Breaking Bad Opioid Sorting*

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January 11, 2026

PRELIMINARY AND INCOMPLETE - DO NOT CITE

Abstract

In many markets, consumers rely on experts for access to goods and services. Consumer and expert preferences over outcomes are linked through consumers' choice of experts, or sorting. We investigate how consumer sorting contributes to observed differences in outcomes and its implications for expert-targeted policies. Using rich employer-sponsored health insurance claims data on opioid prescriptions for chronic pain, we first show that prescription intensity is highly dispersed across physicians. We decompose the variance of physicians' prescription decisions and find that patient sorting is more than three times as important as physicians' inherent prescription propensity for prescription intensity dispersion. Most of this sorting cannot be justified on medical grounds. We develop and estimate an equilibrium model of patient choice of physicians and physicians' prescription decisions. Patients optimally choose their physicians based on both their opioid preferences and their expectations of physicians' prescription decisions. Our counterfactual analysis shows that expert-targeted policies to curb non-medically grounded opioid prescribing will be severely attenuated by patient resorting. We propose an alternative policy that eliminates sorting based on non-medically grounded preferences, while preserving appropriate care for patients with medical needs for prescription opioids.

*We thank participants of the IU Kelley Brownbag for helpful comments. We thank Richard Meraz for his support in accessing the data used in this paper. This research was supported in part by Lilly Endowment, Inc., through its support for the Indiana University Pervasive Technology Institute.

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1 Introduction

In many markets, consumers rely on experts for access to goods and services. For instance, investors turn to asset managers to access complex investment opportunities, and patients consult physicians for medical recommendations and treatment. The stakes of choosing the right expert can be substantial: selecting an asset manager may expose investors to levels of financial risk that differ from their preferences, and choosing a physician can affect long-term health. Given the high stakes, consumers have strong incentives to sort into experts, choosing an expert whose preferences, style, or philosophy closely align with their own. As a result, market outcomes reflect both expert preferences and consumer preferences, linked together through consumer sorting. Despite the importance of disentangling these forces for policy design, empirical evidence quantifying the contribution of each channel remains extremely limited.

In this paper, we study the importance of consumer sorting versus expert preferences for observed outcome differences and their implications for expert-targeted policies. To do so, we focus on opioid prescribing for chronic pain patients in the United States. In this market, patients must obtain prescription opioids from physicians, but in most cases can freely choose their physician. Using employer-sponsored health insurance claims data, we show that patients' choice of physicians, or patient sorting, is more than three times as important in explaining the observed dispersion in opioid prescribing rates across physicians as physicians' inherent prescribing propensity. Moreover, patient sorting is almost exclusively driven by factors unrelated to patients' medical needs. This finding suggests that policies targeting physicians aiming to reduce clinically unwarranted opioid prescribing may be severely attenuated by patient resorting. To understand how patient sorting interacts with physician-targeted policies, we develop and estimate a model of equilibrium patient sorting and physician prescribing. We use this model to simulate several counterfactuals. First, we consider a counterfactual in which the top 5% of physicians by prescription rate are excluded from the market, mimicking expert-targeted policies. Despite being extreme, this policy reduces aggregate prescribing only marginally. We show that this result is driven by patient resorting to non-excluded physicians with similar prescription propensities. In other words, resorting severely attenuates the exclusion policy. If the affected patients were instead randomly reassigned to physicians, aggregate prescribing would fall further. However, randomization breaks sorting indiscriminately, disregarding patients' medical needs. To address this issue, we consider a counterfactual in which we force physicians to prescribe solely based on medical needs but disregard patients' opioid preferences. This eliminates patients' incentive to sort based on non-medical preferences. Breaking only this bad sorting, we find

that this policy would reduce aggregate opioid prescriptions while preserving treatment for patients with medical needs.

We establish these findings using health insurance claims data from the Merative MarketScan Research Databases for the New York City Metropolitan Statistical Area over the period 2016-2022. These visit-level data allow us to link patients, their chosen physicians, and any resulting opioid prescriptions. We begin by showing that physicians' prescription rates are highly dispersed, even after controlling for a rich set of patient severity measures. Only a relatively small fraction of physicians account for most opioid prescriptions. This pattern aligns with the well-documented heterogeneity in physicians' prescription intensity reported in the literature (Finkelstein, Gentzkow, and Williams 2016; Molitor 2018; Cutler, Skinner, Stern, and Wennberg 2019; Badinski, Finkelstein, Gentzkow, and Hull 2023; Clemens, Léger, Nandan, and Town 2024).

Next, we assess the role of patient sorting in the dispersion of prescription rates across physicians. To do so, we decompose the variance of physicians' prescription decisions into patient fixed effects, physician fixed effects, time-varying patient controls, and a patient sorting component, following the two-way fixed effects method by Abowd, Kramarz, and Margolis (1999). There are two identification challenges. First, physician fixed effects are identified from patients who switch physicians. When switching is limited, fixed effects estimates can be severely biased, a problem known as limited mobility bias (Andrews, Gill, Schank, and Upward 2012). We follow recent advances in the labor literature to address the limited-mobility bias by grouping physicians and patients via k-means clustering and estimating group-level fixed effects (Bonhomme, Lamadon, and Manresa 2019; Mourot 2025). Second, fixed effects estimates may be biased if patients' switching decisions are due to time-varying characteristics unobserved by the econometrician. We provide evidence to mitigate this concern.

Using the two-way fixed effects estimator, we find that patient sorting is more than three times as important as physicians' inherent prescribing propensity in explaining the observed dispersion in opioid prescribing rates across physicians. This suggests that patients' choice rather than physicians' inherent prescribing propensity is responsible for observed prescribing heterogeneity across physicians. We further investigate the determinants of patient sorting. In particular, we separate sorting into sorting due to medical needs and sorting due to opioid preferences.

We find that medically grounded characteristics explain little of the variation in opioid prescribing rates. Instead, non-medical preferences account for the majority of the observed dispersion. Accordingly, sorting on non-medical preferences constitutes most of patient sorting in this market. This finding is consistent with anecdotal evidence from online forums,

where patients with strong preferences for opioids actively seek and share information about physicians' propensity to prescribe.[1] This finding suggests that policies that punish or exclude top prescribers to curb unecessary opioid prescriptions may be severely attenuated by patient resorting.

To understand how patient sorting interacts with physician-targeted policies, we develop an equilibrium model of patient choice of physicians and physicians' opioid prescription decisions. We model the patients' choice stage as a static, discrete choice demand model in spirit of Berry, Levinsohn, and Pakes (1995), in which patients optimally choose their physicians, conditional on their own type and their perceptions of physician types. Patient types are time-persistent tuples that summarize both opioid taste and patient information. We allow opioid taste heterogeneity to arise from both medical needs and non-medical preferences. Patients' information types determine how accurately they percive physicians' prescription propensities. When choosing a physician, patients consider the expected prescription probability based on their own opioid taste and information type. In the prescription stage, partially altruistic physicians optimally prescribe opioids based on their own prescribing propensities and patients' opioid tastes.

Estimating our model is challenging because it features three dimensions of unobserved heterogeneity: physicians' prescription propensity, patients' opioid tastes, and patients' information types. To reduce the estimation burden, we estimate our model in three steps using a limited-information maximum-likelihood approach. First, we use our panel on realized opioid prescriptions to estimate both physicians' prescription propensities and patients' opioid tastes with a two-way fixed-effects logit model that includes time-varying controls. This estimation closely mirrors our earlier decomposition of prescription rate variation and follows the grouped fixed-effects approach in Bonhomme, Lamadon, and Manresa (2019) and Mourot (2025). Second, conditional on the first-stage estimates, we estimate the patient choice stage by maximum likelihood. This step recovers mean utilities for each physician, parameters governing idiosyncratic preferences for office visits, and the distribution of time-invariant patient information types by leveraging the panel structure of the data. Finally, we decompose the patient opioid taste estimates from the first stage into a medically grounded component and a non-medical preference component using rich patient-level controls.

We use our estimates to simulate several counterfactuals. We first illustrate how patient sorting interacts with physician-targeted policies such as prescription drug monitoring programs, which identify outlier prescribers and induce changes in prescribing behavior through

[1] For example, https://www.reddit.com/r/hudsonvalley/comments/1ccgimp/pain_management_doctor_that_will_actually_manage/, and https://www.reddit.com/r/grassvalley/comments/1kn7h0i/doctor_that_prescribes_opiates_in_town_or_nc/

feedback, reporting, or enhanced monitoring (Amin-Esmaeili et al. 2023). For physician-targeted policies to work well, much of the variation in prescription rates must reflect differences in physicians' underlying propensity to prescribe. However, our results on preference-based patient sorting cast doubt on their effectiveness. To illustrate this point, we consider an extreme version of such policies by excluding the top 5% of prescribers from the market. We find that even though our policy is extreme, aggregate opioid prescriptions drop only modestly. This muted response arises because patients do not choose physicians randomly. Instead, our results imply that patients sort toward physicians whose prescribing propensity aligns with their own opioid tastes. When physician-targeted policies eliminate these first-best matches, patients optimally re-sort to the remaining physicians. Because high-prescribing physicians are disproportionately chosen by patients with high opioid tastes, this re-sorting disproportionately shifts demand toward the highest-prescribing physicians who remain in the market, attenuating the aggregate reduction in opioid prescribing.

To further illustrate how patient resorting attenuates the exclusion policy effect, we simulate an alternative counterfactual that eliminates patient re-sorting among those who originally chose an excluded physician. In particular, patients who visited an excluded physician in the baseline choose only whether to seek care. Conditional on seeking care, they are randomly assigned to a physician. Under this counterfactual, eliminating the top 5% of physicians by prescription rate reduces aggregate opioid prescriptions even more. These results demonstrate the constraints faced by supply-side-focused policies that are agnostic to demand-side responses: ignoring consumer choice attenuates the effectiveness of expert-targeted policies.

An important drawback of the randomization policy is that it prevents patients from choosing their physician. The medical literature shows that physician choice is crucial for patients' engagement and retention in care (Hsu et al. 2003). Consistent with this evidence, our results predict that when patients are randomized to physicians, most would rather forgo care than accept random assignment. Although randomization aggressively reduces aggregate opioid prescriptions, it achieves so by breaking optimal patient-physician matches, regardless of whether sorting is based on patient medical needs ("good sorting") or on medically unjustified preference for opioids ("bad sorting"). This makes randomization an undesirable policy. To disentangle good from bad sorting, we consider a policy that restricts opioid prescribing to medically grounded patient needs, excluding non-medical preference. By eliminating incentives for patients to choose providers based on non-medical opioid preferences, this policy reduces aggregate prescribing rates by a decent amount while preserving appropriate care for patients with medical needs for opioid treatment.

Literature Review. This paper brings tools from the labor literature to the healthcare setting (Abowd, Kramarz, and Margolis 1999; Card, Jörg Heining, and Kline 2013; Card, Cardoso, Joerg Heining, and Kline 2018; Bonhomme, Lamadon, and Manresa 2019; Bonhomme, Holzheu, et al. 2023; Kline 2024). Our main contribution is to provide the first evidence of strong positive sorting between patients and physicians in the U.S. prescription opioid market. A related paper is Mourot (2025), which studies surgeon–hospital sorting and complementarities in the context of coronary artery bypass graft surgery. We go beyond by developing an equilibrium model of endogeneous patient sorting and physician prescribing decision, which we use to study counterfactual policy interventions. Our approach is similar to "mover design" in healthcare. The most closely related study is Finkelstein, Gentzkow, and D. Li (2025), which separately identifies individual-specific and region-specific drivers of risky opioid use. We differ by focusing on patient sorting toward providers and its interaction with supply-side-targeted opioid policies. Furthermore, we emphasize a distinct counterfactual policy that targets bad sorting based on non-medical preferences, reducing opioid prescribing while preserving appropriate care for patients with legitimate medical needs.

Our analysis contributes to a large and growing literature evaluating the role of physicians in the opioid crisis (Schnell and Currie 2018; Currie and Schwandt 2020; Schnell 2025; Currie, A. Li, and Schnell 2023). While recent work shows that exposure to high-prescribing physicians worsens health and labor market outcomes (Barnett, Olenski, and Jena 2017; Staiger, Baker, and Hernandez-Boussard 2022; Eichmeyer and Zhang 2022; Eichmeyer and Zhang 2023; Alpert, Schwab, and Ukert 2025), surprisingly little is known about why patients continue to seek care from these physicians.[2] By emphasizing patient sorting, we link the demand and supply sides of the opioid market and show that patient preferences play a central role in shaping the effectiveness of supply-side interventions. This perspective is particularly important given the widespread adoption of policies that restrict prescribers (Meara et al. 2016; Buchmueller and Carey 2018; Sacks, Hollingsworth, Nguyen, and Simon 2021; Alpert, Dykstra, and Jacobson 2024). By endogenizing patient sorting, we provide novel evidence that patients with stronger opioid preferences disproportionately sort toward high-prescribing physicians, which attenuates the effectiveness of policies that target top prescribers.

[2]The studies above rely on quasi-random assignment of patients to physicians—for example, through emergency room encounters or physician exit from Medicaid—to identify causal effects, abstracting from endogenous patient decisions.

2 Prescription Opioids for Chronic Pain

In this paper, we focus on the use of prescription opioids for the treatment of chronic pain in outpatient office visits. We first present the setting and afterwards discuss the data we use in our research.

2.1 Setting

We begin by discussing chronic pain in the United States. According to the Centers for Disease Control and Prevention (CDC), chronic pain is defined as an episode of pain that lasts for at least 3 months (Dowell, Ragan, et al. 2022b). Chronic pain affects a significant fraction of the general population. In 2023, around 24% of the United States' adult population suffered from chronic pain (Lucas and Sohi 2024). Due to its nature, chronic pain often leaves affected individuals incapacitated and unable to function properly without treatment. Treatment for chronic pain in the United States commonly involves the use of prescription opioids. Around 22% of US adults suffering from chronic pain rely on prescription opioids for pain management (Dahlhamer et al. 2021). Chronic pain is not a condition of old age and affects adults of all age groups. However, the use of prescription opioids for pain management is most common among working-age adults. According to the National Center for Health Statistics, adults aged 45-64 years exhibit the highest rates of prescription opioid use (Dahlhamer et al. 2021). Because most of the affected patients are of working age, almost 2 in 3 payments for opioid prescription collections are covered by private insurance (Schnell 2025).

In the United States, patients must obtain prescription opioids by prescription from a licensed healthcare provider. About 4 in 5 prescription opioids in the United States are prescribed by physicians (Schnell 2025). In outpatient settings, patients can generally choose the physician they want to see, with limitations on their choice set depending on their respective insurance network. Once a patient has chosen a physician, the physician examines the patient and decides whether to prescribe opioids or not. If prescribing opioids, the physician also has to decide on the number of days of supply. Contrary to acute pain, where initial supply in 33 states is limited to 5 to 7 days or less, no such regulation exists for opioids used for treating chronic pain (Department of Health and Human Services 2025). Large studies have found that the average number of days of supply is around 28 days. After the days of supply are used, patients can get a refill if their prescription allows it, or they have to see a physician to obtain a new prescription.

Prescription opioids are a common part of pain management for both acute and chronic pain in the United States. The use of prescription opioids for *acute pain* for short periods

of time is widely accepted as medically justified (Dowell, Ragan, et al. 2022b). However, the use of prescription opioids for *chronic pain* management is posing substantial health risks while lacking clear evidence of any health benefits for patients (Volkow and McLellan 2016). Metastudies have found an association of adverse health outcomes, such as increased risk of opioid abuse and dependence, all-cause mortality, and myocardial infarction, with long-term opioid treatment for chronic pain (Chou et al. 2020). There is also growing evidence that long-term prescription opioids may make it harder to effectively manage pain in chronic pain patients. Long-term opioid use may result in opioid induced hyperalgesia in patients, a condition that increases pain sensitivity that may extend beyond areas initially affected by chronic pain for which the opioids were prescribed (Lee et al. 2011). As a result, the CDC Clinical Practice Guideline for Prescribing Opioids for Pain only mentions four conditions that unequivocally warrant prescribing opioids for chronic pain: cancer-related pain treatment, sickle cell disease, palliative care, and end-of-life care (Dowell, Ragan, et al. 2022b). Outside of these conditions, prescription opioids should not be used as a first line of treatment, but the decision on whether to use prescription opioids for pain management is generally left to the physician and patient (Dowell, Ragan, et al. 2022b). This ambiguity leaves the eventual decision to use prescription opioids as a course of treatment up to the physicians' discretion and patient preference.

2.2 MarketScan Data

As we discussed above, the majority of patients who receive prescription opioid treatment for chronic pain are privately insured working-age adults. For this reason, we need to assemble a data set that covers the relevant, privately insured working-age population comprehensively. Consequently, we cannot rely on the often-used data from the Centers for Medicare & Medicaid Services. Instead, we rely on data from the Merative MarketScan Research Databases. The MarketScan Commercial Database consists of individual-level, de-identified healthcare claims for millions of enrollees and their dependents in employer-sponsored healthcare plans in the United States. To construct our sample, we combine data from the Commercial Database and the Merative Micromedex RED BOOK for the years 2016 to 2022. We link the Outpatient Services Table, the Inpatient Services Table, and the Outpatient Pharmaceutical Claims Table from the Commercial Database with National Drug Code (NDC)-level information on opioids from the Merative Micromedex RED BOOK.

Using our data sources, we build two data sets for the New York City Metropolitan Statistical Area. We restrict our sample to patients who had an episode of chronic pain and received at least one opioid prescription between 2016 and 2022. The first data set consists

of claims data information on all office visits of covered patients linked with data on their prescription collections. We refer to this data set as the *visit data set*. The second data set supplements these data with information on time periods in which a given patient chose not to see any physician. We refer to this data set as the *choice data set*. We use the former data set to establish patient sorting for our motivating evidence and in our structural estimation, and the second data set solely for our structural estimation.

Step I: Constructing the visit data set.

We construct our data sample in multiple steps. First, we develop a strategy to identify whether a particular office visit for a patient resulted in the prescription of a prescription opioid or not. Following the literature, we define an opioid prescription as any prescription of substances that fall within both, the opioid analgesics category under the American Hospital Formulary Service Classification Compilation Therapeutic Class scheme, and the Drug Enforcement Administration (DEA) drug schedule fall into schedule II or III, indicating high or moderate potential for abuse, respectively (Alpert, Dykstra, and Jacobson 2024; Staiger, Baker, and Hernandez-Boussard 2022).[3] As is common with commercial claims data, we lack national provider identification (NPI) information for the prescribing physician for prescription opioid collections from the Outpatient Pharmaceutical Claims Table. Instead, we use a well-established method to link prescription drug collections with prescribing providers. In particular, we follow Ding and Liu (2021) and assign a prescription to an observed office visit if the prescription opioid collection was within 14 days following the office visit , was the first collection within that time frame among all prescription opioid collections for that patient, and could not be associated with any prior office visit of that patient. Our final variable is a binary indicator for whether a prescription opioid was prescribed during a particular office visit. Note that we are focusing on the extensive rather than the intensive margin.

The MarketScan Commercial Database includes rich demographic and diagnosis information on possible patient risk factors. In particular, for each patient, we observe age, sex, and up to 4 primary diagnoses per outpatient visit. These diagnoses adopt the 10th revision of the International Classification of Diseases, ICD-10 codes. We leverage a patient's medical history within 12 months preceding an office visit to create measures of a patient's health status, as well as possible controls for opioid preference. The first health measure we construct to capture a wide range of comorbidities is the Charlson Comorbidity Index (Charlson, Pompei, Ales, and MacKenzie 1987).[4] Additionally, we follow the CDC Clin-

[3]For the American Hospital Formulary Service Classificationn Compilation (AHFSCC) Therapeutic Class, the opioid analgesics category is "28:08.08".

[4]In particular, we use the 17 categories considered in the popular Charlson/Deyo variant (Deyo 1992). We adopt the more recent weights suggested in Schneeweiss, Wang, Avorn, and Glynn (2003) and provide additional details in the appendix.

ical Practice Guideline for Prescribing Opioids for Pain (Dowell, Ragan, et al. 2022b) to identify whether a patient has a medical condition unequivocally qualifying for prescription opioid treatment. These conditions are cancer-related pain, sickle cell disease, palliative care, and end-of-life care. Next, we construct possible controls for opioid preference by identifying diagnoses for which the CDC guidelines recommend against prescribing or urge caution when prescribing opioids. These conditions are sleep-disordered breathing, renal or hepatic insufficiency, mental health conditions (i.e., anxiety, depression, and post-traumatic stress disorder), substance use disorders, opioid abuse, and non-fatal overdose (Dowell, Ragan, et al. 2022b). We also construct counts of emergency room visits related to non-fatal overdoses, and count inpatient and outpatient visits during the 12 months preceding each office visit. We provide detailed descriptions, including the ICD-10 diagnosis codes used to construct our health status and opioid preference measures, in appendices D and E.

Lastly, we construct measures of out-of-pocket costs for prescription opioids and total outpatient and inpatient spending during the 12 months preceding an office visit, using the financial variables from the MarketScan Commercial Database. Since we do not observe out-of-pocket costs when no opioid was prescribed, we construct out-of-pocket prescription opioid costs per outpatient visit as the mean out-of-pocket cost across insurance-type-month combinations. We provide more details on the construction of this variable in Appendix G. We summarize our first data set in table 1.

Step II: Constructing the choice data set.

For our data set, we use to estimate our structural model, we supplement the above data with additional information on months when a patient could have seen a physician but chose not to see one.[5] For each month, we define the population of active patients (the set of potential patients) as the set of patients who had at least one office visit in the corresponding quarter of that year. If we observe a patient visit a physician in a given month, we record their choice.[6] If we do not observe a patient visiting a physician in a given month for which this patient is part of the active population, we record that the patient chose the outside option of not seeing a physician. If a patient chooses the outside option for a given month, we assume that their characteristics, which we computed for the first data set, are the same as the closest month in that quarter.

[5] We use a month in accordance with our evidence on average days of supply.

[6] 13% of patient-months involve more than one visit. For these cases, we collapse multiple visits into a single patient-month observation if they are all with the same physician (which occurs in about two thirds of these cases), and we record an opioid prescription if any of the visits resulted in one. We exclude patient-months in which a patient saw more than one physician during that month.

Table 1: Summary Statistics of Chronic Pain Patients

Variable	Mean	SD	25 Perc	50 Perc	75 Perc
Panel A: Patient Severity and Constraints					
Age (years)	48.20	11.61	40.00	50.49	58.00
Sex (Male=1)	0.47	0.50	0.00	0.00	1.00
Charlson Commorbidity Index	1.23	1.59	0.00	1.00	2.00
Counts of Prior Inpatient Visits	0.13	0.40	0.00	0.00	0.00
Counts of Prior Outpatient Visits	65.26	70.60	23.50	45.50	83.40
Counts of Prior ED Visits	0.48	1.31	0.00	0.00	0.50
Prior OOP Spending	1696.09	2019.36	394.57	1065.30	2315.74
Out-of-pocket Cost	1.04	0.37	0.79	0.93	1.25
Panel B: Conditions Justifying Opioid Prescription					
Sickle Cell Disease	0.00	0.07	0.00	0.00	0.00
Cancer-Related Pain	0.05	0.23	0.00	0.00	0.00
Panel C: Conditions Discouraging Opioid Prescription					
Renal/Hepatic Deficiency	0.02	0.15	0.00	0.00	0.00
Mental Health Conditions	0.33	0.47	0.00	0.00	1.00
Opioid Misuse	0.04	0.21	0.00	0.00	0.00
Substance Use Disorder	0.12	0.33	0.00	0.00	0.00
Prior Nonfatal Overdose	0.03	0.18	0.00	0.00	0.00
Counts of ED Visits Related to Overdose	0.00	0.05	0.00	0.00	0.00
Work in Construction or Transportation	0.08	0.27	0.00	0.00	0.00
Observations					
Number of unique patients			11,909		
Total observations			59,227		

For our second data set, we also compute additional variables for physicians. Based on the choices of physicians or the outside option by patients, we compute the market shares for physicians for each month. The market share is defined as the number of patients we observe choosing a given physician in a given month, divided by the total number of patients active in that particular month. A common problem in defining market shares based on observable choices is that some options (physicians) may not be chosen in each month. If this happens for some of our physicians, we follow the standard approach in the discrete choice literature and assume that this physician was not active in a given month. We interpret this as the possibility that physicians might close their offices periodically for vacation. We summarize our data set for structural estimation in table 2.

Table 2: Physician Market Share Summary Statistics

Variable	Mean	SD	25 Perc	50 Perc	75 Perc
Physician Market Share (%)	0.09	0.09	0.04	0.06	0.09
Inside Share in a Market (%)	46.97	2.82	45.40	47.06	48.81
Observations					
Number of markets			84		
Number of physicians			8059		

3 Establishing Patient Sorting

In this section, we first document variation in opioid prescription rates for chronic pain patients across physicians. We then decompose the sources of this variation. A physician's prescribing rate reflects not only their underlying prescribing propensity, but also differences in patient severity, patient preferences, and patient sorting into physicians based on both medical needs and non-medical preferences. We are particularly interested in assessing the relative importance of patient sorting versus physician prescribing propensity in explaining cross-physician differences in prescription rates. Finally, we extend the analysis beyond prescribing to opioid misuse, examining the extent to which patient sorting contributes to risky opioid use.

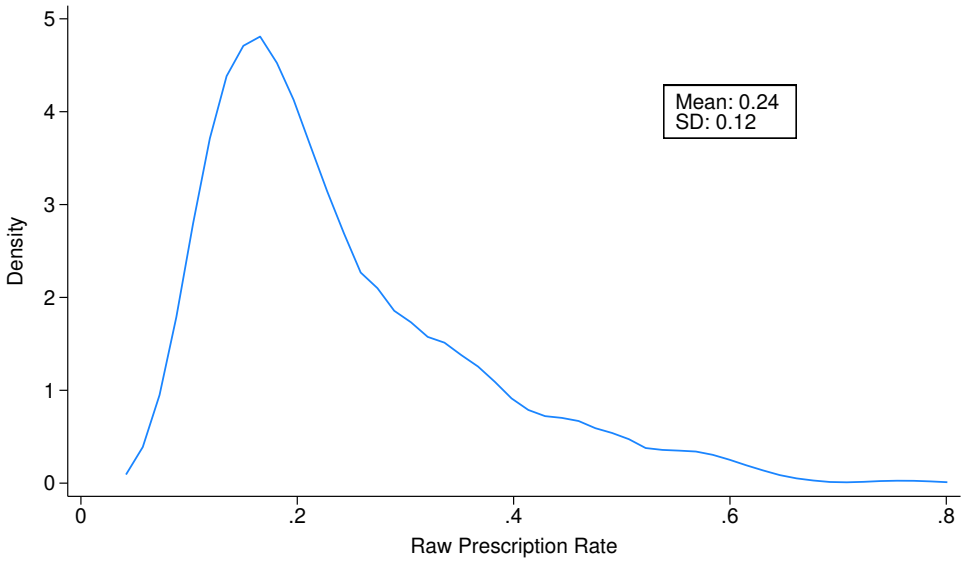
Cross-Physician Variation in Prescription Rates. Our primary outcome is an indicator equal to one if an office visit results in an opioid prescription. We estimate physician-level raw prescription rates by regressing this indicator on physician fixed effects:

$$\text{prescribe}_{it} = a_{j(i,t)} + \varepsilon_{it}, \tag{1}$$

where prescribe$_{it}$ equals one if patient i receives an opioid prescription at visit t, $a_{j(i,t)}$ denotes the fixed effect for physician j, capturing physician j's average prescription rate in the data, and ε_{it} is the error term. Because estimates of $a_{j(i,t)}$ can be noisy for physicians with relatively few patient visits, we apply an empirical Bayes shrinkage estimator that shrinks imprecisely estimated fixed effectstowards the overall mean, following Chandra, Finkelstein, Sacarny, and Syverson (2016).

Figure 1 plots the density of the empirical Bayes–adjusted physician fixed effects, $\hat{a}_{j(i,t)}$. The distribution reveals substantial heterogeneity in raw prescription rates across physicians: the standard deviation is one-half of the mean prescription rate. This finding is consistent with prior evidence documenting large differences in drug prescribing intensity across providers (Finkelstein, Gentzkow, and Williams 2016; Molitor 2018; Cutler, Skinner, Stern, and Wennberg 2019; Badinski, Finkelstein, Gentzkow, and Hull 2023; Clemens, Léger, Nandan, and Town 2024). The distribution also features a thick upper tail, indicating that a nontrivial share of physicians prescribe opioids at rates far above the average.

Figure 1: Raw Physician Prescription Rate



Notes: This figure plots the distribution of the empirical Bayes–adjusted physician fixed effects from equation (1). We restrict the sample to patients with at least 10 visits and physicians with at least 10 patient visits over the sample period.

A natural question is whether the large variation in opioid prescribing rates primarily reflects differences in patient case mix, specifically, whether some physicians treat sicker patients who are more likely to receive opioids. To assess this possibility, we risk-adjust prescribing decisions for a rich set of patient observables.

These observables fall into three categories: (1) health severity and patient-specific con-

straints, such as patient age, sex, the Charlson comorbidity index, counts of historical inpatient, outpatient, and emergency-department visits, historical out-of-pocket spending, and patient cost sharing; (2) patient medical conditions for which opioid use may be clinically warranted under the CDC's opioid prescribing guidelines (Dowell, Ragan, et al. 2022a). These include sickle-cell disease and cancer-related pain; and (3) diagnoses and risk indicators for which the CDC recommends caution or avoidance in the management of chronic pain, given the availability of safer and more effective non-opioid alternatives. This group includes diagnoses of renal or hepatic insufficiency, mental health conditions, opioid misuse or substance-use disorder, prior nonfatal overdose, counts of emergency-department visits related to overdose, and an indicator for employment in construction or transportation industries.

To obtain a risk-adjusted prescription rate for each physician, we control for the full set of patient observables described above, denoted by X_{it}. We also include the year fixed effects, τ_t, to absorb common time-varying factors such as policy changes and guideline updates in the following regression:

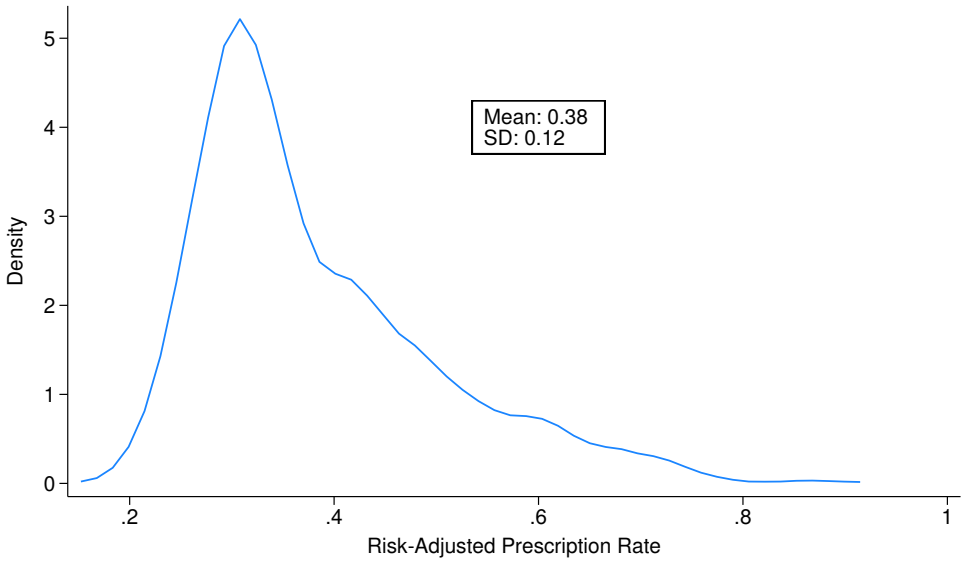
$$\text{prescribe}_{it} = a_{j(i,t)} + X_{it}b + \tau_t + \epsilon_{it}. \tag{2}$$

where $a_{j(i,t)}$ captures the physician-specific risk-adjusted mean prescription rate, abstracting from observable patient characteristics and common time effects. After applying the empirical Bayes shrinkage procedure to correct the estimated $\hat{a}_{j(i,t)}$ for measurement error, we plot the density for the empirical Bayes–adjusted $\hat{a}_{j(i,t)}$ in Figure 2.

Figure 2 shows that controlling for patient observables and year fixed effects leaves the dispersion in prescription rates largely unchanged relative to Figure 1. In other words, the prescription rate heterogeneity across physicians is not primarily driven by patient observables or common time trends; otherwise, the distribution of risk-adjusted prescription rates would be much more compressed.

Taken at face value, this pattern appears to provide a natural empirical rationale for policies that target high-prescribing physicians, under the interpretation that the remaining variation reflects differences in physicians' intrinsic prescribing propensities. However, a physician's high observed prescription rate may instead reflect unobserved patient preferences and positive sorting of high-preference patients into high-prescribing physicians. Under such positive sorting, even modest differences in physicians' underlying prescribing propensities can generate amplified differences in observed prescribing rates. Conversely, if patient sorting is negative, the true dispersion in physician prescribing propensities may be larger than what is implied by the observed prescription rates.

Figure 2: Risk-adjusted Prescription Rate



Notes: This figure plots the distribution of the empirical Bayes–adjusted, risk-adjusted physician fixed effects from equation (2). We restrict the sample to patients with at least 10 visits and physicians with at least 10 patient visits over the sample period.

Patient Sorting. To assess the importance of patient sorting relative to physicians' prescribing propensities in explaining the dispersion of prescription rates, we exploit the panel structure of the data to decompose variation in raw prescription decisions into components attributable to patient type, physician type, and sorting of patients into physicians whose prescribing styles they prefer. We further distinguish sorting based on medical needs versus on non-medical preferences.

We adopt the well-known two-way fixed effects estimator of Abowd, Kramarz, and Margolis (1999) to regress prescription decisions on patient fixed effects, physician fixed effects, patient observables and year dummies:

$$\text{prescribe}_{it} = \eta_{j(i,t)} + \theta_i + X_i\beta + \tau_t + \varepsilon_{it}, \tag{3}$$

where $\eta_{j(i,t)}$ represents the physician prescribing propensity, θ_i represents patient unobserved type, and X_i is a vector of patient observables defined as above.[7] τ_t are year dummies and ε_{it} is the error term representing unobserved time-varying patient characteristics.

Note that in equation (3), β and θ_i are not separately identified because they are both

[7]Because most of these observables exhibit little within-patient variation over time, we use patient-level averages and treat them as time-invariant characteristics. Including time-varying versions of these variables when available yields highly similar results in terms of the relative importance of each component in explaining variation in prescription rates.

patient-specific. Therefore, we define $\Theta_i \equiv \theta_i + \beta X_i$ and treat Θ_i as patient fixed effect for estimation in the spirit of Abowd, Kramarz, and Margolis (1999). We now rewrite equation (3) as

$$\begin{aligned} \text{prescribe}_{it} &= \eta_{j(i,t)} + \underbrace{\theta_i + X_i\beta}_{\equiv\Theta_i} + \tau_t + \varepsilon_{it} \\ &= \eta_{j(i,t)} + \Theta_i + \tau_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

Obtaining unbiased fixed effects in an Abowd, Kramarz, and Margolis (1999) style model is challenging, because physician fixed effects are identified only from patients who switch physicians. When switching is limited, fixed effects estimates can be severely biased, a problem known as limited mobility bias (Andrews, Gill, Schank, and Upward 2012; Bonhomme, Holzheu, et al. 2023). Recent advances in the labor literature show that this bias can be mitigated using a two-step estimator that first groups firms and then estimates group-level fixed effects (Bonhomme, Lamadon, and Manresa 2019). We adopt the approach of Bonhomme, Lamadon, and Manresa (2019) and follow Mourot (2025) to a healthcare setting of drug prescription. In the first stage, we group physicians and patients using k-means clustering based on physician-level and patient-level risk-adjusted prescription rates, respectively.[8] Appendix A provides details on the grouping algorithm. Following standard practice (Kline 2024), we use ten groups for physicians and ten groups for patients. We assess robustness by varying the number of groups. In the second stage, we estimate equation (4) using group-level physician and patient fixed effects.

After obtaining the group-level fixed effects estimates $\hat{\eta}_{j(i,t)}$ and $\hat{\Theta}_i$, we further decompose $\hat{\Theta}_i$ into parts explained by patient medical needs and non-medical preferences. To do so, we regress patient fixed effects estimates, $\hat{\Theta}_i$, on X_i, all the patient observables.

$$\hat{\Theta}_i = \underbrace{X_{1i}\beta_1}_{\text{medical needs}} + \underbrace{X_{2i}\beta_2 + \theta_i}_{\text{non-medical preferences}}, \tag{5}$$

We categorize X_i into two sets of time-invariant patient characteristics: medical needs, X_{1i}, and non-medical preferences, X_{2i}. X_{1i} include variables under (1) health severity and patient-specific con- straints, as defined before, and (2) diagnoses that warrant opioid use, including sickle-cell disease and cancer-related pain. While not all of these variables reflect clinical appropriateness in a narrow sense, they capture patient characteristics commonly

[8] Mourot (2025) groups surgeons and hospitals, whereas we group patients and physicians.

considered in pain management decisions emphasized in CDC guidance. All remaining factors that are not medically justified are in X_{2i}. This set includes (3) characteristics for which the CDC explicitly recommends caution or avoidance of opioid use for managing chronic pain, as well as the residualized patient fixed effects obtained after partialing out X_i from $\hat{\Theta}_i$.

We now introduce a variance decomposition of the prescribing decision. Focusing on the variation in prescribing that can be explained by patient type, physician type, and their covariance, we write

$$\begin{aligned} var(\text{prescribe}_{it}^{E}) &\equiv var(\eta_{j(i,t)} + X_{1i}\beta_1 + X_{2i}\beta_2 + \theta_i) \\ &= var(\eta_{j(i,t)}) + var(X_{1i}\beta_1) + var(X_{2i}\beta_2 + \theta_i), \\ &+ 2cov(X_{1i}\beta_1, \eta_{j(i,t)}) + 2cov(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)}) + 2cov(X_{1i}\beta_1, X_{2i}\beta_2 + \theta_i) \end{aligned} \tag{6}$$

where $var(X_{1i}\beta_1)$ captures variation in prescribing explained by patient medical needs relevant for opioid use, while $var(X_{2i}\beta_2 + \theta_i)$ reflects variation associated with patient non-medical preferences. The term $var(\eta_{j(i,t)})$ represents variation attributable to physician prescribing propensity. The covariance term $cov(X_{1i}\beta_1, \eta_{j(i,t)})$ captures patient sorting based on medical needs, whereas $cov(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})$ captures sorting based on non-medical preferences. Finally, $cov(X_{1i}\beta_1, X_{2i}\beta_2 + \theta_i)$ reflects the correlation between patients' medical needs and non-medical preferences. We report the results of our variance decomposition in table 3. Following the recommendation of Kline (2024), we scale each component of the decomposition by $var(\text{prescribe}_{it}^{E})$. This normalization ensures the comparability of our results with related studies.

In Table 3, under the baseline specification, we form ten groups of patients and physicians and restrict the sample to patients with at least 2 visits and physicians with at least 2 patient visits over the sample period. We then assess the robustness of the variance decomposition by varying the number of groups and the sample restrictions, and by using empirical Bayes–adjusted estimates of the risk-adjusted prescription rates for grouping.

Across specifications, and irrespective of whether we apply Bayesian shrinkage, table 3 shows strong positive assortative matching between patients and physicians.[9] Patient sorting based on medical needs explains only about 5 percent of the variation in prescription rates, whereas sorting on non-medical preferences accounts for more than 30 percent. Perhaps surprisingly, physicians' intrinsic prescribing propensity explains only around 10 percent of the variation in prescribing decisions. Taken together, patient sorting into physicians accounts for roughly three times as much of the observed heterogeneity in prescribing rates

[9]Due to space constraints, we do not report the term $2cov(X_{1i}\beta_1, X_{2i}\beta_2 + \theta_i)$, which is close to zero. As a result, summing the first five rows for a given column yields nearly 100%.

as providers' own prescribing propensity. Consistent with this finding, the correlation coefficient between patients' non-medical preferences and their chosen physicians' prescribing propensity is as high as 0.66.

Table 3: Percentage of Variance Explained in Raw Prescription Rates (%)

	Baseline	**Alternative Number of Groups**				**Alternative Sample Restrictions,** $K = 10$			**Bayesian Shrinkage**
	$K = 10$ ≥ 2 visits/patient ≥ 2 visits/provider	$K = 5$	$K = 15$	$K = 20$	$K = 50$	≥ 1 visits/patient ≥ 1 visits/provider	≥ 5 visits/patient ≥ 5 visits/provider	≥ 10 visits/patient ≥ 10 visits/provider	$K = 10$ ≥ 10 visits/patient ≥ 10 visits/provider
Patient									
$\frac{\text{Var}(X_{2i}\beta_2 + \theta_i)}{\text{Var}(\text{prescribe}^E)}$	49.58	49.08	50.70	50.79	51.68	49.15	50.89	51.16	52.70
$\frac{\text{Var}(X_{1i}\beta_1)}{\text{Var}(\text{prescribe}^E)}$	4.70	4.62	4.74	4.81	4.65	2.82	3.66	4.42	5.04
Provider									
$\frac{\text{Var}(\eta_{j(i,t)})}{\text{Var}(\text{prescribe}^E)}$	12.12	12.65	11.29	11.28	11.04	17.16	14.49	12.26	10.11
Sorting									
$2 \times \frac{\text{Cov}(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})}{\text{Var}(\text{prescribe}^E)}$	31.70	31.49	31.38	31.33	30.99	30.13	30.10	30.73	30.22
$2 \times \frac{\text{Cov}(X_{1i}\beta_1, \eta_{j(i,t)})}{\text{Var}(\text{prescribe}^E)}$	1.90	2.16	1.89	1.79	1.63	0.74	0.85	1.42	1.93
Correlation									
$\text{corr}(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})$	0.66	0.65	0.66	0.66	0.65	0.52	0.55	0.62	0.67
$\text{corr}(X_{1i}\beta_1, \eta_{j(i,t)})$	0.13	0.14	0.13	0.12	0.11	0.05	0.06	0.10	0.14

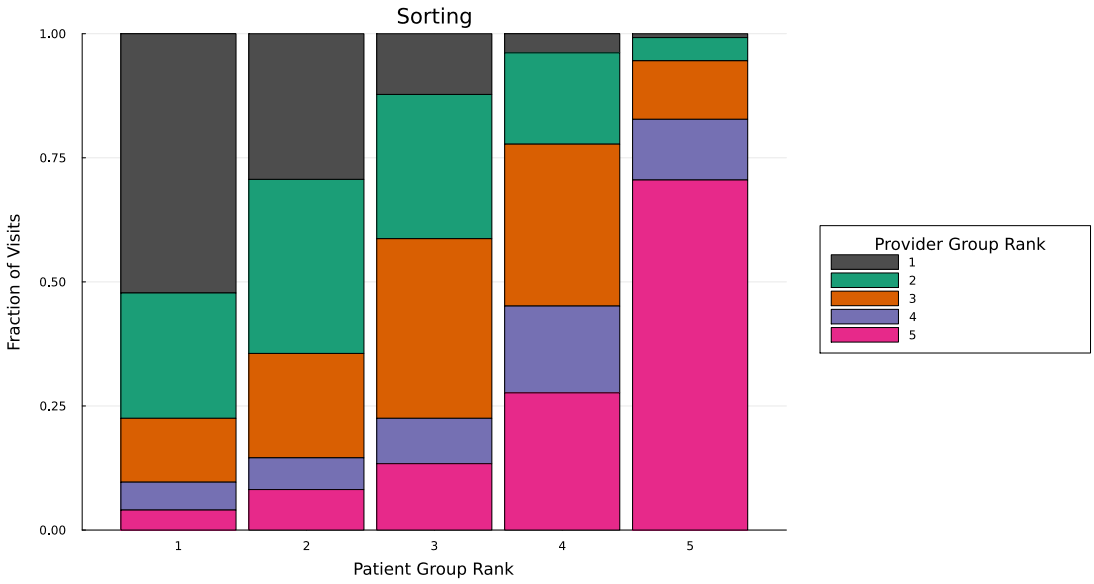


Figure 3: Patient Sorting

We further illustrate strong positive assortative matching in Figure 3. Figure 3 shows that patients with low opioid preference (group 1) make more than half of their visits to providers who prescribe the least opioids (group 1). Conversely, patients with high opioid preference (group 5) disproportionally choose providers with the highest prescription rates (group 5). Appendix Figure 8 shows the same patterns when patients and providers are divided into 10 groups instead of 5.

Positive patient sorting implies that the observed differences in prescription rates across physicians are larger than the underlying differences in physicians' true prescribing propensities. In other words, positive sorting amplifies variation in prescribing behavior, leading to a steeper gradient in the raw prescription rate. Figure 4 illustrates this mechanism: the horizontal axis represents ten physician groups ranked by their raw prescription rates. Each blue triangle shows the raw prescription rate for a physician group, while each red circle indicates the estimated physician fixed effect, i.e., the group's prescribing propensity, scaled by the base prescription rate of group 5. The fitted line for the raw prescription rate is visibly steeper, reflecting positive patient sorting. At the upper end of the distribution, physicians appear to prescribe much more than they truly do; their true propensities are overstated if one relies solely on raw prescription rates. Conversely, physicians in the lower percentiles appear to prescribe far less, even though their true propensities are not that different from those of higher prescribers.

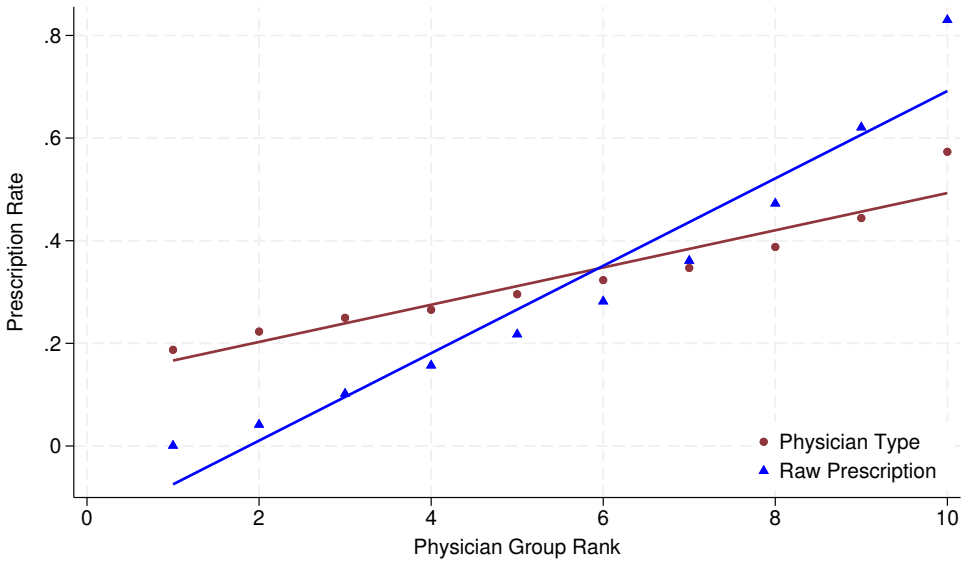


Figure 4: Patient Sorting Versus Physician Propensity Type

Patient Sorting Contributes to Risky Opioid Use. We have established that variation in observed cross-physician prescription rates is driven less by differences in physicians' prescribing propensities and more by patients sorting into physicians according to those propensities. We now examine whether such positive patient sorting plays an important role in explaining adverse health outcomes. To do so, we revisit the decomposition exercise in equation (4), replacing the prescription outcome variable with an indicator for opioid misuse at that visit. Following the literature, a visit is classified as involving opioid misuse if the patient's daily MED is 120 mg or greater, given the documented correlation between such prescription levels and opioid abuse (Meara et al. 2016; Staiger, Baker, and Hernandez-Boussard 2022; Finkelstein, Gentzkow, and D. Li 2025). We provide details on the construction of our measure of daily MED in Appendix F. We focus on this health outcome because it is well defined at the visit level and provides a more objective measure than opioid-abuse–related diagnoses, which depend on the physician's or patient's willingness to test and assessment. Moreover, opioid misuse is both a strong risk factor for, and a precursor to, opioid addiction. Based on this definition, 6% of visits involve risky opioid use.

In Table 4, we decompose the explained variation in opioid misuse into components attributable to patient medical needs ($X_{1i}\beta_1$), patient non-medical preferences ($X_{2i}\beta_2 + \theta_i$), physician prescribing propensity ($\eta_{j(i,t)}$), and patient sorting on both medical needs and non-medical preferences ($Cov(X_{1i}\beta_1, \eta_{j(i,t)})$ and $Cov(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})$). All specifications yield similar results. The patterns closely mirror those from the decomposition of raw opioid prescription rates. Patient sorting explains nearly one-third of the variation in opioid

misuse, far outweighing the contribution of physician prescribing propensity, which accounts for less than 10% in the baseline specification. The correlation coefficient between patient non-medical preference type and physician propensity is as high as 0.64. Moreover, the contribution of patient medical needs is much smaller in this context, suggesting that non-medical preferences play a central role in driving opioid misuse. These results indicate that patient sorting not only drives high opioid prescription rates but is also associated with worse health outcomes, thereby amplifying the opioid epidemic.

Table 4: Percentage of Variance Explained in Opioid Misuse (%)

	Baseline	**Alternative Number of Groups**				**Alternative Sample Restrictions,** $K = 10$			**Bayesian Shrinkage**
	$K = 10$ ≥ 2 visits/patient ≥ 2 visits/provider	$K = 5$	$K = 15$	$K = 20$	$K = 50$	≥ 1 visits/patient ≥ 1 visits/provider	≥ 2 visits/patient ≥ 2 visits/provider	≥ 5 visits/patient ≥ 5 visits/provider	$K = 10$ Bayes shrinkage
Patient									
$\frac{\text{Var}(X_{2i}\beta_2 + \theta_i)}{\text{Var}(\text{opioid misuse}^E)}$	61.30	52.80	60.66	60.76	60.61	57.24	62.64	65.47	62.27
$\frac{\text{Var}(X_{1i}\beta_1)}{\text{Var}(\text{opioid misuse}^E)}$	0.70	0.90	0.72	0.76	0.87	0.53	0.67	0.72	0.92
Provider									
$\frac{\text{Var}(\eta_{j(i,t)})}{\text{Var}(\text{opioid misuse}^E)}$	8.40	13.34	8.54	8.59	8.85	13.14	9.93	7.48	8.05
Sorting									
$2 \times \frac{\text{Cov}(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})}{\text{Var}(\text{opioid misuse}^E)}$	29.21	32.51	29.73	29.53	29.36	28.89	26.53	25.97	28.36
$2 \times \frac{\text{Cov}(X_{1i}\beta_1, \eta_{j(i,t)})}{\text{Var}(\text{opioid misuse}^E)}$	0.39	0.45	0.36	0.37	0.30	0.21	0.23	0.36	0.39
Correlation									
$\text{corr}(X_{2i}\beta_2 + \theta_i, \eta_{j(i,t)})$	0.65	0.62	0.66	0.65	0.64	0.53	0.53	0.59	0.64
$\text{corr}(X_{1i}\beta_1, \eta_{j(i,t)})$	0.08	0.07	0.07	0.07	0.05	0.04	0.05	0.08	0.07

Threat to Identification. Including patient fixed effects, which absorb all time-invariant unobserved patient characteristics, addresses many sources of confounding. However, fixed effects estimates may still be biased if patients' switching decisions are correlated with unobserved time-varying characteristics ε_{it}. Following the labor literature, we provide evidence that switching is not driven by omitted time-varying unobservables in our setting. In particular, Card, Cardoso, Joerg Heining, and Kline (2018) show that if worker switching is exogenous, workers exhibit symmetric wage responses with opposite signs when switching to higher- versus lower- type firms. Analogously, if patient switching is exogenous in our context, patients who switch to more aggressive prescribers should experience prescription probability changes that are symmetric, with opposite signs, to those who switch to less aggressive prescribers.

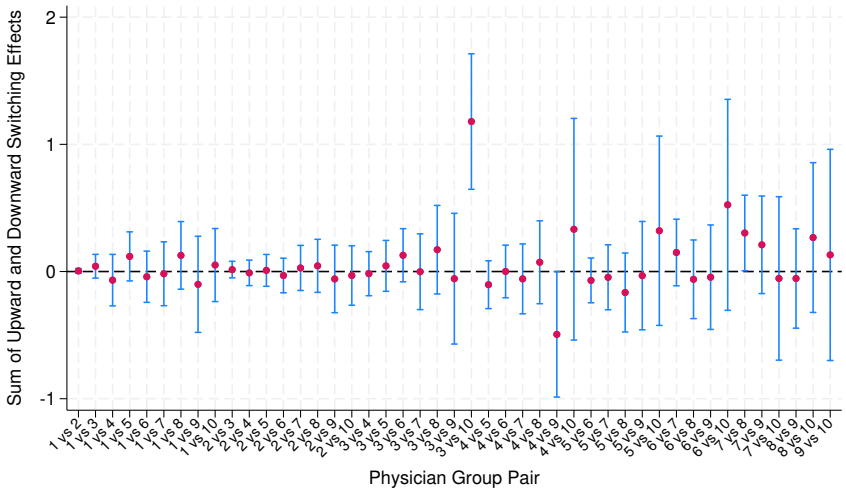
We test this implication in Figure 5 (with implementation details provided in Appendix). The figure presents pairwise analyses of movers between physician groups. For each pair of physician groups, we estimate the effect of switching across groups relative to remaining within the same group. For example, for the physician group pair 1 and 2, some patients move from physician group 1 to group 2 ("move up"), others move from group 2 to group 1 ("move down"), while patients who switch physicians but remain within the same group serve as a control group. We implement a difference-in-differences–style design to estimate the effect of crossing groups relative to staying within a group.

Across all 45 group pairs, with one exception, we find that the change in prescription probability has opposite signs for move-up and move-down patients, and that the magnitudes are highly similar. As shown in Figure 5, each dot reports the sum of the estimated move-up and move-down effects, which is generally close to zero and statistically insignificant. This symmetric response pattern holds across all pairs of physician groups.

We further conduct an event-study analysis, pooling all movers into move-up and move-down categories, to examine whether switching is preceded by differential pre-trends. As shown in Figure 6, we find no evidence of pre-trends in prescribing behavior prior to the switch. This absence of pre-trends further suggests that switching is not driven by patients' gradual learning or other time-varying unobserved factors.

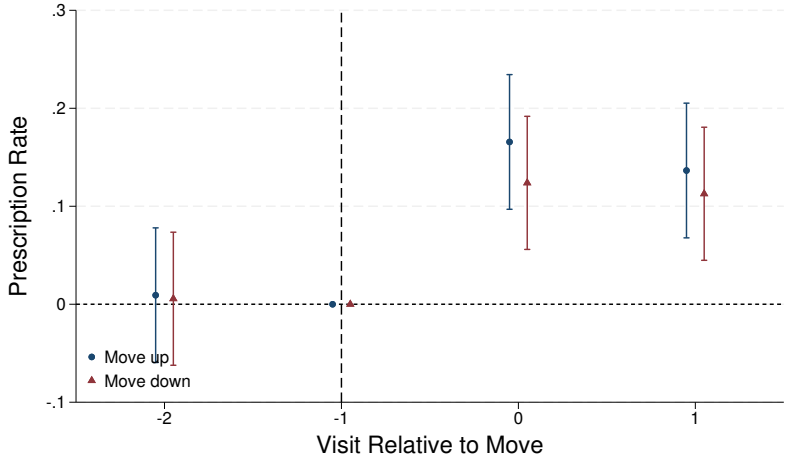
Discussion. Our finding that patient sorting dominates providers' prescribing propensity in explaining variation in both prescription rates and opioid misuse has important policy implications. First, policies that target only high prescribers are unlikely to be effective in curbing prescription rate or opioid misuse, as patients who initially sought care from these top prescribers are likely to re-sort toward other providers whose prescribing propensity is just below the targeted prescribers. Second, explioting patient sorting might be a promising

Figure 5: Net Prescription Rate Response to Upward and Downward Patient Switching



Notes: This figure plots the sum of the changes in prescription rates for patients who switch upward and downward within each pair of physician groups. Physician groups are defined based on physician-level risk-adjusted prescription rates and are ordered from 1 (lowest-prescribing group) to 10 (highest-prescribing group).

Figure 6: Magnitude of Prescription Rate Responses to Patient Switching



Notes: This figure plots the magnitude of changes in prescription rates for patients who switch to higher-prescribing physicians ("move up") and to lower-prescribing physicians ("move down"). Time 0 corresponds to the visit at which the physician switch occurs.

revenue to address opoioid over-prescription, especially if a policy could disencourage patient sorting based on non-medical preferences while preserving patient sorting based medical needs.

To examine how patient sorting interacts with different physicisn-targeted policies and evaluate alternative policies, we propose and estimate a structural model that explicitly accounts for patient sorting in the next section.

4 Model

Our results in section 3 suggest that patients choose physicians according to physicians' prescribing type. We present a one-period model of physician-patient interaction that captures patient sorting we uncovered in section 3. The game proceeds in two stages. In the first stage, the *choice stage*, patients choose a physician based on their beliefs about physicians' prescribing behaviors. Then, in the second stage, the *prescription stage*, the chosen physicians decide whether to prescribe or not. We illustrate our two-stage model for a single month t and a single patient i in figure 7.

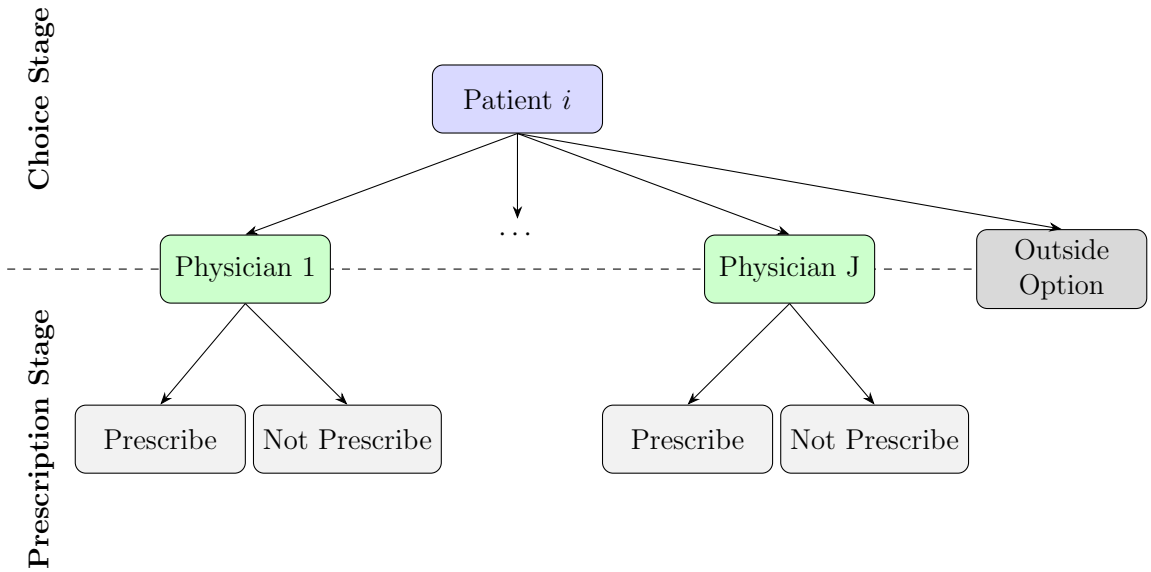


Figure 7: Illustration of two-stage model for each month t.

4.1 Indirect Utility Functions

We start by defining the indirect utility function of physicians. In each month t, physician j makes a treatment decision for patient i if patient i chose physician j. This treatment

decision is a binary choice between prescribing an opioid or not prescribing one. Physician j's indirect utility from treating patient i is given by

$$V_{ijt} = \pi_{jt} + \eta_j a_{ijt} + \beta(U_{ijt}(a_{ijt}) - \gamma) + \varepsilon_{ijt}(a_{ijt}). \tag{7}$$

Here, π_{jt} represents the base profit from treating a patient measured in utils, η_j is a physician-specific fixed effect measuring prescribing propensity, a_{ijt} equals 1 if a physician prescribes an opioid and 0 otherwise, β is a parameter measuring the weight the physician puts on patient i's utility $U_{ijt}(a_{ijt})$, γ represents Euler's constant, and ε is an i.i.d., alternative-specific T1EV shock independent of everything else.

Note that the physician-specific fixed effect η_j captures both the net profit from treating a patient i, as well as physician j's inherent tendency to prescribe opioids, such as treatment philosophy, graduate medical education, risk tolerance, and regulatory scrutiny. Thus, we interpret η_j as a physician's prescribing type. Everything else equal, physicians with larger η_j will tend to prescribe more often, whereas physicians with lower η_j will prescribe less often *independently* of a patient's actual needs (or derived utility from a prescription). The parameter β captures the weight physicians put on patient i's indirect utility $U_{ijt}(a_{ijt})$. If $\beta > 0$, we interpret this parameter as an altruism parameter. Conversely, if $\beta < 0$ we interpret β as animus of physicians towards patients.

Physicians rely on their medical expertise to understand patients' needs and combine them with their own treatment preference to arrive at a prescription decision. While physicians are medical experts, we assume that when making the prescription decision, physicians cannot fully observe a patient's preference. We further assume that preferences the physician can observe and cannot observe are additively separable such that

$$U_{ijt}(a_{ijt}) = u_{ijt}(a_{ijt}) + \nu_{ijt}, \tag{8}$$

where $u_{ijt}(a_{ijt})$ represents the part of patient utility observable to the physician, and ν_{ijt} the unobservable part. We assume that while physicians cannot observe the realization of ν_{ijt}, physicians know the distribution of ν_{ijt}. Note that not only is ν_{ijt} unobservable to physicians, but it is also independent of their treatment decision. Last, we assume that this informational structure is common knowledge for both patients and physicians.

We will now define patient i's indirect utility further. We start by defining the type of a patient in our model. We assume that a patient's type is a tuple (Θ_i, ζ_i). That is, we assume that patients' types can be separated into two time-persistent components: a term Θ_i capturing both preferences and medical needs, and a term ζ_i that measures how informed patient i is about physicians' prescription types. We assume that Θ_i enters patients' indirect

utility but that patients' information type ζ_i does not directily enter indirect utility. We will refer to Θ_i as patients' *benefit type* and to ζ_i as patients' *information type*.

Next, we will describe patients' choice of physician. Patients have to periodically obtain prescriptions to obtain prescription opioids. We assume that patients make a decision on whether to see a physician or not every month. Each month t, patient i can choose between seeing any physician j among the set of all physicians $\mathcal{J}_t$ in their market and not seeing a physician at all. We define patient i's indirect utility from choosing physician j at time t as

$$U_{ijt} = \underbrace{\delta_{jt} + a_{ijt}(\Theta_i + X_{it}\alpha) + Z_{it}\phi}_{\equiv u_{ijt}} + \nu_{ijt}, \tag{9}$$

where δ_{jt} denotes the mean utility of choosing physician j, Θ_i measures patient i's benefit from prescription, X_{it} denote time-varying patient characteristics affecting the benefit from prescription at time t, Z_{it} denote time-varying patient characteristics affecting the benefit from an office visit at time t, and ν_{ijt} is an i.i.d. T1EV shock. We normalize the value of the outside option of not seeing any physician to $U_{i0t} = \nu_{i0t}$.

The mean utility parameter δ_{jt} differs across physicians because different physicians may offer different levels of amenities or face different demand shocks. For example, a physician could have more friendly front desk staff, offer complementary appointment reminders, or in general may have better perceived medical expertise for treating chronic pain independent of their prescription decision.

Note that the preference heterogeneity captured by the benefit type Θ_i combines factors inherent to a patient. Therefore, Θ_i combines both the health benefit of opioid prescription for patient i as well as other perceived benefits that we refer to as patient i's opioid preference. A positive preference for opioids might be due to opioid misuse or addiction. Resembling our approach when documenting patient sorting, we assume that patients' benefit types are a linearly seperable function of patients' medical needs and opioid preference,

$$\Theta_i = X_i b + \theta_i. \tag{10}$$

Here, X_i is a vector of patient i's time-invariant traits that can be partitioned into two observable components, $X_i = [X_{i1}, X_{i2}]$. We assume that X_{i1} are observable factors determining a patient's true medical need and X_{i2} are observable factors determining a patient's true preference for opioids. Lastly, we interpret θ_i as the residual preference for opioids independent of X_i.

As for physicians, we assume that patients do not have perfect information about physicians' preferences. In particular, we assume that patients cannot perfectly predict a physi-

cian's treatment decision at the time of choosing a physician. However, we assume that patients have an understanding of whether or not a particular physician they consider to visit will prescribe an opioid.

We divide the uncertainty that patients face about physicians into two components. First, we assume that patients cannot observe the alternative specific preference shock ε_{ijt} since it will only be realized if a physician is chosen. We assume however that patients know the distribution of this shock.

Next, patients additionally face uncertainty about physicians' prescription preference when choosing a physician. We allow patients to differ in their level of informedness, represented by their information type ζ_i. A patient's information type ζ_i directly captures uncertainty about a physician's prescription type η_j. In particular, we assume that the patient's information ω_{ij} about a physician's prescription type can be summarized as

$$\omega_{ij} = \eta_j + \zeta_i. \tag{11}$$

We further assume that $\zeta \overset{\text{i.i.d.}}{\sim} N(0, \sigma_\zeta)$. Note that this information structure implies that a patient either overestimates or underestimates *all* physician prescription propensities by the same amount. We interpret this assumption as reflecting that patients hold a uniform bias in their expectations, such as general optimism or skepticism about physicians' willingness to prescribe, rather than idiosyncratic misperceptions about individual physicians. If all patients have accurate perception on each physician, the variance of ζ_i will be zero.

Lastly, we assume that the information structure of the game is common knowledge for both physicians and patients. That is, there is no uncertainty about the uncertainty that each of these players faces.

4.2 Equilibrium

Our model is a two-stage, one-period model. As such, it can be solved by backwards induction. We start by describing a physician's optimal prescribing behavior given the choice of a patient. We then present the optimal choice of patients in the first stage.

4.2.1 Optimal Prescription Choice

In section 4.1 we assumed that the physician can observe a patient's utility as a function of the prescription decision up to the match value ν_{ijt}. We can now rewrite V_{ijt} as an explicit function of the prescription decision a_{ijt}

$$V_{ijt}(a_{ijt}=1) = \pi_{jt} + \eta_j + \beta\delta_{jt} + \beta[\Theta_i + X_{it}\alpha] + \beta Z_{it}\phi + \varepsilon_{ijt}(1), \quad \text{and} \tag{12}$$

$$V_{ijt}(a_{ijt}=0) = \pi_{jt} + \beta\delta_{jt} + \beta Z_{it}\phi + \varepsilon_{ijt}(0). \tag{13}$$

Physician j will choose to prescribe if her indirect utility from prescribing an opioid weakly exceeds the indirect utility from not prescribing it,

$$V_{ijt}(a_{ijt}=1) - V_{ijt}(a_{ijt}=0) = \eta_j + \beta[\Theta_i + X_{it}\alpha] + \varepsilon_{ijt}(1) - \varepsilon_{ijt}(0) \geq 0. \tag{14}$$

Note that this difference and, therefore, the physician's prescription decision is *independent* of the demand side parameters δ_{jt}, the patient's information type ζ_i, and the base profit from treating a patient π_{jt}. This implies that, when making the prescription decision, the physician considers neither the relative attractiveness of herself to the patient nor the information a patient has about her prescription type in the first stage. The physician bases her prescription decision solely on the patient's benefit from prescription and the physician's own preference for prescribing opioids.

Since we assumed that the alternative-specific error terms ε are distributed type 1 extreme value, we can express the probability of physician j prescribing an opioid for patient i at time t as

$$\rho_{ijt} = \frac{\exp(\eta_j + \beta[\Theta_i + X_{it}\alpha])}{1 + \exp(\eta_j + \beta[\Theta_i + X_{it}\alpha])}. \tag{15}$$

4.2.2 Optimal Physician Choice

Patients face a discrete choice among J_t physicians in a market, given their information about physicians. We denote a patient i's choice of physician j at time t as $Y_t(i)$. As described in section 4.1, patients face uncertainty about a provider's prescription propensity when choosing a physician. In particular, patients do not know the realization of the type 1 extreme value terms ε and only have a potentially inaccurate perception ω_{ij} for each physician's prescription intensity η_j. Based on this information, patients form beliefs over the probability of receiving a prescription from physician j,

$$\tilde{\rho}_{ijt} = E[\rho|\omega, \cdot] = \frac{\exp(\omega_{ij} + \beta[\Theta_i + X_{it}\alpha])}{1 + \exp(\omega_{ij} + \beta[\Theta_i + X_{it}\alpha])}. \tag{16}$$

Given the patient's beliefs about a provider's prescription choice if chosen $\tilde{\rho}_{ijt}$ and our

type 1 extreme value assumption for ν_{ijt}, we can now express the choice probability of patient i choosing physician j at time t as

$$s_{ijt} = \Pr(Y_t(i) = j) = \frac{\exp(\delta_{jt} + \tilde{\rho}_{ijt} \times (\Theta_i + X_{it}\alpha) + Z_{it}\phi)}{1 + \sum_k \exp(\delta_{kt} + \tilde{\rho}_{ikt} \times (\Theta_i + X_{it}\alpha) + Z_{it}\phi)}. \tag{17}$$

Lastly, we can obtain aggregate choice probabilities s_{jt} by integrating over individual choice probabilities s_{ijt}

$$s_{jt} = \int s_{ijt} \mathrm{d}i. \tag{18}$$

5 Estimation and Results

In this section, we describe how we estimate the parameter vector of our structural model. Since our model implies seperability of the choice stage and the prescription stage, it naturally suggests the use of a limited instead of a more complicated full information maximum likelihood estimation procedure. We split estimation into three steps. In the first step, we estimate patients' benefit types Θ, price sensitivity α, and physicians' prescribing types η using realized prescription decsions and their correlations with both physician and patient characteristics. In the second step, we estimate the demand parameters δ and patients' information types ζ conditional on our first stage parameter estimates from variation in patients' physician choices. In the last stage, we decompose patients' types Θ into patients' opioid preference θ and patients' medical needs.

5.1 Estimation

We start with outlining our estimation procedure. The key insight that considerably simplfies estimating our model is that we can partition our model's parameter vector $\boldsymbol{\Xi}$ into two sets: one set of parameters affecting *both* the prescription and the choice stage, $\boldsymbol{\Xi}_1$, and and one set of parameters affecting *only* the choice stage, $\boldsymbol{\Xi}_2$. Using this insight, in a first step, we can estimate the set of parameters that affect both the the prescription stage and the choice stage, $\boldsymbol{\Xi}_1$, using data from the prescription stage only. In the second step, we then condition on the estimated parameters of the prescription stage, $\widehat{\boldsymbol{\Xi}}_1$, and estimate the remaining parameters affecting only the choice stage of our model, $\boldsymbol{\Xi}_2$, using our data for the choice stage. This is possible because, as we outlined in section 4, a physician's prescription choice does not depend on the demand side parameters δ_{jt}, σ_ζ, and $\boldsymbol{\phi}$.

Step I: Estimation of $\Xi_1 = \{\Theta, \eta, \alpha\}$ from the prescription stage

We first note that the perscription stage only depends on $\Xi_1 = \{\Theta, \eta, \alpha\}$ and gives rise to a reduced form. From section 4, we have that a physician's prescription probability is equal to[10]

$$\rho_{ijt} = \frac{\exp(\eta_j + \Theta_i + \alpha X_{it})}{1 + \exp(\eta_j + \Theta_i + \alpha X_{it})}. \tag{19}$$

Taking logs and collecting terms, we can reformulate this equation to the following two-way fixed effects logistic regression model

$$\log(\frac{\rho_{ijt}}{1 - \rho_{ijt}}) = \eta_j + \Theta_i + \alpha X_{it}. \tag{20}$$

Note that this reduced-form equation of the prescription stage of our model closely resembles our Abowd, Kramarz, and Margolis (1999)-style equation in (4) which we used to document patient sorting. It differs from equation (4) only due to the additional parametric type 1 extreme value assumptions we made for the error term ε.

Since equation (20) closely resembles equation (4), it shares similar identification issues. Limited mobility might cause non-trivial bias when estimating the fixed effects (Andrews, Gill, Schank, and Upward 2012; Bonhomme, Lamadon, and Manresa 2019). Additionally, it is well known that logit models suffer from incidental parameter bias when including fixed effects for each patient and physician. Therefore, we again follow Bonhomme, Lamadon, and Manresa (2019) and Mourot (2025) and group both patients and physicians based on equations 25 and 26. Note that the grouping addresses both the limited mobility bias as well as the incidental parameter bias. We then estimate the grouped parameters using our prescription stage panel data using maximum likelihood. After this step, we have estimates for $\Xi_1 = \{\Theta, \eta, \alpha\}$. We use our estimates $\widehat{\Xi}_1$ for step II.

Step II: Estimation of $\Xi_2 = \{\boldsymbol{\delta}, \sigma_\zeta, \boldsymbol{\phi}\}$ from the choice stage

Conditional on our estimates $\widehat{\Xi}_1$ from the prescription stage, we can now directly estimate the demand side parameters $\boldsymbol{\delta}$ and $\boldsymbol{\phi}$, as well as the information parameter σ_ζ in a second step. Our approach again employs a maximum likelihood estimator. Our approach shares many similarities with commonly used estimators in the health economics literature and more broadly in industrial organization (Goolsbee and Petrin 2004; Ho 2006) but additionally leverages the panel dimension of our choice stage data.

[10]Note that we already normalized $\beta = 1$ here.

Although theoretically the choice stage of our model could be estimated via unconstrained maximum likelihood, estimating thousands of δ parameters is a huge computational burden. Our data consists of thousands of physicians over 84 months making estimating one parameter per physician-month combination impracticable. We therefore follow the industrial organization literature concentrating out the demand side parameters δ by imposing a share constraint (Berry 1994; Berry, Levinsohn, and Pakes 1995). We then maximize the constrained loglikelihood of the choice stage of our model over $\Xi_2 = \{\sigma_\zeta, \boldsymbol{\phi}\}$ only.

The constrained loglikelihood of our model's choice stage given our estimates from the prescription stage $\widehat{\Xi}_1$ can be written as

$$\mathcal{L}_2 = \sum_{i=1}^{N} \log \int \prod_{t \in T_i} \prod_{j \in J_t} (s_{ijt}(\zeta; \Xi_2, \widehat{\Xi}_1))^{y_{ijt}} f(\zeta; \sigma_\zeta) d\zeta \tag{21}$$

$$s.t. \quad s_{jt}(\Xi_2, \widehat{\Xi}_1) = \mathcal{S}_{jt}, \tag{22}$$

where y_{ijt} is an indicator function equal to 1 if patient i chooses physician j in month t, and 0 otherwise. $\mathcal{S}_{jt}$ are the observed market shares from our data.

Next, since we use a two-step estimator, we need to adjust the standard errors for $\widehat{\Xi}_2$ in the second stage. Since both of our steps are estimated using maximum likelihood, it can be shown that under standard regularity conditions, the variance-covariance matrix for the second-step, $\widehat{\boldsymbol{V}}_{\widehat{\Xi}_2}$, is given by (Murphy and Topel 2002)

$$\widehat{\boldsymbol{V}}_{\widehat{\Xi}_2} = \widehat{\boldsymbol{V}}_2 + \widehat{\boldsymbol{V}}_2 (\widehat{\boldsymbol{A}} \widehat{\boldsymbol{V}}_1 \widehat{\boldsymbol{A}}') \widehat{\boldsymbol{V}}_2, \tag{23}$$

where $\widehat{\boldsymbol{V}}_1$ is the variance-covariance matrix from the first step logit estimation, $\widehat{\boldsymbol{V}}_2$ the variance-covariance matrix from the second step likelihood estimation, and $\widehat{\boldsymbol{A}}$ is defined as

$$\widehat{\boldsymbol{A}} = \sum_i \left(\frac{\partial \mathcal{L}_{i2}}{\partial \widehat{\Xi}_2}\right)\left(\frac{\partial \mathcal{L}_{i2}}{\partial \widehat{\Xi}_1'}\right). \tag{24}$$

Here, $\mathcal{L}_{i2}$ denotes the individual likelihood contribution of patient i to the second step likelihood.

Step III: Separating Patient's Opioid Preference from Patient's Medical Needs

An important question for policy is whether prescription opioids are prescribed for medical reasons or whether they are prescribed due to patient preference. To answer this question, we leverage our rich vector of patient characteristics and medical histories. To distinguish medical needs vs. patient preference, we further decompose patients' benefit type Θ_i. To

do so, we estimate equation 10 using OLS. Again, we need to adjust our standard errors of step III for the multistep estimation procedure. We adjust the standard errors analogous to equation (23) following Murphy and Topel (2002).

5.2 Results (Work-in-Progress

In this section, we present the results of our estimation procedure as outlined in section 5.1. We start with presenting the estimates of our prescription stage estimator. In this work-in-progress version, we abstract away from X_{it} and Z_{it}. In a later version, we will also decompose patients opioid type analogously to section 3.

Table 5: Estimated Model Parameters

	Estimate	**(Std. Error)**
Patient Information Type		
σ_ζ	3.314	(0.010)
Patient Benefit Type (θ_i)		
θ_2	-10.379	(0.728)
θ_3	-7.880	(0.218)
θ_4	-5.536	(0.165)
θ_5	-4.347	(0.160)
θ_6	-3.895	(0.159)
θ_7	-3.592	(0.159)
θ_8	-3.142	(0.159)
θ_9	-2.861	(0.160)
θ_{10}	-2.250	(0.163)
Physician Prescribing Type (η_j)		
η_2	-8.695	(0.608)
η_3	-6.031	(0.226)
η_4	-3.877	(0.196)
η_5	-3.562	(0.190)
η_6	-3.346	(0.188)
η_7	-3.219	(0.188)
η_8	-3.087	(0.187)
η_9	-2.903	(0.188)
η_{10}	-2.599	(0.190)
constant	6.336	(0.229)
Year FE	✓	
Data		
Patients (N)	11,909	
Physicians (J)	8,059	
Months (T)	84	
Total Observations	126,357	

Notes: This table reports estimated model parameters from the structural model. Standard errors are shown in parentheses. Note that for the patient information type parameter, we currently report the standard error without implementing the Murphy-Topel correction. This will be updated in a future iteration of this paper.

6 Counterfactual Simulations (Work-in-Progress)

In this section, we sketch our plan for several counterfactuals, highlighting how patient sorting can affect the effectiveness of provider-targeted policies. Additionally, we show how implementing a stricter interpretation of the CDC guidelines would lead to a more effective reduction in prescription opioids. This section focuses on the economic mechanisms underlying our results. We provide a more detailed discussion of the technical implementation of each counterfactual in appendix H.

6.1 Excluding top prescribers

The first counterfactual simulation we study is the *exclusion* of the top 10% of prescribing physicians by prescription rate across all markets. This is an extreme counterfactual that we use to illustrate the mechanisms of physician-targeted policies. Our counterfactual policy prevents patients from choosing any physician in the excluded set. We therefore simulate the counterfactual choices for all patients who see an excluded physician in the baseline. We allow patients who chose an excluded physician in the baseline to either see any non-excluded physician or to choose the outside option of not seeing any physician in that month. We hold fixed the choices of patients who did not see an excluded physician.

[Figure 8 about here]

We first focus on aggregate opioid prescriptions. Aggregate opioid prescriptions are a key metric for policymakers.[11] We provide other metrics comparing our baseline with this counterfactual in table TBD. Figure 8 compares the baseline aggregate prescriptions to the counterfactual aggregate prescriptions.

Figure 8 shows that even an aggressive policy, such as permanently excluding the top x% of prescribing physicians by prescription rate across all markets, only reduces aggregate prescriptions by about TBD%. This is surprising, given that, as we showed in section 3, the prescription intensity distribution of physicians has a fairly long tail with only a couple of physicians responsible for a significant fraction of aggregate prescriptions. Everything else equal, excluding high-prescribing physicians, therefore appears to have to reduce opioid prescription rates dramatically. However, this argument ignores the demand side response to physician-targeted policies. When we intervene and prevent patients from optimally choosing their physician by limiting their choice sets to a subset of physicians, affected patients will re-optimize by choosing the physician who most closely aligns with their preferences for

[11] see e.g. https://www.cdc.gov/overdose-prevention/data-research/facts-stats/opioid-dispensing-rate-maps.html.

prescription opioids. The key economic mechanism affecting our policy's effectiveness is therefore patient *resorting*.

[Figure 9 about here]

Figure 9 demonstrates the importance of patients resorting under our policy. The baseline panel of figure 9 shows that high-prescribing physicians disproportionally attract high-type patients. In other words, patients sort into physicians under the baseline scenario. Breaking this initial sorting of high-type patients forces patients to re-optimize. The counterfactual panel of figure 9 shows that re-optimization, given the restricted choice set, leads high-type patients to disproportionately choose physicians who are of the highest remaining prescription type. This drives up the observed prescription rates of the remaining physicians and attenuates the policy's effect on aggregate prescriptions. We demonstrate this effect on observed prescription rates across physicians in Figure 10. In fact, *any* physician-targeted policy resulting in either exclusion of high prescribing physicians or in reduction of high prescribing physicians' prescribing propensity only will be attenuated by the resorting of patients.[12]

[Figure 10 about here]

We will next study a counterfactual to highlight the importance of the resorting channel for policy effectiveness.

6.2 Excluding top prescribers & preventing resorting

A surprising outcome of our first counterfactual policy simulation is that even extremely aggressive exclusion of high-prescribing physicians results in only modest reductions of aggregate opioid prescriptions. This is even more surprising, as we showed that most opioid prescriptions originate from only a relatively small number of physicians. We reasoned that the policy's effect is attenuated by affected patients resorting to remaining physicians who are, everything else equal, most likely to prescribe opioids. In this counterfactual, we will isolate the resorting effect by explicitly preventing affected patients from choosing their physician. We only allow patients to choose between seeking care and being randomly assigned a physician, and not seeking care in a given month. As before, we hold all choices of unaffected patients constant.

[12] In this argument, we implicitly disregard the edge case in which all or no physicians would be excluded.

[Figure 11 about here]

We again focus on aggregate opioid prescriptions. As for counterfactual 1, we provide other metrics comparing our baseline with this counterfactual in table TBD. Figure 11 illustrates the importance of the resorting channel for aggregate opioid prescriptions. Without allowing patients to re-optimize, the exclusion policy we studied in counterfactual 1 would be TBD% more effective, reducing the opioid prescription rate by an additional TBD percentage points. This highlights how important patient resorting for policy is. If policymakers naïvely ignore this channel, they will ex ante overestimate the policy's effect and face a strongly attenuated effect after implementation.

Our results, however, also highlight the cost of completely shutting down the resorting channel for affected patients. Panel TBD in Table TBD shows that preventing affected patients from choosing their physician optimally based on their preferences results in patients overwhelmingly forgoing care. This happens because we estimate strong heterogeneity in benefit types Θ and prescribing propensity types η. Random assignment makes it very likely that a patient will be matched with a physician whose prescribing type does not align with the patient's preference *irrespective* of the patient's benefit type. Note that a patient's benefit type includes both medical necessity and preference for opioids due to addiction. Even patients who would, under any reasonable definition, such as the CDC guidelines, be qualified to receive prescription opioid treatment would potentially be prevented from obtaining appropriate care. This is a clearly undesirable outcome for policy.

In our next counterfactual, we explicitly address the issue of potentially denying care to patients who have medically qualifying conditions for opioid treatment when implementing policies that aim to prevent sorting based on opioid preference.

6.3 Breaking Bad Opioid Sorting: A stricter interpretation of the CDC guidelines

In our last set of counterfactuals, we will propose a feasible policy that allows patients with objective medical needs to stay in care while at the same time eliminating opioid prescriptions that are based on patients' preferences for prescription opioids. To do so, we combine our estimates, decomposing patients' benefit type Θ into medical needs and opioid preferences with the CDC Clinical Practice Guideline for Prescribing Opioids for Pain (Dowell, Ragan, et al. 2022b). In our counterfactual simulation, we enforce that physicians can only prescribe for legitimate medical reasons. Physicians cannot consider opioid preferences for prescribing.

To conduct our counterfactual simulation, we take the following steps. For each patient in our data set, we allow physicians to consider the following in prescribing opioids.

1. Consistent with the CDC guideline (Dowell, Ragan, et al. 2022b), a physician will consider the full benefit type Θ if the patient suffers from sickle cell disease, cancer-related pain, or is in end-of-life care or palliative care.

2. In all other cases, a physician can only consider medical needs $x\beta$ rather than the full benefit type Θ. Note that this implies that if a patient has any conditions mentioned in the CDC guideline (Dowell, Ragan, et al. 2022b) that warrant caution, Physicians cannot prescribe opioids for pain based on this preference. Consistent with the CDC guideline, the conditions we consider as warranting caution are sleep-disordered breathing, renal or hepatic insufficiency, certain mental health conditions, substance abuse, a previous overdose, as well as working in safety-critical occupations.[13][14]

In other words, we do not interfere with opioid prescriptions for chronic pain for conditions that are specifically named in the CDC guideline as medically justified. We explicitly enforce the CDC's recommendation to use caution when prescribing opioids if a patient suffers from sleep-disordered breathing, renal or hepatic insufficiency, certain named mental health conditions, substance use abuse, a previous overdose, or is working in a safety-critical occupation. Lastly, we reduce ambiguity and eliminate discretionary prescription of opioids by letting physicians only consider medical needs.

We first demonstrate that the median patient in our data set is unaffected by such a policy. Figure TBD shows the baseline prescription probability distribution and the counterfactual prescription probability distribution for each patient-physician pair. Introducing our stricter prescription guidelines mostly affects patients with strong preferences for opioids. Moving from the baseline to the counterfactual policy, prescription rate heterogeneity is strongly reduced.

7 Conclusion

TBD

[13] Mental health conditions warranting caution are anxiety, posttraumatic stress disorder, and depression (Dowell, Ragan, et al. 2022b).

[14] Occupations warranting caution include driving, using heavy equipment, climbing ladders, working at heights or around moving machinery, or working with high-voltage equipment (Dowell, Ragan, et al. 2022b).

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A Grouping Algorithm

To group both patients and providers, we first run two regressions to construct the average risk-adjusted prescription rate across patients for providers, and the average risk-adjusted prescription rate across providers for patients. In particular, we run

$$\text{prescribe}_{ijt} - X_{it}\beta = \tilde{\eta}_j + \epsilon_{ijt}, \tag{25}$$

and

$$\text{prescribe}_{ijt} - X_{it}\beta = \tilde{\theta}_i + \epsilon_{ijt}, \tag{26}$$

where X_{it} is the patient characteristics defined as before. We then use our estimates for $\tilde{\eta}_j$ and $\tilde{\theta}_i$ to group patients and providers using the k-mean clustering algorithm (Bonhomme, Lamadon, and Manresa 2019) as in Mourot (2025). In the second stage, we can then consistently estimate the two-way fixed effects model in equation (4) using our groups from the first stage.

B Appendix stuff

B.1 Figures

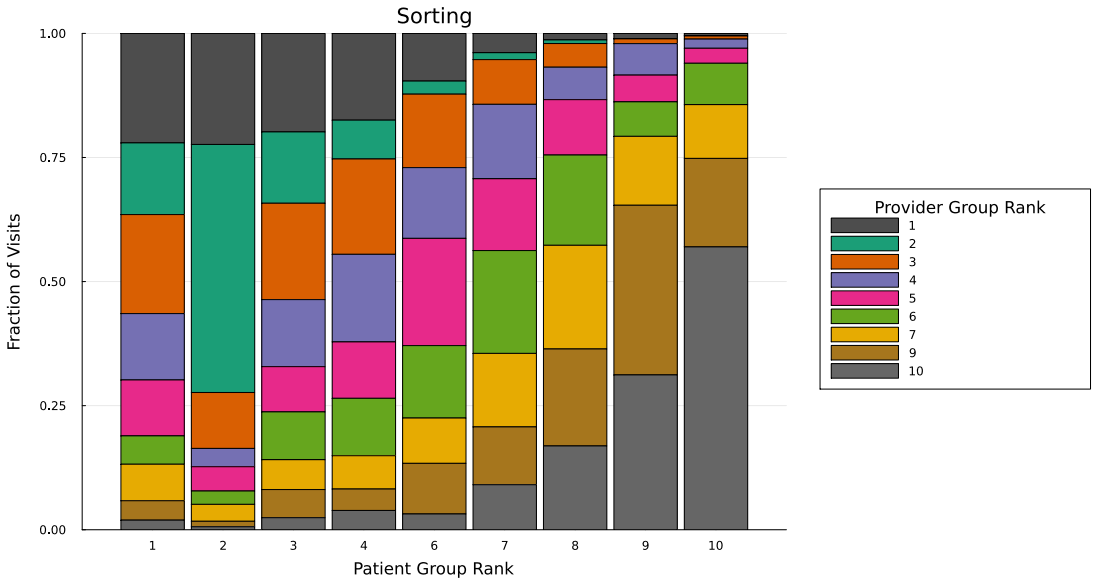

Figure 8: Sorting

C Gradients

First, we define

$$s_{ijt} = \int_{-\infty}^{+\infty} s_{ijth} di, \tag{27}$$

and

$$\tilde{\rho}_{ijt} = \int_{-\infty}^{+\infty} \tilde{\rho}_{ijth} di, \tag{28}$$

where s_{ijth} is the individual choice probability at each integration node h, and $\tilde{\rho}_{ijth}$ is the perceived prescription probability at each node. We can now derive the following partial derivatives. For each element m of the ϕ vector, we have

$$\frac{\partial s_{jt}}{\partial \phi^{\{m\}}} = \sum_i \int_{-\infty}^{+\infty} \frac{\partial s_{ijth}}{\partial \phi^{\{m\}}} di = \sum_i \int_{-\infty}^{+\infty} z_i^{\{m\}} s_{ijth} s_{i0th} di. \tag{29}$$

Let ζ_h be the value of the integration node. Then with some abuse of notation (integral vs sum)

$$\frac{\partial s_{jt}}{\partial \sigma_\zeta} = \sum_i \int_{-\infty}^{+\infty} \frac{\partial s_{ijth}}{\partial \sigma_\zeta} di = \sum_i \int_{-\infty}^{+\infty} s_{ijth}(\Theta_i + \alpha X_{it}) \zeta_h [\tilde{\rho}_{ijth}(1-\tilde{\rho}_{ijth}) - \sum_k \tilde{\rho}_{ikth}(1-\tilde{\rho}_{ikth}) s_{ikth}] di. \tag{30}$$

For each element m of the η vector we have

$$\frac{\partial s_{jt}}{\partial \eta_j^{\{m\}}} = \int_{-\infty}^{+\infty} \frac{\partial s_{jit}}{\partial \eta_j^{\{m\}}} di = \sum_i \int_{-\infty}^{+\infty} s_{ijth}(\Theta_i + \alpha X_{it}) [\tilde{\rho}_{ijth}(1-\tilde{\rho}_{ijth}) - \sum_k \tilde{\rho}_{ikth}(1-\tilde{\rho}_{ikth}) s_{ikth}] di. \tag{31}$$

Similarly, for the constant term, we have

$$\frac{\partial s_{jt}}{\partial cons} = \int_{-\infty}^{+\infty} \frac{\partial s_{jit}}{\partial cons} di = \sum_i \int_{-\infty}^{+\infty} s_{ijth}(\Theta_i + \alpha X_{it}) [\tilde{\rho}_{ijth}(1-\tilde{\rho}_{ijth}) - \sum_k \tilde{\rho}_{ikth}(1-\tilde{\rho}_{ikth}) s_{ikth}] di. \tag{32}$$

For each element m of Θ_i, we have that

$$\frac{\partial s_{jt}}{\partial \Theta_i^{\{m\}}} = \int_{-\infty}^{+\infty} \frac{\partial s_{jit}}{\partial \Theta_i^{\{m\}}} di = \tag{33}$$

$$\sum_i \int_{-\infty}^{+\infty} s_{ijth}[\tilde{\rho}_{ijth}(1-\tilde{\rho}_{ijth})(\Theta_i + \alpha X_{it}) + \tilde{\rho}_{ijth} - \sum_k (\tilde{\rho}_{ikth}(1-\tilde{\rho}_{ikth})(\Theta_i + \alpha X_{it}) + \tilde{\rho}_{ikth}) s_{ikth}] di. \tag{34}$$

For each element m of α we have

$$\frac{\partial s_{jt}}{\partial \alpha^{\{m\}}} = \int_{-\infty}^{+\infty} \frac{\partial s_{jit}}{\partial \alpha^{\{m\}}} di = \tag{35}$$

$$\sum_i \int_{-\infty}^{+\infty} s_{ijth} X_{it}^{\{m\}} [\tilde{\rho}_{ijth}(1-\tilde{\rho}_{ijth})(\Theta_i + \alpha X_{it}) + \tilde{\rho}_{ijth} - \sum_k (\tilde{\rho}_{ikth}(1-\tilde{\rho}_{ikth})(\Theta_i + \alpha X_{it}) + \tilde{\rho}_{ikth}) s_{ikth}] di. \tag{36}$$

For the partial derivatives with respect to δ, we have

$$\frac{\partial s_{jt}}{\partial \delta_{jt}} = \sum_i \int_{-\infty}^{+\infty} \frac{\partial s_{ijth}}{\partial \delta_{jt}} di = \sum_i \int_{-\infty}^{+\infty} s_{ijth}(1 - s_{ijth}) di, \tag{37}$$

and

$$\frac{\partial s_{jt}}{\partial \delta_{lt}} = \sum_i \int_{-\infty}^{+\infty} \frac{\partial s_{ijth}}{\partial \delta_{lt}} di = \sum_i \int_{-\infty}^{+\infty} -s_{ijth}(1 - s_{ilth}) di. \tag{38}$$

The fixed point imposes that the predicted shares are equal to the observed shares. That is, $0 = s_{jt}(\Xi) - \mathcal{S}_{jt}$. By the implicit function theorem, we have that

$$\left(\frac{d\boldsymbol{\delta_t}}{d\sigma_\zeta} \quad \frac{d\boldsymbol{\delta_t}}{d\boldsymbol{\phi}} \quad \frac{d\boldsymbol{\delta_t}}{d\boldsymbol{\eta}} \quad \frac{d\boldsymbol{\delta_t}}{dcons} \quad \frac{d\boldsymbol{\delta_t}}{d\boldsymbol{\Theta}} \quad \frac{d\boldsymbol{\delta_t}}{d\boldsymbol{\alpha}} \right) = -\frac{\partial \boldsymbol{s_t}}{\partial \boldsymbol{\delta_t}}^{-1} \left[\frac{\partial \boldsymbol{s_t}}{\partial \sigma_\zeta} \quad \frac{\partial \boldsymbol{s_t}}{\partial \boldsymbol{\phi}} \quad \frac{\partial \boldsymbol{s_t}}{\partial \boldsymbol{\eta}} \quad \frac{\partial \boldsymbol{s_t}}{\partial cons} \quad \frac{\partial \boldsymbol{s_t}}{\partial \boldsymbol{\Theta}} \quad \frac{\partial \boldsymbol{s_t}}{\partial \boldsymbol{\alpha}} \right].$$

Now, we can use these to form the gradients of the loglikelihood with respect to σ_ζ and ϕ.

$$\frac{ds_{ijt}}{d\sigma_\zeta} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{d\sigma_\zeta} di = \int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{d\sigma_\zeta} + \frac{d\tilde{\rho}_{ijth}}{d\sigma_\zeta} - \sum_k (\frac{d\delta_{kt}}{d\sigma_\zeta} + \frac{d\tilde{\rho}_{ikth}}{d\sigma_\zeta}) s_{ikth}] di \tag{39}$$

$$\frac{ds_{ijt}}{d\phi^{\{m\}}} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{d\phi^{\{m\}}} di = \int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{d\phi^{\{m\}}} + z_i^{\{m\}} - \sum_k (\frac{d\delta_{kt}}{d\phi^{\{m\}}} + z_i^{\{m\}} s_{ikth}]di \tag{40}$$

$$\frac{ds_{ijt}}{d\eta_j} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{d\eta_j} di = \int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{d\eta_j} + (\Theta_i + \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\eta_j} - \sum_k (\frac{d\delta_{kt}}{d\eta_j} + (\Theta_i - \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\eta_j}) s_{ikth}]di \tag{41}$$

$$\frac{ds_{ijt}}{dcons} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{dcons} di = \int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{dcons} + (\Theta_i + \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{dcons} - \sum_k (\frac{d\delta_{kt}}{dcons} + (\Theta_i - \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{dcons}) s_{ikth}]di \tag{42}$$

$$\frac{ds_{ijt}}{d\Theta_i} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{d\Theta_i} di = \int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{d\Theta_i} + (\Theta_i + \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\Theta_i} + \tilde{\rho}_{ijth} - \sum_k (\frac{d\delta_{kt}}{d\Theta_i} + (\Theta_i - \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\Theta_i} + \tilde{\rho}_{ikth}) s_{ikth}]di \tag{43}$$

$$\frac{ds_{ijt}}{d\alpha^{\{m\}}} = \int_{-\infty}^{+\infty} \frac{ds_{ijth}}{d\alpha^{\{m\}}} di = \tag{44}$$

$$\int_{-\infty}^{+\infty} s_{ijth}[\frac{d\delta_{jt}}{d\alpha^{\{m\}}} + X_{it}^{\{m\}} \tilde{\rho}_{ijth} + (\Theta_i + \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\alpha^{\{m\}}} - \sum_k (\frac{d\delta_{kt}}{d\alpha^{\{m\}}} + X_{it}^{\{m\}} \tilde{\rho}_{ikth} + (\Theta_i - \alpha X_{it}) \frac{d\tilde{\rho}_{ijth}}{d\alpha^{\{m\}}}) s_{ikth}]di \tag{45}$$

Note that we can easily calculate the gradients for the outside good choice probabilities because $s_{i0t} = 1 - \sum_k s_{ikt}$. Therefore, the respective gradients are

$$\frac{ds_{i0t}}{d\sigma_\zeta} = -\sum_j \frac{ds_{ijt}}{d\sigma_\zeta}, \tag{46}$$

and

$$\frac{ds_{i0t}}{d\phi^{\{m\}}} = -\sum_j \frac{ds_{ijt}}{d\phi^{\{m\}}}. \tag{47}$$

Lastly, we can plug the total gradients directly into the gradients of the loglikelihood.

$$\frac{d\mathcal{L}}{d\sigma_\zeta} = \sum_t \sum_j \sum_i y_{ijt} \frac{1}{s_{ijt}} \frac{ds_{ijt}}{d\sigma_\zeta} \tag{48}$$

$$\frac{d\mathcal{L}}{d\phi^{\{m\}}} = \sum_t \sum_j \sum_i y_{ijt} \frac{1}{s_{ijt}} \frac{ds_{ijt}}{d\phi^{\{m\}}} \tag{49}$$

D Charlson Commorbidity Index (CCI)

We use weights in Schneeweiss, Wang, Avorn, and Glynn 2003 for each of the 17 conditions suggested for the Charlson/Deyo variant (Deyo 1992). The 17 conditions are:

On top of these conditions, patients in the following age group receive additional points for their Charlson Commorbidity Index:

Comorbid Condition	**ICD10 Diagnosis Codes**	**Weight**
Myocardial Infarction	I21, I22, I25.2	1
Congestive Heart Failure	I09.9, I11.0, I13.0, I13.2, I25.5, I42.0, I42.5–I42.9, I43, I50, P29.0	1
Peripheral Vascular Disease	I70, I71, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9	1
Cerebrovascular Disease	G45, G46, H34.0, I60–I69	1
Dementia	F00–F03, F05.1, G30, G31.1	1
Chronic Pulmonary Disease	I27.8, I27.9, J40–J47, J60–J67, J68.4, J70.1, J70.3	1
Connective Tissue Disease	M05, M06, M31.5, M32–M34, M35.1, M35.3, M36.0	1
Peptic Ulcer Disease	K25–K28	1
Mild Liver Disease	B18, K70.0–K70.3, K70.9, K71.3–K71.5, K71.7, K73, K74, K76.0, K76.2–K76.4, K76.8, K76.9, Z94.4	1
Diabetes w/o Complications	E10.0–E10.1, E10.6, E10.8–E10.9, E11.0–E11.1, E11.6, E11.8–E11.9, E12.0–E12.1, E12.6, E12.8–E12.9, E13.0–E13.1, E13.6, E13.8–E13.9, E14.0–E14.1, E14.6, E14.8–E14.9	1
Diabetes w/ Chronic Complications	E10.2–E10.5, E10.7, E11.2–E11.5, E11.7, E12.2–E12.5, E12.7, E13.2–E13.5, E13.7, E14.2–E14.5, E14.7	2
Paraplegia and Hemiplegia	G04.1, G11.4, G80.1, G80.2, G81, G82, G83.0–G83.4, G83.9	2
Renal Disease	I12.0, I13.1, N03.2–N03.7, N05.2–N05.7, N18, N19, N25.0, Z49.0–Z49.2, Z94.0, Z99.2	2
Cancer	C00–C26, C30–C34, C37–C41, C43, C45–C58, C60–C76, C81–C85, C88, C90–C97	2
Moderate or Severe Liver Disease	I85.0, I85.9, I86.4, I98.2, K70.4, K71.1, K72.1, K72.9, K76.5–K76.7	3
Metastatic Carcinoma	C77–C80	6
HIV/AIDS	B20–B22, B24	6

Table 6: Charlson Comorbidity Index: ICD10 Diagnoses and Weights

Age	Score
<50 years	0
50–59 years	+1
60–69 years	+2
70–79 years	+3
≥80 years	+4

E CDC Clinical Practice Guideline for Prescribing Opioids for Pain

Dowell, Haegerich, and Chou 2016; Dowell, Ragan, et al. 2022b provides recommendations for clinicians providing pain care, including those prescribing opioids, for outpatients aged ≥18 years. For BREAKIN BAD SORTING SECTION, we follow the guidelines in determining which patients deserve an opioid prescription and which patients do not deserve an opioid prescription.

Medical Diagnosis	ICD10 Diagnosis Codes
sickle cell disease	D57
cancer-related pain	G89.3
palliative / end-of-life care	Z51.5

Table 7: Medical Diagnosis deserving of opioids

Medical Diagnosis	ICD10 Diagnosis Codes
sleep-disordered breathing	G47.3
renal or hepatic insufficiency	N17, K72
mental health condition (anxiety, depression and post-traumatic stress disorder)	F32, F41, F43
opioid abuse	F11, T40
substance use disorder	F10, F12-F19
non-fatal overdose	T36 - T39, T41 - T50

Table 8: Medical Diagnosis not deserving of opioids

F Constructing a measure of opioid misuse

Following the literature, we classify an outpatient visit as involving opioid misuse if the patient's daily Morphine Equivalent Dosage (MED) exceeds 120 mg, given the documented correlation between such prescription levels and opioid abuse (Meara et al. 2016; Finkelstein, Gentzkow, and D. Li 2025; Staiger, Baker, and Hernandez-Boussard 2022). In this section, we describe how we calculate the MED for an outpatient visit.

For a visit t, we observe all prescription drugs d, their active opioid ingredients o, and the respective dosages in milligrams (mg). [15] Following the CDC guidelines (Dowell, Ragan, et al. 2022b), we consider commonly prescribed opioid ingredients in pain management: codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, tapentadol, and tramadol. For each prescription drug d, we define its morphine equivalent dosage (MED) as the sum of all opioid's dosage multiplied by the conversion factor:

$$MED_d = \sum_{o \in N_d^{opioid}} dosage_o \times conversion_o$$

N_d^{opioid} denotes all the opioid ingredients found in drug d. $conversion_o$ is the conversion factor used by the CDC to standardize the comparisons between opioids relative to morphine and are found in Dowell, Ragan, et al. 2022b. Hence, patient i's daily MED in outpatient visit t is defined as the sum of all drug's total daily MED:

$$MED_{it} = \sum_{d \in N_{it}^{drug}} \frac{MED_d \times METQTY_{dit}}{DAYSUPP_{dit}}$$

N_{it}^{drug} denotes all the drugs prescribed to patient i in outpatient visit t. $METQTY_{dit}$ is the metric quantity of drug d for patient i in outpatient visit t (i.e., number of pills prescribed). $DAYSUPP_{dit}$ is drug d's days of supplement for patient i in outpatient visit t. Hence, an outpatient visit t is defined as an opioid misuse if MED_{it} exceeds 120 mg.

G Constructing expected out-of-pocket prescription opioid costs

In our data, out-of-pocket opioid costs are observed only for chronic pain patients who fill an opioid prescription. Following the demand-estimation literature (Berry, Levinsohn,

[15] Dosages in micromilligram (mcg) are divided by 1,000 to convert to milligrams (mg).

and Pakes 1995; Goolsbee and Petrin 2004), we construct a measure of expected out-of-pocket costs by computing the average opioid OOP cost at the plan–year–month level among observed users. The year-month level of aggregation lets us smooth high-frequency variation arising from insurance contract nonlinearities and seasonality—such as deductible exhaustion and end-of-year resets—that generate predictable spikes in patient cost sharing.

$$\bar{OOPD}_{it} = \frac{1}{N_{plan(i)t}} \sum_{i' \in \text{plan}(i)t} OOPD_{i't}$$

$N_{plan(i)t}$ is the number of patients in the same plan as patient i in year-month t that had an opioid prescription. $\bar{OOPD}_{it}$ is the average OOPD for all patient i' that are in the same insurance plan as patient i in year-month t.

H Technical Details on Counterfactual Simulations

We consider four counterfactual scenarios. Table 9 presents each of the scenarios. When we exclude any physicians, we focus on the counterfactual shares of the patients who chose the excluded physicians while holding the others fixed. We need (s_{ijt} and ρ_{ijt}), along with the affected patient identity, to examine the counterfactual physician choice and opioid prescriptions. Note: BBS = break bad sorting.

	Did s_{ijt} change?	Did ρ_{ijt} change?	affected patient
CF1 (exclude, resort)	Yes	No	Patients that chose excluded physicians
CF2 (exclude, randomize)	Yes	No	Patients that chose excluded physicians
CF3 (exclude, BBS)	Yes, through $\tilde{\rho}$	Yes	Category B and C patients that chose excluded physicians
CF4 (BBS)	Yes, through $\tilde{\rho}$	Yes	Category B and C patients that chose inside physicians

Table 9: Our counterfactuals

H.1 CF1: Exclude top % physician and affected patients resort

We simulate the exclusion policy by dropping physicians in the top n^{th} percentile of risk-adjusted prescription rate. We set the mean utility δ_{jt} of the excluded physicians as $-\infty$. We use Gaussian quadrature to calculate the choice probabilities s_{ijt}. Thus, the patient's perceived prescription probabilities $\tilde{\rho}_{ijth}$ at each integration node h is:

$$\tilde{\rho}_{ijth} = \frac{\exp(\eta_j + \Theta_i + X_{it}\alpha) * \exp(\sigma_h)}{1 + \sum_k \exp(\eta_j + \Theta_i + X_{it}\alpha) * \exp(\sigma_h)}$$

and each $\sigma_h = \sqrt{2} * \sigma_\zeta * \zeta_h$, where ζ_h is the integration node. The patient's choice probabilities s_{ijth} are:

$$s_{ijth} = \frac{\exp(\delta_{jt} + \tilde{\rho}_{ijth} \times (\Theta_i + X_{it}\alpha) + \phi Z_{it})}{1 + \sum_k \exp(\delta_{kt} + \tilde{\rho}_{ikth} \times (\Theta_i + X_{it}\alpha) + \phi Z_{it})}$$

then s_{ijt} is:

$$s_{ijt} = \sum_h w_h s_{ijth}$$

H.2 CF2: Exclude top % physician and randomize affected patient choise

For this counterfactual, we use Monte Carlo integration to calculate choice probabilities, s_{ijt}. At each Monte Carlo draw m, we have $J+1$ T1EV errors and one standard normal draw for

each patient i, scaled by the dispersion of information type, σ_ζ. The perceived prescription probabilities are:

$$\tilde{\rho}_{ijtm} = \frac{\exp(\eta_j + \Theta_i + X_{it}\alpha) * \exp(\zeta_m)}{1 + \sum_k \exp(\eta_j + \Theta_i + X_{it}\alpha) * \exp(\zeta_m)}$$

The indirect utility of a non-excluded physician is given by:

$$u_{ijtm} = \delta_{jt} + [\tilde{\rho}_{ijtm} * (\Theta_i + X_{it}\alpha)] + Z_{it}\phi + \nu_{jtm}$$

We calculate the weighted-average utility of all non-excluded physicians and compare it with the realized T1EV error of the outside option. The weights are the conditional market share of the non-excluded physicians. Patients choose the outside option if and only if:

$$\nu_{0tm} \geq \bar{u}_{itm}$$

where ν_{0tm} is the T1EV of the outside option in market t at MC draw m and $\bar{u}_{itm}$ is the weighted average utility of the non-excluded physicians and takes the form:

$$\bar{u}_{itm} = \sum_{j \notin \text{excluded}} s^*_{jt} \times u_{ijtm}$$

s^*jt is the conditional market share of the non-excluded physicians. We implement this 1000 times per patient and use the average across 1000 trials to calculate the counterfactual probability of choosing the outside option, s_{i0t}. We calculate the counterfactual choice probabilities s_{ijt} by multiplying $1 - s_{i0t}$ with the conditional market shares of the non-excluded physicians.

H.3 CF3: CF1 + lower prescription rate for Category B and C

This counterfactual exercise is similar to CF1, where we exclude physicians and allow patients to resort. Additionally, we enforce the CDC guidelines and remove elements in Θ_i related to opioid preference (i.e., $X_2 b_2$ and θ_i) for patients in Categories B and C. The prescription probabilities for patients in Category A remain unchanged. For example:

$$\text{Category A: } \rho_{ijt} = \frac{\exp(\eta_j + \overbrace{(c + X_1 b_1 + X_2 b_2 + \theta_i)}^{\Theta_i} + X_{it}\alpha)}{1 + \sum_k \exp(\eta_j + \underbrace{(c + X_1 b_1 + X_2 b_2 + \theta_i)}_{\Theta_i} + X_{it}\alpha)}$$

$$\text{Category B, C: } \rho_{ijt} = \frac{\exp(\eta_j + \overbrace{(c + X_1 b_1)}^{\hat{\Theta}_i} + X_{it}\alpha)}{1 + \sum_k \exp(\eta_j + \underbrace{(c + X_1 b_1)}_{\hat{\Theta}_i} + X_{it}\alpha)}$$

As a result, the choice probabilities s_{ijt} for Category A patients remain unchanged; whereas the choice probabilities for Categories B and C patients are:

$$s_{ijt} = \frac{\exp(\delta_{jt} + \overbrace{\hat{\hat{\rho}}_{ijt}}^{f(\hat{\Theta}_i = c + X_1 b_1)} \times (\overbrace{\Theta_i}^{unchanged} + X_{it}\alpha) + \phi Z_{it})}{1 + \sum_k \exp(\delta_{kt} + \underbrace{\hat{\hat{\rho}}_{ikt}}_{f(\hat{\Theta}_i = c + X_1 b_1)} \times (\underbrace{\Theta_i}_{unchanged} + X_{it}\alpha) + \phi Z_{it})}$$

H.4 CF4: Lower prescription rate for Category B and C

Similar to CF3, we follow the CDC guidelines and lower prescription rates for Category B and C patients. We do not exclude any physicians and allow patients to resort, knowing that physicians are now strictly following the CDC guidelines for opioid prescriptions. We examine the counterfactual shares of patients who originally chose a physician, holding fixed the shares of patients who chose the outside option.