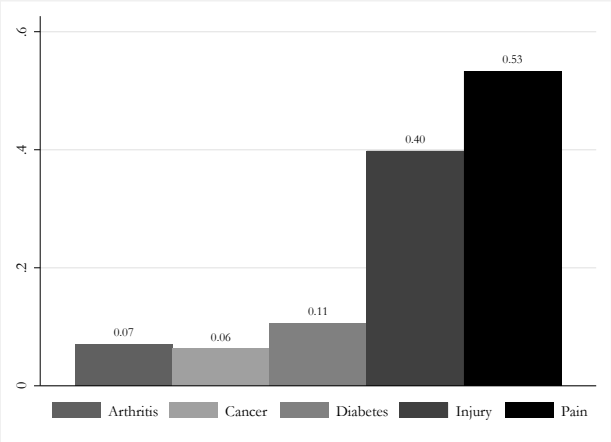
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



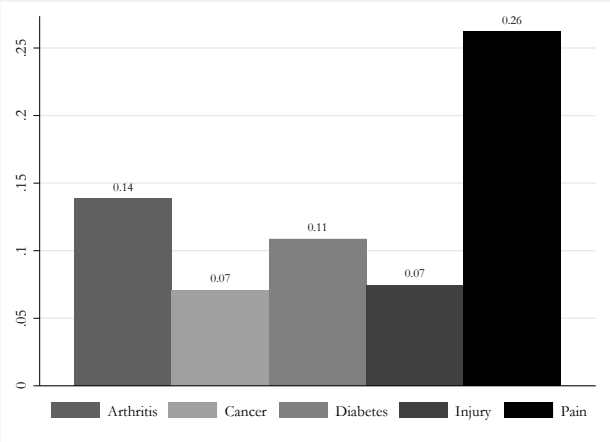
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



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



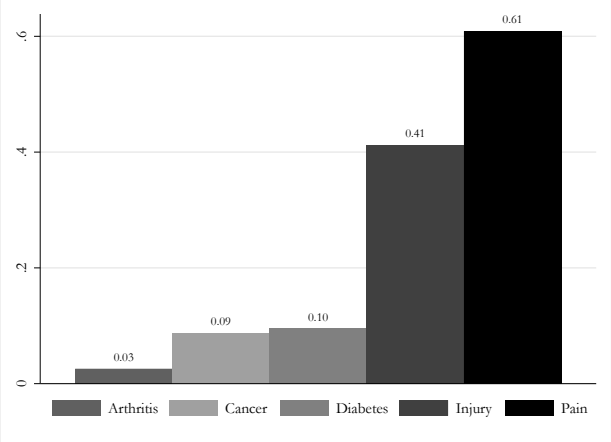
(d) Share of Non-Opioid Prescriptions Involving Selected Diagnosis Codes



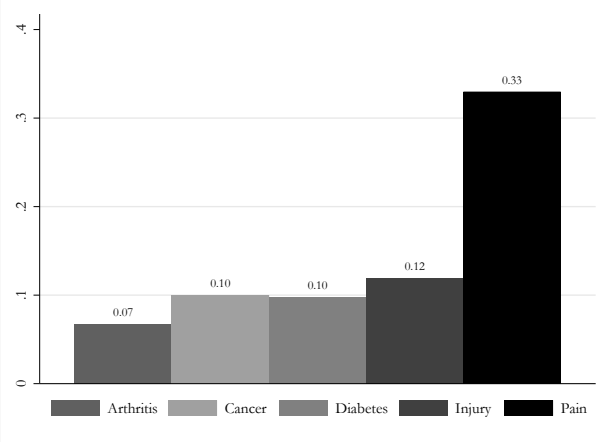
Notes: Figures OA.2.10b and OA.2.10d display, for opioid and non-opioid prescriptions filled respectively, the average of five indicator variables capturing whether any outpatient visit within the 90 days prior to the prescription included a diagnosis related to: (1) cancer, (2) arthritis, (3) pain, (4) injury, or (5) diabetes. For example, the third bar in Figure OA.2.10b shows that 27% of opioid prescriptions were preceded within 90 days by an outpatient visit involving a diagnosis related to pain. Figures OA.2.10a and OA.2.10c present analogous measures, but instead focus on the reported reasons or symptoms for the visit. Percentages within each figure do not sum to 1 because the RAND HIE data allow for multiple entries per visit—up to three diagnoses and up to four reasons/symptoms can be recorded for each line-item claim, and more than one line-item claim can be associated with a single visit.

Figure OA.2.11: Common Diagnosis Codes and Reasons for Outpatient Physician Visits Underlying Painkiller Prescriptions - 180 Days Lookup Window

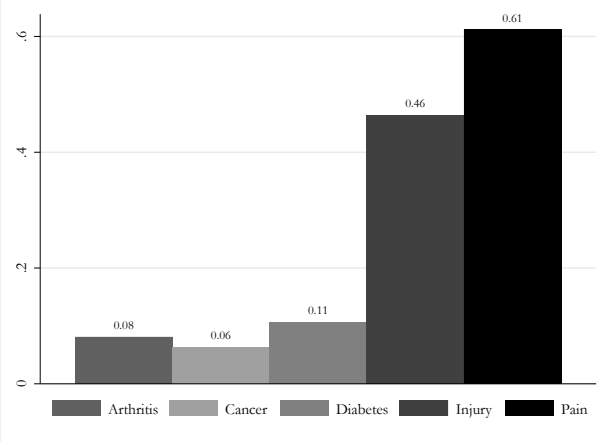
(a) Share of Opioid Prescriptions Involving Selected Reasons for Visiting Provider



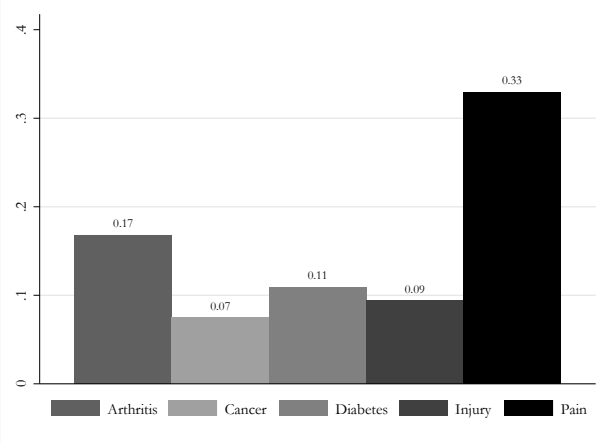
(b) Share of Opioid Prescriptions Involving Selected Diagnosis Codes



(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.2.11b and OA.2.11d display, for opioid and non-opioid prescriptions filled respectively, the average of five indicator variables capturing whether any outpatient visit within the 180 days prior to the prescription included a diagnosis related to: (1) cancer, (2) arthritis, (3) pain, (4) injury, or (5) diabetes. For example, the third bar in Figure OA.2.11b shows that 36% of opioid prescriptions were preceded within 180 days by an outpatient visit involving a diagnosis related to pain. Figures OA.2.11a and OA.2.11c present analogous measures, but instead focus on the reported reasons or symptoms for the visit. Percentages within each figure do not sum to 1 because the RAND HIE data allow for multiple entries per visit—up to three diagnoses and up to four reasons/symptoms can be recorded for each line-item claim, and more than one line-item claim can be associated with a single visit.

OA.3 Analyses of Non-Opioid Painkillers

In this section, we document the response of prescribed non-opioid painkiller use to differences in health insurance generosity. 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 in Section 5.2.

The results for non-opioid painkillers are reported in Table OA.3.1. 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.

Table OA.3.1: 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.

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

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

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 (45.0%) 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 treatment effects on opioid and non-opioid painkiller purchases, respectively, prescribed exclusively by non-dentist providers. 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	0.809	(0.39)	0.724	(0.45)	0.701	(0.46)	0.709	(0.45)	0.644	(0.48)	0.604	(0.49)
17. Number of visits	4.790	(7.81)	3.470	(5.80)	3.387	(6.12)	2.997	(4.37)	3.369	(6.20)	2.871	(5.37)
18. Annual spending (2019 $1K)	0.108	(0.22)	0.073	(0.14)	0.079	(0.19)	0.057	(0.13)	0.079	(0.19)	0.057	(0.13)
19. Any opioid Rx | any visit	0.142	(0.35)	0.115	(0.32)	0.115	(0.32)	0.088	(0.28)	0.115	(0.32)	0.103	(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 (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)	0.219	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-dentist providers 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-Opioiod 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-dentist providers 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 treatment effects on opioid and non-opioid painkiller purchases, respectively, prescribed exclusively by dentists. Overall, our main conclusions remain robust after excluding opioid and non-opioid purchases prescribed by non-dentist providers.

Table OA.5.1: Summary Statistics - All Painkillers (Dental 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	0.049	(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	0.664	(0.47)	0.538	(0.50)	0.518	(0.50)	0.526	(0.50)	0.477	(0.50)	0.473	(0.50)
17. Number of visits	2.230	(2.70)	1.663	(2.50)	1.663	(2.52)	1.563	(2.27)	1.573	(2.64)	1.425	(2.23)
18. Annual spending (2019 $1K)	0.182	(0.51)	0.107	(0.35)	0.121	(0.43)	0.089	(0.33)	0.117	(0.40)	0.088	(0.33)
19. Any opioid Rx | any visit	0.058	(0.23)	0.046	(0.21)	0.048	(0.21)	0.040	(0.20)	0.047	(0.21)	0.036	(0.19)
# 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 (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)	0.061	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-dentist providers 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-dentist providers 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 and Analysis by Provider Type

Table OA.6.1: 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
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 ordinary least squares regressions and indicate the effect of the various plans on the outcome given in the left-hand column (i.e., coefficients on plan dummies from regressions without a constant). The p-value in the last column tests the null that all plan coefficients are equal. 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 III because newborns during the experiment were incorporated after enrollment.

Table OA.6.2: 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 (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of opioid and non-opioid painkillers, (2-3) annual spending on painkillers, (4) annual days of supply of painkillers, and (5) annual number of prescriptions purchased. All outcomes account for purchases prescribed by dentists and non-dentist providers. All regressions, except for column 3, include the full set of pre-randomization covariates as controls: all outcome variables in Tables IV and OA.6.1. 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.6.3: 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. (1)	Covs. (2)	Adj. (3)	Covs. (4)	Covs. (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 (whose mean is given by the constant term). The outcomes are: (1) a dummy variable for annual purchase of non-opioid painkillers, (2-3) annual spending on non-opioid painkillers, (4) annual days of supply of non-opioid painkillers, and (5) annual number of non-opioid prescriptions purchased. All outcomes account for purchases prescribed by dentists and non-dentist providers. All regressions, except for column 3, include the full set of pre-randomization covariates as controls: all outcome variables in Tables IV and OA.6.1. 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.6.4: 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. (1)	Covs. (2)	Covs. (3)	Adj. (4)	Covs. (5)	Covs. (6)	Covs. (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 (whose mean is given by the constant term). 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. All outcomes account for opioid purchases prescribed by non-dentist providers. All regressions, except for column 4, include the full set of pre-randomization covariates as controls: all outcome variables in Tables IV and OA.6.1. 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.6.5: 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. (1)	Covs. (2)	Covs. (3)	Adj. (4)	Covs. (5)	Covs. (6)	Covs. (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 (whose mean is given by the constant term). 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. All outcomes account for opioid purchases prescribed by dentists only. All regressions, except for column 4, include the full set of pre-randomization covariates as controls: all outcome variables in Tables IV and OA.6.1. 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.6.6: 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, 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.

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

	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)	0.261	23.460	8.526	0.880	0.184	0.036	10.637	2.588	7.971	0.520
	(0.008)	(2.052)	(0.810)	(0.064)	(0.007)	(0.003)	(1.125)	(0.303)	(0.366)	(0.048)
25% Coinsurance	-0.073	-11.715	-4.416	-0.433	-0.057	-0.019	-6.494	-1.636	-2.962	-0.297
	(0.012)	(2.192)	(0.946)	(0.067)	(0.009)	(0.004)	(1.082)	(0.292)	(0.483)	(0.047)
Mixed Coinsurance	-0.083	-13.376	-5.201	-0.479	-0.066	-0.018	-6.488	-1.582	-3.120	-0.305
	(0.013)	(2.085)	(0.843)	(0.066)	(0.011)	(0.004)	(1.109)	(0.304)	(0.549)	(0.049)
50% Coinsurance	-0.117	-14.726	-5.859	-0.527	-0.087	-0.027	-6.780	-1.725	-4.012	-0.320
	(0.013)	(2.236)	(0.916)	(0.076)	(0.010)	(0.004)	(1.201)	(0.368)	(0.626)	(0.056)
Ind. Deductible	-0.166	-17.279	-6.315	-0.651	-0.124	-0.027	-7.912	-1.861	-5.367	-0.394
	(0.008)	(1.813)	(0.741)	(0.059)	(0.007)	(0.003)	(1.036)	(0.283)	(0.359)	(0.044)
95% Coinsurance	-0.151	-15.900	-5.884	-0.613	-0.114	-0.026	-8.041	-1.885	-4.962	-0.394
	(0.009)	(2.429)	(0.934)	(0.069)	(0.007)	(0.003)	(1.197)	(0.330)	(0.411)	(0.049)
25% Co. × Hit MDE	0.068	7.690	2.737	0.344	0.058	0.007	3.813	1.008	2.136	0.208
	(0.023)	(3.550)	(1.508)	(0.108)	(0.018)	(0.008)	(1.388)	(0.417)	(0.946)	(0.067)
Mixed Co. × Hit MDE	0.111	22.486	7.647	0.586	0.084	0.033	11.811	3.525	4.133	0.310
	(0.026)	(7.473)	(2.446)	(0.162)	(0.021)	(0.011)	(4.971)	(1.424)	(1.178)	(0.094)
50% Co. × Hit MDE	0.106	3.625	1.141	0.206	0.099	0.009	2.856	0.770	4.108	0.182
	(0.022)	(1.702)	(0.688)	(0.063)	(0.020)	(0.007)	(0.787)	(0.240)	(1.078)	(0.042)
Ind. Ded. × Hit MDE	0.190	16.726	6.376	0.543	0.145	0.027	7.440	1.910	6.485	0.301
	(0.013)	(3.141)	(1.189)	(0.066)	(0.012)	(0.005)	(2.179)	(0.649)	(0.609)	(0.046)
95% Co. × Hit MDE	0.140	11.185	4.416	0.463	0.120	0.025	6.172	1.809	5.484	0.299
	(0.015)	(2.694)	(1.109)	(0.085)	(0.012)	(0.005)	(1.347)	(0.495)	(0.661)	(0.055)
Adjusted R^2	0.11	0.03	0.03	0.05	0.07	0.02	0.02	0.02	0.05	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: Reported coefficients are from ordinary least squares regressions and represent the effect of each health insurance plan on the outcome listed in the column, relative to the free-care plan (whose mean is given by the constant term). Coefficients reflect both the main effects of each plan and their interactions with a dummy equal to one if the family reached the Maximum Dollar Expenditure (MDE) in a given year. 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 OA.6.8: Plans' Effects on Prescribed Painkiller Purchases - Deadline Effect

	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)	0.259	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.

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)	0.244	0.248
	(0.009)	(0.009)
25% Coinsurance	-0.030	-0.028
	(0.011)	(0.011)
Mixed Coinsurance	-0.035	-0.032
	(0.014)	(0.014)
50% Coinsurance	-0.059	-0.056
	(0.013)	(0.013)
Ind. Deductible	-0.034	-0.031
	(0.010)	(0.011)
95% Coinsurance	-0.051	-0.047
	(0.011)	(0.011)
B. First Stage: Provider Visit		
Constant (Free Care Plan)	1.447	1.591
	(0.285)	(0.285)
25% Coinsurance	-0.407	-0.415
	(0.072)	(0.070)
Mixed Coinsurance	-0.455	-0.463
	(0.077)	(0.077)
50% Coinsurance	-0.461	-0.467
	(0.092)	(0.093)
Ind. Deductible	-0.690	-0.695
	(0.057)	(0.057)
95% Coinsurance	-0.791	-0.803
	(0.064)	(0.064)
PCP per Capita	0.069	0.066
	(0.005)	(0.005)
Av. Days to App.	0.044	0.041
	(0.004)	(0.004)
Av. Fee GPs	-0.260	-0.260
	(0.030)	(0.030)
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 corresponding outcome 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: 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)	0.198	0.192	0.753	0.752	0.754
	(0.008)	(0.007)	(0.018)	(0.018)	(0.026)
25% Coinsurance	-0.027	-0.027	-0.109	-0.103	-0.080
	(0.011)	(0.011)	(0.033)	(0.033)	(0.056)
Mixed Coinsurance	-0.027	-0.028	-0.067	-0.072	-0.091
	(0.013)	(0.013)	(0.037)	(0.037)	(0.055)
50% Coinsurance	-0.055	-0.052	-0.071	-0.067	-0.153
	(0.012)	(0.012)	(0.043)	(0.043)	(0.065)
Ind. Deductible	-0.023	-0.023	-0.093	-0.098	-0.052
	(0.010)	(0.009)	(0.029)	(0.029)	(0.043)
95% Coinsurance	-0.040	-0.040	-0.063	-0.064	-0.075
	(0.010)	(0.010)	(0.032)	(0.031)	(0.049)
Some Pain		-0.103		-0.078	-0.028
		(0.027)		(0.034)	(0.047)
A Little Pain		-0.137		-0.121	-0.067
		(0.025)		(0.031)	(0.050)
No Pain at All		-0.152		-0.137	-0.071
		(0.026)		(0.035)	(0.053)
Fair Health		-0.043		0.021	-0.023
		(0.041)		(0.046)	(0.071)
Good Health		-0.064		0.041	0.038
		(0.039)		(0.045)	(0.068)
Excellent Health		-0.086		0.042	0.048
		(0.040)		(0.048)	(0.078)
Adjusted R^2	0.06	0.07	0.04	0.05	0.34
Prescriber FE	No	No	No	No	Yes
# Families	2890	2890	1233	1233	1233
# Individuals	5496	5496	1478	1478	1478
# Individual-Years	16369	16369	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.

Table OA.7.3: 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 (1)	Spending in $ (2)	Number of Provider Visits (3)	Baseline (4)	Pain and Health Dummies (5)	Baseline (6)	Pain and Health Dummies (7)	Pain and Health Dummies, + Prescriber FE (8)
Const. (Free Care Plan)	0.778	455.140	4.849	0.204	0.197	0.817	0.818	0.814
	(0.010)	(18.084)	(0.178)	(0.008)	(0.008)	(0.017)	(0.017)	(0.025)
25% Coinsurance	-0.103	-127.878	-1.487	-0.027	-0.027	-0.097	-0.093	-0.072
	(0.019)	(25.467)	(0.270)	(0.011)	(0.011)	(0.034)	(0.034)	(0.066)
Mixed Coinsurance	-0.095	-107.038	-1.253	-0.027	-0.028	-0.042	-0.047	-0.030
	(0.021)	(32.648)	(0.294)	(0.013)	(0.013)	(0.031)	(0.031)	(0.054)
50% Coinsurance	-0.126	-161.058	-1.791	-0.060	-0.056	0.019	0.022	-0.066
	(0.022)	(25.173)	(0.253)	(0.013)	(0.013)	(0.038)	(0.038)	(0.067)
Ind. Deductible	-0.157	-113.476	-1.415	-0.030	-0.030	-0.088	-0.094	-0.073
	(0.016)	(25.777)	(0.247)	(0.011)	(0.010)	(0.028)	(0.027)	(0.042)
95% Coinsurance	-0.217	-200.146	-2.019	-0.038	-0.039	-0.036	-0.038	-0.016
	(0.017)	(20.635)	(0.230)	(0.011)	(0.011)	(0.028)	(0.028)	(0.044)
Some Pain					-0.085		-0.060	-0.020
					(0.028)		(0.027)	(0.040)
A Little Pain					-0.131		-0.081	-0.049
					(0.027)		(0.027)	(0.042)
No Pain at All					-0.146		-0.106	-0.081
					(0.027)		(0.030)	(0.050)
Fair Health					-0.035		0.025	-0.044
					(0.044)		(0.033)	(0.056)
Good Health					-0.071		0.025	-0.008
					(0.043)		(0.031)	(0.058)
Excellent Health					-0.097		0.029	-0.006
					(0.043)		(0.036)	(0.070)
Adjusted R^2	0.09	0.06	0.06	0.05	0.07	0.06	0.07	0.35
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2780	2780	1133	1133	1133
# Individuals	5922	5922	5922	5227	5227	1319	1319	1319
# Individual-Years	20004	20004	20004	14218	14218	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: (1) a dummy variable for any outpatient visit to an individual provider, (2) annual spending on visits, (3) number of visits, (4-5) a dummy variable for any opioid painkiller prescription, and (6-8) the share of filled opioid prescriptions. All regressions exclude opioid painkillers prescribed by dentists. 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.

Table OA.7.4: 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 (1)	Spending in $ (2)	Number of Provider Visits (3)	Baseline (4)	Pain and Health Dummies (5)	Baseline (6)	Pain and Health Dummies (7)	Pain and Health Dummies, + Prescriber FE (8)
Const. (Free Care Plan)	0.651	909.735	2.356	0.101	0.100	0.864	0.868	0.860
	(0.012)	(37.289)	(0.059)	(0.006)	(0.006)	(0.022)	(0.022)	(0.038)
25% Coinsurance	-0.122	-252.980	-0.494	-0.001	-0.000	-0.109	-0.114	-0.135
	(0.024)	(45.807)	(0.094)	(0.009)	(0.009)	(0.041)	(0.040)	(0.084)
Mixed Coinsurance	-0.134	-265.253	-0.587	-0.005	-0.004	-0.123	-0.140	-0.144
	(0.023)	(53.132)	(0.105)	(0.010)	(0.010)	(0.055)	(0.055)	(0.084)
50% Coinsurance	-0.149	-297.544	-0.662	-0.002	-0.001	-0.145	-0.159	-0.195
	(0.029)	(75.869)	(0.120)	(0.010)	(0.010)	(0.061)	(0.059)	(0.107)
Ind. Deductible	-0.182	-284.631	-0.691	-0.007	-0.007	-0.075	-0.078	-0.098
	(0.018)	(40.959)	(0.082)	(0.008)	(0.008)	(0.040)	(0.039)	(0.069)
95% Coinsurance	-0.189	-350.480	-0.785	-0.019	-0.018	-0.125	-0.133	-0.128
	(0.020)	(38.614)	(0.080)	(0.008)	(0.007)	(0.041)	(0.041)	(0.083)
Some Pain					-0.032		-0.018	0.008
					(0.024)		(0.056)	(0.095)
A Little Pain					-0.044		-0.150	-0.099
					(0.022)		(0.054)	(0.090)
No Pain at All					-0.035		-0.136	-0.088
					(0.022)		(0.057)	(0.094)
Fair Health					-0.057		-0.131	-0.049
					(0.043)		(0.094)	(0.172)
Good Health					-0.054		-0.024	0.058
					(0.042)		(0.087)	(0.159)
Excellent Health					-0.061		-0.009	0.110
					(0.042)		(0.088)	(0.159)
Adjusted R^2	0.08	0.03	0.07	0.03	0.04	0.14	0.15	0.06
Prescriber FE	No	No	No	No	No	No	No	Yes
# Families	3100	3100	3100	2406	2406	630	630	630
# Individuals	5922	5922	5922	4361	4361	704	704	704
# Individual-Years	20004	20004	20004	11071	11071	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: (1) a dummy variable for any outpatient visit to an individual provider, (2) annual spending on visits, (3) number of visits, (4-5) a dummy variable for any opioid painkiller prescription, and (6-8) the share of filled opioid prescriptions. All regressions exclude opioid painkillers prescribed by non-dentist providers. 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.