The Last Mile to First Treatment: Search for Opioid Use Disorder Medication

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Despite growing policy support for buprenorphine, the leading medication for opioid use disorder, treatment uptake remains low. Administrative insurance data from Washington State show only half of first-time patients fill their buprenorphine prescriptions, well below rates for other chronic conditions. I find uptake is hindered by limited availability and patients' inability to verify it beforehand. To quantify their impact, I develop a structural sequential search model in which patients are uncertain which pharmacies carry buprenorphine. Using purchase data alone, the model recovers search costs by assuming patients always visit their default (most frequently visited) pharmacy. This implies latent utility from the default depends only on preferences, while that from non-defaults reflects both preferences and search costs. I find fewer than 40% of patients search more than once. Counterfactual analysis shows that providing prescribers with real-time pharmacy inventory—to inform patients at the point of care—would increase buprenorphine uptake by approximately 45%.

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I. Introduction

The opioid crisis remains the deadliest ongoing public health emergency in the United States. In 2024 alone, opioids caused 57,449 overdose deaths, bringing the 20-year cumulative toll to nearly one million. Among adults aged 16 to 65, opioids now account for 8.2% of all deaths—exceeding those from suicide, firearm-related fatalities, and traffic accidents.[1] Buprenorphine, a partial opioid agonist, is among the most effective treatments for opioid use disorder (OUD). By binding to the same receptors as opioids without producing the same euphoric high, it alleviates withdrawal symptoms and cravings, reducing the risk of relapse and overdose (Larochelle et al., 2018; Ma et al., 2019; Dever et al., 2024). Yet despite broad clinical and policy support, 87% of individuals with OUD remain completely untreated (Krawczyk et al., 2022).

This paper focuses on patients newly prescribed buprenorphine, for whom timely access is most critical. Delays at initiation often lead to a return to opioid use, derailing recovery before it begins. Yet after obtaining a prescription, nearly half of patients fail to fill it, a rate far below that for other chronic conditions. Why does treatment break down in the last mile?

Two reinforcing barriers contribute to the high rate of prescription non-fulfillment. First, buprenorphine remains difficult to access: only 57% of pharmacies nationwide stocked the medication in 2022 (Weiner et al., 2023). Patients often must visit multiple locations to find buprenorphine, increasing their search costs. Second, patients face informational frictions: pharmacies are not required to disclose inventory and often decline to confirm buprenorphine availability by phone, citing concerns about diversion and theft. Even addiction specialists lack visibility into pharmacy inventories, limiting their ability to guide patients effectively. As one provider noted, "filling the prescription is entirely on the patient." These frictions are particularly acute during the study period, when physicians typically issued handwritten prescriptions for controlled substances rather than transmitting them electronically.[2] Patients had to visit pharmacies in person merely to learn whether the medication was available.

These barriers leave many patients unable to access treatment even after receiving a valid prescription. The resulting shortfall in prescription fulfillment raises a natural policy question: how

[1] Mortality counts are obtained from the CDC Wonder provisional multiple cause of death data [Accessed: 2025-07-18].

[2] In 2018, only 15.9% of controlled substance prescriptions in Washington State were transmitted electronically, according to Surescripts: Surescripts 2018 National Progress Report [Accessed: 2025-07-18].

can uptake be improved? A blanket mandate requiring all pharmacies to carry buprenorphine may seem sufficient, but can similar gains be achieved at lower cost? Designing effective policy requires disentangling patient preferences, search frictions, and uncertainty about availability.

To disentangle the aforementioned factors, I combine detailed insurance data from Washington State—including patients with OUD, who are typically excluded from research due to federal privacy protections—with a structural model of sequential search. The primary dataset is Washington State's All-Payer Claims Database (APCD), an individual-level health insurance dataset that links medical diagnoses and prescription drug claims across Medicaid, Medicare, and commercial insurers. From patients' medical claims, I observe detailed diagnostic histories; from pharmacy claims, I observe the drug use histories.[3] I further incorporate the Automated Reports and Consolidated Ordering System (ARCOS), which records shipments of controlled substances to every retail pharmacy in the state. I infer pharmacy-level availability by linking ARCOS shipment data to pharmacy claims.

To analyze patients' search behavior, I adapt the framework of Moraga-González et al. (2023), which recasts the dynamic sequential search problem of Weitzman (1979) as a static discrete choice model. I introduce two key modifications to account for availability. First, I embed beliefs about pharmacy-level availability directly into search costs. Rather than identifying beliefs and search costs separately, I estimate their composite, an *effective search cost* that scales inversely with perceived availability. For example, if a patient believes there is a 50% chance that a pharmacy has buprenorphine in stock, the effective cost of visiting that pharmacy doubles. Second, pharmacies that do not stock buprenorphine are never chosen. Thus, the discrete choice model is constructed over a choice set limited to pharmacies that carry buprenorphine.

To separately identify preferences and search costs, I assume that patients always visit their default pharmacy. This assumption is empirically supported in two ways. First, default pharmacies are well-defined: 96% of patients in the data fill the majority of their prescriptions at a single location. Second, patients act on this default: fill rates drop from 70% to 18% when the default pharmacy does not carry buprenorphine. This sharp decline suggests that patients

[3]The data also include individual demographics, such as age, sex, insurance type (Medicaid versus other), and residential ZIP code, which I use to measure travel distances to nearby pharmacies. To supplement individual characteristics, I merge in ZIP Code Tabulation Area–level data from the American Community Survey.

typically begin their search at the default and, when it is unavailable, often do not continue searching. Because the default pharmacy is always searched, I normalize its effective search cost to zero. Utility at the default pharmacy reflects preferences alone, while utility at non-default options incorporates both preferences and search costs. This structure enables identification using purchase data alone, without requiring information on search sequences. Under these assumptions, the model reduces to a standard logit, with utility determined by preference and search cost parameters, allowing the same covriates to affect both.

The estimated model delivers three main findings. First, vulnerable groups—including Black patients, Medicaid and Medicare enrollees, and those with multiple diagnosed conditions—are less likely to search beyond their default pharmacy and exhibit lower estimated willingness to obtain buprenorphine. Second, distance is a meaningful barrier to search. Traveling one additional mile raises the effective search cost by \$0.62, roughly 3% of the average insured out-of-pocket cost for buprenorphine (\$21.33). While this may seem modest, it implies a much higher search cost relative to price than estimated in other settings.[4] Third, search is limited overall. Fewer than 40% of patients search beyond their default, indicating most rely on a single pharmacy, even when it lacks the medication. Together, these patterns suggest that high effective search costs reduce treatment uptake, particularly among the most vulnerable populations.

I use the estimated model to evaluate a set of counterfactual policies designed to reduce search frictions. As a benchmark, I simulate a universal availability mandate in which all pharmacies are required to carry buprenorphine. This eliminates uncertainty and expands the patient choice set. Under the status quo, I assume patients form beliefs based on the average availability rate among nearby pharmacies. When availability becomes known with certainty, these beliefs no longer inflate effective search costs, which are correspondingly reduced. In this scenario, treatment uptake rises to 71%, comparable to fill rates for other chronic medications.

I then examine two feasible interventions that improve patient access to information about pharmacy-level buprenorphine availability. A central challenge is that pharmacies cannot publicly advertise buprenorphine availability due to concerns about diversion and theft. Prescribers

[4]For example, in the European car market, Moraga-González et al. (2023) estimate that traveling one kilometer imposes an average cost of €148. Given an average car price of €19,917, the search cost amounts to just 1% of the product's value per mile.

are natural intermediaries: they can convey availability information to patients at the point of care while shielding pharmacies from having to disclose inventory directly to individuals.

In the first intervention, the state provides prescribers with real-time access to pharmacy inventory. At the time of prescribing, clinicians can inform patients which nearby pharmacies currently have buprenorphine in stock. This prevents patients from searching unavailable locations and raises treatment uptake by 45% relative to the status quo. The effect is comparable to mandating universal availability, but achieved at significantly lower cost. In the second intervention, I consider a more decentralized alternative. Even in the absence of a statewide system, prescribers may develop informal relationships with a small number of local pharmacies, such as five, that reliably stock buprenorphine for their patients. Patients remain free to choose any pharmacy, but knowing that a subset has buprenorphine in stock reduces uncertainty and lowers effective search costs. Even this modest intervention raises treatment uptake by 10%.

Finally, I evaluate mandatory electronic prescribing for controlled substances, which aims to curb diversion and prescription fraud. As of 2025, all states require some form of e-prescribing for controlled substances. As discussed earlier, handwritten prescriptions must be physically presented at each pharmacy, forcing patients to visit in person just to check availability. E-prescribing removes the burden of manual verification by transmitting prescriptions electronically, allowing patients to confirm availability in advance and thereby reducing effective search costs by scaling perceived availability, as in previous counterfactuals. However, this certainty comes at a cost: prescriptions cannot be transferred without contacting the prescriber for a new one. This rigidity raises search costs when patients attempt to switch pharmacies, discouraging continued search. Despite this constraint, I find that the informational benefit of certainty dominates. Treatment uptake improves under e-prescribing unless search costs more than double—a threshold unlikely to be met under typical conditions. This suggests that e-prescribing can expand buprenorphine access without requiring costly pharmacy mandates.

Related Literature: This paper proposes a novel approach to estimating sequential search models without direct data on search behavior, by assuming zero search cost for one designated option—in this case, the default. This method is especially useful in settings where search data are unavailable but understanding consumer behavior is crucial. Consider school choice and assignment problems, where students are assigned by default to neighborhood public schools. Even when higher-quality alternatives exist, many parents remain with the default (Hastings et al., 2009). Researchers typically lack data on how many alternatives parents consider or whether they engage in any search at all. By normalizing the search cost of the default to zero, the model enables separate identification of preferences and search frictions. What appears as inertia can be attributed to parental inattention, but it may also reflect substantial search costs. Some parents may begin searching but stop after one or two attempts due to high search costs, limiting access to better options. This distinction matters for policy: eliminating the default assignment may prompt active choice, but it will not necessarily increase enrollment at higher-quality schools if search costs remain high.[5]

This paper contributes to a growing body of work evaluating policy responses to the opioid crisis. Most existing interventions have focused on restricting supply—such as the 2010 OxyContin reformulation (Severtson et al., 2013; Alpert et al., 2018; Evans et al., 2019) and DEA crackdowns on rogue distributors (Donahoe, 2022; Gui et al., 2024; Soliman, 2024). While these efforts curtailed access to prescription opioids, they often failed to improve health outcomes and, in some cases, accelerated substitution into illicit markets. In contrast, demand-side policies have shown greater promise: expanding naloxone access reduces overdose mortality (Abouk et al., 2019; Rees et al., 2019), and increasing the number of authorized buprenorphine prescribers improves treatment uptake (Gui, 2024). In this paper, I use availability at a patient's default pharmacy as an instrument for treatment uptake and find that initiation reduces ER visits by 20% relative to similar patients. This result offers causal confirmation of earlier observational findings (Sullivan et al., 2021; Skains and et al., 2023; Yarborough et al., 2024). More broadly, nearly all demand-side interventions depend on patients ultimately receiving medication for OUD. Reducing last-mile barriers can therefore amplify the effects of upstream policies aimed at expanding treatment uptake.

Second, this paper contributes to the empirical literature on estimating sequential search models. It builds on the foundational framework of Weitzman (1979), as extended by Moraga-

[5]Similar dynamics arise in settings such as online shopping (e.g., defaulting to Amazon), voting (e.g., sticking to a party-line ballot), and retirement savings (e.g., auto-enrollment in investment plans). In all these cases, direct data on search behavior are often unavailable, yet search plays an important role in shaping choices.

González et al. (2023), who follow Armstrong (2017) and Choi et al. (2018) in reformulating dynamic search as a static discrete choice problem. Moraga-González et al. (2023) impose parametric restrictions on search cost distributions, yielding a tractable logit model of individual-specific choice sets. I extend this framework to account for product unavailability, a feature relevant in settings with supply disruptions such as the 2022 infant formula shortage or access constraints caused by natural disasters (e.g., Luco et al., 2024). In contrast to prior models, I allow consumers to search options that may not carry the product. In addition, this approach avoids reliance on search path data. Instead, I assume that patients always search their default pharmacies. When richer data on search are available (e.g., Santos et al., 2012, 2017; Compiani et al., 2024; Honka, 2014), those moments can and should be incorporated. But in many settings, such data are unavailable. In these cases, my framework offers a tractable, data-efficient way to estimate search costs and preferences using purchase decisions alone.

Third, the paper contributes to the literature on default options in consumer choice, particularly in healthcare. Defaults carry significant weight in high-friction environments where consumers often deviate from the "best" option. As shown by Hortaçsu et al. (2017) and Abaluck and Adams-Prassl (2021), reducing switching costs can improve welfare for consumers who remain anchored to suboptimal defaults. Models of inattention, such as those in Abaluck and Adams-Prassl (2021), Heiss et al. (2021), Ho et al. (2017), and Hortaçsu et al. (2017), typically sort consumers into two types: those who are inattentive and choose only the default or opt out, and those who are attentive and select from the full choice set. I propose an alternative model that embeds the default within a sequential search process. Departing from the default, meaning filling a prescription at a non-default pharmacy, requires incurring search costs. These costs are only worthwhile when the expected utility gain exceeds the cost of searching. This structure allows for intermediate behavior. Consumers may not be fully inattentive, but they also do not consider all available options. Instead, they evaluate a limited set of options shaped by the search process. The search-based view of default adherence offers a parsimonious, behaviorally grounded framework for modeling consumers who lie between fully attentive and fully inattentive, similar to the hybrid model proposed by Abaluck and Adams-Prassl (2021).

This paper proceeds as follows. Section II provides institutional background on OUD treatment and the limited availability of buprenorphine at pharmacies. Sections III and IV describe the data and highlight key empirical patterns. Section V presents a sequential search model under uncertain availability and outlines an estimation strategy that does not require search path data. Section VI reports the estimation results and discusses their implications. Section VII presents counterfactual policy analyses aimed at improving access to buprenorphine. Section VIII concludes with a summary of findings and implications for policy. Additional empirical facts and details on data construction appear in the Appendix.

II. Institution Background

This section provides institutional background on OUD treatment, with a focus on understanding the drivers of low buprenorphine prescription fulfillment. I highlight how pharmacy stocking decisions and limited information about availability contribute to treatment drop-off.

A. Medication for Opioid Use Disorder

> "If you were to just imagine a medicine, or a chemical compound, that could stop the opioid epidemic, that medicine would probably look a lot like buprenorphine."
> —Ethan Brook, The Atlantic

Buprenorphine is one of three medications approved by the U.S. Food and Drug Administration for treating OUD, alongside methadone and naltrexone. Among these, buprenorphine is distinguished by its safety profile and flexibility in administration, making it the most commonly prescribed treatment in office-based settings.

Methadone, a full opioid agonist, is subject to tight federal restrictions. It can only be dispensed through licensed opioid treatment programs, and patients are generally required to attend daily visits during the first 90 days of care.[6] Naltrexone, an opioid antagonist, is more often prescribed for alcohol use disorder and requires complete detoxification prior to initiation, a barrier many patients are unable to overcome. In contrast, buprenorphine is a partial agonist with a ceiling effect that mitigates overdose risk while effectively suppressing cravings and withdrawal

[6]Following regulatory changes during the COVID-19 pandemic, take-home methadone doses became more accessible. This flexibility has since been extended at the discretion of the prescribing practitioner. See SAMHSA guidance: Methadone Take-Home Flexibilities Extension.

symptoms. Certified prescribers can offer it in office-based settings, expanding access beyond the confines of OTPs. During the study period, over 80% of pharmacologically treated OUD patients received buprenorphine.[7]

The treatment pathway for buprenorphine resembles those of other long-term therapies for chronic conditions. Patients begin with an induction phase focused on clinical stabilization, followed by maintenance therapy that may extend for months or years. Behavioral therapy and peer support are often encouraged as complementary elements. Addiction specialists frequently liken buprenorphine to "insulin for OUD"—not a cure, but a cornerstone of sustained disease management that enables individuals to return to functional daily life.

Initiating buprenorphine treatment is therefore a pivotal step in the recovery process. As with other chronic illnesses, early access and continuity of care are critical to achieving favorable outcomes. Yet, as this paper shows, frictions in access, especially at the pharmacy level, can obstruct treatment, even for patients who have already secured a valid prescription.

B. Pharmacy Stocking Behaviors

Despite buprenorphine's central role in treating OUD, its availability at retail pharmacies remains limited. Nationally, only 57.9% of pharmacies stocked the medication as of 2022 (Weiner et al., 2023). In Washington (2014–2019), only 56% of pharmacies that received any opioid shipments ever received buprenorphine. Given that its therapeutic role is often compared to insulin for diabetes, the reluctance of pharmacies to carry, let alone consistently stock, buprenorphine is striking.

The reasons pharmacies choose not to stock buprenorphine are not fully understood. A policy roundtable convened by the Substance Abuse and Mental Health Services Administration identified several commonly cited barriers.[8] First, pharmacies may fear stigmatization, including concerns that stocking buprenorphine could attract clientele perceived as undesirable. Second, regulatory uncertainty, particularly regarding ordering thresholds, may discourage pharmacists

[7] Buprenorphine is available in two formulations: one combined with naloxone (commonly branded as Suboxone) and one without. The combination is recommended as first-line treatment due to its deterrent effects on misuse. The mono-product is typically reserved for patients contraindicated for naloxone, such as pregnant women. Nearly all prescriptions in this study pertain to the combination formulation.

[8] See: SAMHSA Policy Priority Roundtable on Buprenorphine Access in Pharmacies.

from requesting inventory, out of fear of triggering compliance violations.[9] Third, the economics of dispensing buprenorphine are often unfavorable. Pharmacists report high labor costs associated with verifying prescriptions and navigating insurance coverage, paired with low reimbursement rates. One widely circulated estimate suggests that pharmacies lose approximately $10 per buprenorphine fill.

The challenge extends beyond whether a pharmacy ever stocks buprenorphine. Among those that do, inventory is often inconsistent or chronically insufficient. Because buprenorphine must be initiated within a narrow window after the onset of withdrawal, even short delays can disrupt treatment. As a result, patients are frequently forced to search across multiple pharmacies—introducing frictions that delay or deter initiation altogether.

C. Frictions in Learning About Availability

Patients cannot easily resolve uncertainty about buprenorphine availability before visiting a pharmacy. Pharmacists are not legally required to disclose inventory levels, and many adopt a policy of nondisclosure for controlled substances. This practice, especially common in the early 2010s amid heightened fears of diversion, reflects concerns that confirming stock over the phone could attract individuals seeking opioids for non-medical use or increase the risk of theft.

These concerns appear in professional discourse. In a 2014 thread on *studentdoctor.net*, a forum used by pharmacists, contributors described common responses to telephone inquiries:

- "If it's a control, no matter what I say: 'out of stock.' I don't want any more of 'those' types of patients."
- "Just ask for the strength and quantity. Pretend to check. Then politely say no."

Many pharmacies will not even check inventory without first seeing a valid prescription. During the study period, most prescriptions for controlled substances were handwritten and physically

[9] The Drug Enforcement Administration shut down Oak Hill Hometown Pharmacy, citing an "imminent danger to public health and safety" due to its high volume of buprenorphine dispensing. Although a federal judge later ruled in the pharmacy's favor, noting it had acted professionally and within legal bounds, the DEA's action effectively ended its operations. Wholesale suppliers, wary of regulatory scrutiny, refused to resume shipments. See NPR Coverage [Accessed: 2025/07/19]

carried by the patient. As of 2018, only 15.9% of controlled substance prescriptions were transmitted electronically. This meant that patients often had to visit pharmacies in person simply to determine whether the medication was available.

Even under electronic prescribing, where prescriptions can be transmitted before a patient arrives, new frictions emerge. If a pharmacy is out of stock, the prescriber must cancel the original and issue a new one; there is no mechanism for redirection. At the same time, federal regulations prohibit sending the same prescription to multiple pharmacies. In practice, this imposes added burdens on patients: when the default pharmacy lacks buprenorphine, each additional search requires contacting the prescriber to reroute the prescription again.

These institutional frictions have implications for the counterfactual scenarios considered later in the paper. Even if e-prescribing reduces uncertainty about inventory, it may raise the cost of switching pharmacies by requiring patients to contact their provider each time a redirection is needed. As a result, patients frequently initiate searches only after a failed fill attempt at their default pharmacy—and often without reliable information about which pharmacies are likely to stock buprenorphine.

III. Stylized Facts

This section presents empirical patterns that motivate the analysis. I first document the prevalence of default pharmacy behavior and show that prescription fulfillment is low. Much of this shortfall is driven by lack of buprenorphine availability at patients' default pharmacies. Wherever appropriate, I benchmark buprenorphine against levothyroxine, the standard treatment for hypothyroidism.[10] Levothyroxine is widely prescribed, routinely available, and not subject to the restrictions governing controlled substances. While both medications are first-line treatments for chronic conditions, a key distinction lies in their relative availability at pharmacies.

In Appendix B, I document three additional stylized facts. First, buprenorphine prescriptions must be filled within a narrow therapeutic window. Second, when the default pharmacy is unavailable, patients tend to substitute to pharmacies near either their home ZIP or the default

[10]Hypothyroidism, a condition in which the thyroid gland does not produce enough thyroid hormone, affects roughly 5% of the U.S. population.

pharmacy. Third, patients who initiate buprenorphine experience at least a 20% reduction in number of subsequent emergency room visits.

A. *Default Pharmacy Behavior*

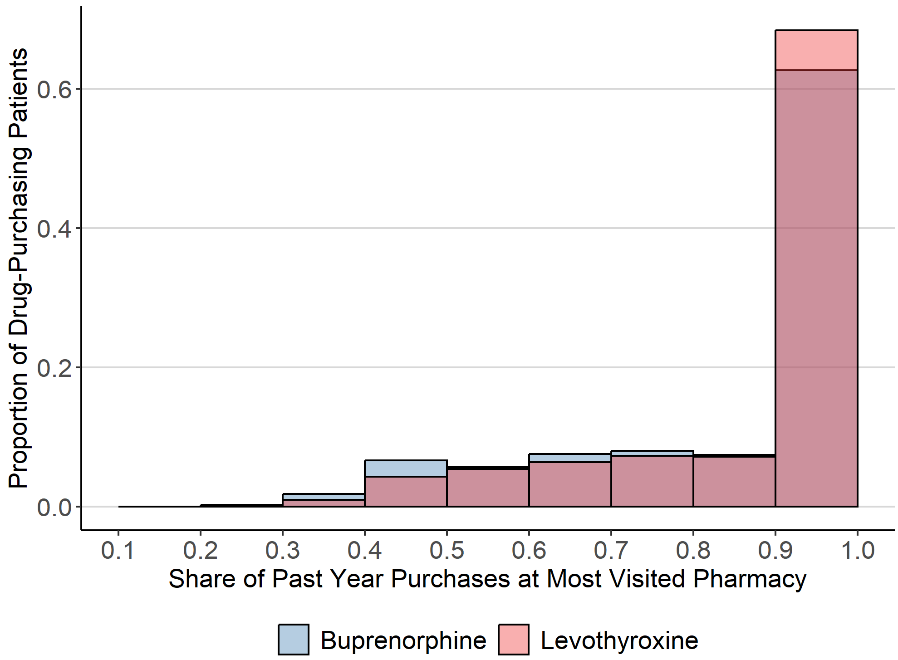


Figure 1. Default Option Market Share

Note: This figure shows the market share of the default pharmacy for first-time buprenorphine and levothyroxine prescriptions. Market share is defined as the share of prescriptions filled at the patient's default pharmacy—the most frequently visited pharmacy in the year prior to the associated medical claims.

I define a patient's default pharmacy as the pharmacy they visited most frequently in the year prior to their index diagnosis.[11] Figure 1 shows that default pharmacy behavior is common for both buprenorphine and levothyroxine patients. Among those newly diagnosed with OUD or hypothyroidism, over 90% of patients filled at least half of their prescriptions at the same pharmacy prior to diagnosis. Specifically, 93% of buprenorphine patients and 88% of levothyroxine

[11]In rare cases, patients may split prescription volume evenly across multiple pharmacies. If so, I define the default pharmacy as the one nearest to the patient's home ZIP code. In addition, if a patient moves during the year—as indicated by a change in residential ZIP code—I assign the default based on the pharmacy most frequently visited prior to the move.

patients relied on a single pharmacy for the majority of their prior fills.

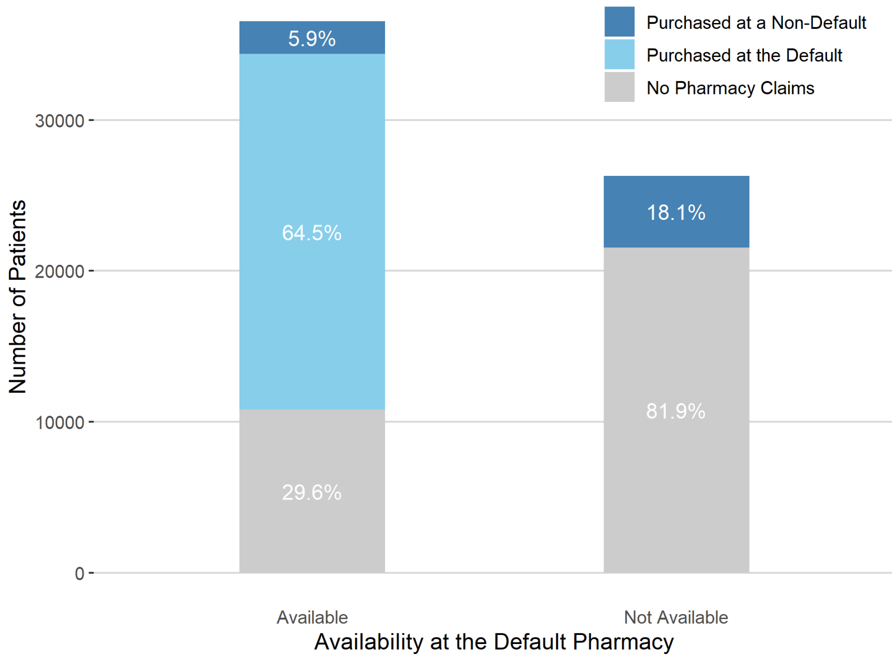
This consistent pattern across drug types suggests that default pharmacy behavior is not unique to OUD patients, but reflects a broader feature of prescription filling. While e-prescribing for controlled substances was limited during the study period, e-prescribing for non-controlled medications, such as levothyroxine, was already widespread. Most patients' prior prescriptions include at least some non-controlled substances, which are routinely transmitted electronically. These e-prescriptions are typically directed to the patient's preferred pharmacy on file, a default that remains fixed unless actively changed. E-prescribing platforms reinforce this behavior by auto-filling the last-used pharmacy, and medical guidelines encourage patients to consolidate prescriptions at a single location to reduce the risk of adverse drug interactions (Marcum et al., 2014). Therefore, patients tend to develop a default pharmacy. In what follows, I use the default pharmacy as the starting point for modeling patient search and decision-making under uncertainty.

B. High Non-Fulfillment in OUD Treatment

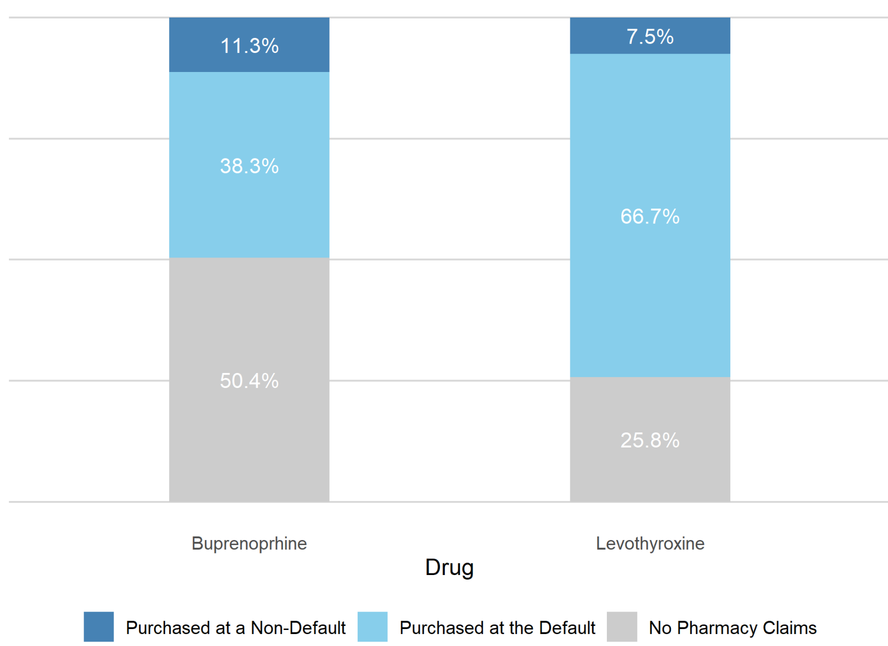
This section examines prescription non-fulfillment among patients who have received a prescription.[12] I classify patient behavior into three categories: filling the prescription at the default pharmacy, filling it at a non-default pharmacy, or not filling it at all.

Figure 2a displays the share of patients in each fulfillment category, conditional on whether buprenorphine was available at the patient's default pharmacy on the prescription date. I approximate daily inventory levels by linking pharmacy claims to ARCOS shipment data (see Appendix A.A2 for details). Three key patterns emerge. First, although most patients had default pharmacies with buprenorphine in stock, the majority of non-fills occurred when the drug was unavailable at the default. Second, availability at the default pharmacy significantly increased uptake: only 30% of patients failed to fill the prescription when buprenorphine was in stock. Third, when the default pharmacy lacked the medication, just 20% of patients filled the prescription elsewhere—suggesting that most do not search extensively or are unable to locate

[12]This inference is based on medical claims data, which do not specify the exact drug prescribed. However, both hypothyroidism and OUD are life-threatening without medication, making it highly likely that treatment was prescribed. Among patients who had a follow-up visit with the same provider, only 3% failed to generate any pharmacy claims, further supporting the presumption of prescribing.



(a) Purchase Location Conditional on Default Pharmacy Availability



(b) Purchase Location Following Initial Diagnosis

Figure 2. Pharmacy Purchase Patterns for New Patients

Note: This figure illustrates where first-time patients fill their prescriptions—either at their default pharmacy, at a non-default pharmacy, or not at all. Panel (a) conditions on the availability of buprenorphine at the default pharmacy, defined as having sufficient inventory to fill the prescription on the date it was written. Panel (b) shows the unconditional purchase shares for patients prescribed buprenorphine (used to treat OUD) and levothyroxine (a common and widely available treatment for hypothyroidism).

an alternative with supply.[13]

Figure 2b presents unconditional purchase patterns for buprenorphine and levothyroxine patients—that is, patterns not conditioned on drug availability. About 25% of hypothyroidism patients fail to fill a prescription following diagnosis, compared to nearly 50% of OUD patients. Among levothyroxine users, fills occur at the default pharmacy six times more often than at non-default locations. For buprenorphine, that ratio falls to 2:1, indicating greater deviation from the default—either due to increased search effort or lower availability at the usual pharmacy. Crucially, when restricting to buprenorphine patients whose default pharmacy has the drug available (in prior figure), their fill rates and default usage closely resemble those of levothyroxine patients. This pattern suggests that low buprenorphine uptake is not driven primarily by patient non-compliance, but by limited availability and the resulting search frictions.

One might imagine a simple fix: reassigning each patient's default pharmacy to one that consistently stocks buprenorphine, or mandate that every pharmacy stock the drug. While such policies could improve access in theory, they are unlikely to be practical at scale. A more feasible intervention would be to provide patients with information about which pharmacies have buprenorphine in stock. If patients knew where to go, they could search more efficiently. But when faced with uncertainty, patients are less likely to initiate or persist in search. This information barrier, and its implications for patient behavior, is central to the counterfactual scenarios considered in later sections.

IV. Data

To study pharmacy search behavior and buprenorphine access in Washington State, I use three primary datasets. This section summarizes the key features of each dataset relevant to the analysis. Table E1 reports summary statistics for the main variables used.

[13]For this group of patients, I examine subsequent purchase patterns. As shown in Appendix B, patients tend to purchase from pharmacies located either near their home ZIP code or their default pharmacy. This empirical pattern motivates the structure of the search model.

A. Washington All-Payer Claims Database

I use the Washington All-Payer Claims Database (WA-APCD) to analyze buprenorphine prescribing and fulfillment behavior. The WA-APCD includes medical and pharmacy claims for most insured residents of Washington State, covering public payers (Medicaid and Medicare) as well as a subset of private plans. It provides detailed claim-level information on patient demographics, diagnoses, procedures, provider identifiers, payment amounts, and residential ZIP codes. As a patient-centered dataset, the WA-APCD allows for the reconstruction of individual medical histories—such as prior diagnoses of substance use disorder and prior-quarter opioid consumption—and enables linkage between medical visits and subsequent pharmacy fills.

A unique feature of this dataset is that it includes patients diagnosed with OUD, a subset of substance use disorders historically excluded from administrative claims data due to federal privacy protections. To my knowledge, this is the first paper to use detailed patient-level insurance data to study treatment-seeking behavior among individuals with an OUD diagnosis.

I restrict the sample to patients who received their first OUD diagnosis between 2014 and 2019. Using medical claims, I identify the initial OUD-related visit and then track whether the patient filled a buprenorphine prescription, and at which pharmacy, using pharmacy claims. Further details on sample construction are provided in Appendix A.A1. I focus on first-time OUD diagnoses for two reasons. First, search frictions and pharmacy availability are particularly important for new patients who have not yet established a pharmacy relationship. In contrast, refills can often be coordinated in advance, even if the pharmacy is not currently stocked. Second, the first filled prescription is a crucial margin: prior research shows that patients who initiate buprenorphine are substantially more likely to remain engaged in OUD treatment compared to those who do not.

B. Automation of Reports and Consolidated Orders System

The Automation of Reports and Consolidated Orders System (ARCOS) is a national surveillance system maintained by the Drug Enforcement Administration under the Controlled Substances Act of 1971. ARCOS tracks opioid shipments across the supply chain, from manufacturers and distributors to hospitals and pharmacies. For each transaction, the dataset records the shipment date, quantity, dosage, National Drug Code, and the identities of sender and recipient.

ARCOS plays a central role in this paper by enabling the construction of daily pharmacy-level inventory for buprenorphine. Pharmacy claims contain information on drug formulation, strength, and fill date, which I use to measure daily outflows. Shipment data from ARCOS provide the corresponding inflows. By aggregating shipments and claims over time and subtracting cumulative claims from cumulative shipments, I estimate whether a pharmacy had buprenorphine in stock on a given day, including the date of a patient's prescription. This inventory measure is not without limitations. In particular, not all buprenorphine is dispensed through insurance claims, and I abstract from formulation differences by focusing on the presence of buprenorphine as the active ingredient. Construction details and a discussion of caveats appear in Appendix A.A2.

C. Other Data Sources

ZCTA-Level Demographics. Because individual-level demographic data in the WA-APCD are limited, I supplement the analysis with ZIP Code Tabulation Area (ZCTA)-level characteristics from the American Community Survey (ACS) 5-year estimates. These include median income, educational attainment (above high school), poverty rate, and unemployment rate.

Provider Characteristics. I use the National Plan and Provider Enumeration System (NPPES) to obtain information on prescribers, including specialty, gender, and years of experience. Historical NPPES snapshots were accessed through the NBER data repository.[14]

Product Classification. To distinguish buprenorphine formulations intended for opioid use disorder (OUD) from those used for pain management, I rely on data scraped from the DailyMed website. By querying National Drug Codes for buprenorphine products, I obtain detailed product descriptions and labeled indications for use.

V. Model

This section presents a sequential search model among individuals seeking buprenorphine treatment for the first time. The framework builds on Weitzman (1979)'s optimal sequen-

[14]Link to NBER collection [Accessed: 2025-01-15].

tial search strategy, extending it to account for cases where a search attempt results in a reward equals to zero—specifically, when the patient discovers that a pharmacy does not have buprenorphine available.[15] Building on this foundation, the estimation approach follows Moraga-González, Sándor, and Wildenbeest (2023), which applies insights from Armstrong (2017) and Choi, Dai, and Kim (2018) to reformulate sequential search as a discrete choice problem. In this framework, consumers select the option that maximizes the minimum of their reservation value and realized utility across all available alternatives. Importantly, the model does not require auxiliary data on search sequences or the number of pharmacies visited. Identification hinges on asymmetries in the utility specification between default and non-default options. Specifically, the utility of selecting the default pharmacy is not subject to search costs, whereas all non-default options incur such costs. This asymmetry generates variation in observed choices that can be exploited for estimation.

A. *Utility Specification*

I consider a market with J different pharmacies, indexed by $j = 1, 2, \ldots, J$. The indirect utility that consumer i derives from visiting pharmacy j and obtaining buprenorphine is given by:

$$u_{ij} = \beta_0 + \alpha P_{ij} + X_{ij}\beta + \epsilon_{ij}, \tag{1}$$

where P_{ij} is the price paid by consumer i at pharmacy j.[16] The vector X_{ij} includes consumer, provider, and pharmacy characteristics: demographics (e.g., age, gender, race), health indicators (e.g., past-quarter opioid consumption, prior diagnoses of substance use disorder or mental illness), physician characteristics (e.g., addiction specialization, years of experience), pharmacy characteristics (e.g., chain affiliation, same-chain indicator with the default pharmacy), and insurance type (e.g., Medicaid, Medicare, or commercial coverage).

[15]This is discussed in the Application section of Weitzman (1979), where box i contains one of two outcomes: either zero reward ("failure") with probability $1 - p_i$, or a positive reward ("success") with probability p_i.

[16]Prices in this setting are largely determined by insurance contracts and network agreements, limiting pharmacies' ability to adjust prices in response to consumer search. In contrast to standard search markets where firms may exploit inattention through markups (Moraga-González et al., 2023), price endogeneity is not a primary concern here.

The idiosyncratic term ϵ_{ij} is assumed to be *i.i.d.* across pharmacies and distributed Type I Extreme Value. It represents a match-specific parameter that captures the "fit" between consumer i and pharmacy j. While the drug itself is homogeneous, the match value ϵ_{ij} varies across pharmacies and patients. One interpretation is that it reflects factors only revealed upon visiting a pharmacy, such as the quality of pharmacist interactions or wait times. These interactional frictions are especially relevant in OUD treatment, where stigma remains a substantial barrier to care. The utility of not filling a buprenorphine prescription is denoted by $u_{i0} = \epsilon_{i0}$, where $j = 0$ represents the outside option.

Equation (1) applies only to pharmacies where buprenorphine is available. For pharmacies that are out of stock, I define the realized utility as $u_{ij} = u_{i0} - \iota$, where ι is an arbitrarily small positive value. This ensures that unavailable pharmacies are strictly dominated by the outside option and thus never chosen.

Consumers must visit a pharmacy to learn the realization of ϵ_{ij} and thus their true utility. I model any trip beyond the default pharmacy as a discrete search attempt—originating from either the patient's home ZIP code or the default pharmacy.[17] Search is sequential and ordered, with costless recall. After visiting a pharmacy, the consumer decides whether to purchase, continue searching, or opt for the outside option. Before initiating search, the consumer knows the location of each pharmacy, the utility of the outside option, and the distribution F from which ϵ_{ij} is drawn.

Let $\tilde{c}_{ij}$ denote the effective search cost in conjunction of patient i's belief on availability for patient i when visiting pharmacy j. Effective search costs vary across consumers and pharmacies. I assume that the cumulative distribution of effective search costs, $F_{ij}^{\tilde{c}}$, depends on search cost covariates through a location parameter μ_{ij}. The effective search cost distribution has full support, though only its non-negative portion affects consumer behavior.

B. *Optimal Sequential Search*

I characterize optimal consumer search behavior using a modified version of the Weitzman rule. Let $\phi_{ij} \in (0, 1]$ denote patient i's belief about the probability that pharmacy j has buprenorphine

[17]I remain agnostic about whether the search originates from home or from the default pharmacy; both distances are included as covariates in the search cost function.

available.[18] In this framework, consumers decide whether to search a given option by comparing the expected benefit of searching to the cost of search. In my context, the expected benefit of searching pharmacy j depends on both the likelihood of availability and the potential gain in utility if buprenorphine is indeed available.

Let r denote the best utility the consumer has observed so far. The expected gain from searching pharmacy j is:

$$\phi_{ij} \underbrace{\int_r^\infty (z - r) dF_{ij}(z),}_{\equiv H_{ij}(r)} \tag{2}$$

where $F_{ij}(z)$ is the cumulative distribution function of the realized utility when pharmacy j has buprenorphine available.

The expected gain has two components: the probability of availability, ϕ_{ij}, and the expected utility gain conditional on availability, denoted $H_{ij}(r)$. By assumption, if a pharmacy does not have buprenorphine, its realized utility is set to be infinitesimally lower than the utility of the outside option. Thus, the expected gain from searching an unavailable pharmacy is effectively zero. This justifies modeling the total expected gain as $\phi_{ij} H_{ij}(r)$, with the zero-utility outcome implicitly folded into the belief term ϕ_{ij}.

If consumer i's expected gains from searching pharmacy j exceed the cost c_{ij}, the consumer will choose to search. I define the corresponding *reservation value* r_{ij} as the solution to the following equation:

$$\phi_{ij} H_{ij}(r_{ij}) - c_{ij} = 0. \tag{3}$$

In addition, I define the *effective search cost* as:

$$\tilde{c}_{ij} \equiv \frac{c_{ij}}{\phi_{ij}}, \tag{4}$$

[18]The case $\phi_{ij} = 0$ corresponds to full certainty that pharmacy j lacks inventory, in which case the pharmacy is excluded from the consideration set.

where c_{ij} reflects the physical or cognitive cost of visiting pharmacy j, independent of availability beliefs. Equation (4) highlights the key insight: lower expected availability inflates the effective cost of search. For instance, if $\phi_{ij} = 0.5$, the effective cost doubles.[19] I do not separately identify c_{ij} and ϕ_{ij}, but recover their composite effect $\tilde{c}_{ij}$. For example, a patient may avoid a chain pharmacy like CVS either because verification is time-consuming (high c_{ij}) or because they believe it is unlikely to stock buprenorphine (low ϕ_{ij}). While individual components are not identified, their joint effect on behavior is fully captured by $\tilde{c}_{ij}$.

Importantly, since H_{ij} is decreasing and strictly convex, Equation (3) has a unique solution. Therefore, $r_{ij} = H_{ij}^{-1}(\tilde{c}_{ij})$.

Following Lemma 1 from Moraga-González et al. (2023), the reservation value r_{ij} can be expressed as:

$$r_{ij} = \delta_{ij} + H_0^{-1}(\tilde{c}_{ij}) \tag{5}$$

where $H_0(r) = \int_r^\infty (z - r)dF(z)$, and δ_{ij} is the deterministic component of utility from Equation (1). This expression makes clear that the reservation value depends on both the expected utility from choosing a given pharmacy and the costliness of searching it. Specifically, higher effective search cost $\tilde{c}_{ij}$ lowers the reservation value, making consumers more selective in which pharmacies to visit. Conversely, higher observable match quality δ_{ij} lowers the bar for search.

C. Discrete Choice Problem

Armstrong (2017) and Choi, Dai, and Kim (2018) show that the optimal sequential search strategy can be equivalently expressed as a max-min decision rule: the consumer selects the option that maximizes the minimum of the reservation value and the realized utility. This framework can be extended to incorporate product availability. In my setting, consumers visit pharmacies in descending order of reservation values. At each pharmacy, they observe whether buprenorphine is available and, if so, draw the realized utility. If the drug is unavailable, the realized utility is strictly lower than that of the outside option. Search continues until the

[19]Standard sequential search models assume $\phi_{ij} = 1$ and estimate c_{ij} directly.

realized utility at a visited pharmacy exceeds the reservation value of the next-best unvisited option. A formal proof of this equivalence is provided in Appendix C.

A key feature of the model is that pharmacies without buprenorphine are excluded from the patient's choice set because they cannot dispense the medication. This exclusion reflects both institutional constraints—patients cannot purchase buprenorphine from a pharmacy that does not have it—and modeling assumptions, namely that the realized utility from such pharmacies is strictly lower than that of the outside option. Accordingly, the discrete choice problem is defined over the set of pharmacies with buprenorphine available to consumer i, denoted A_i. For each available pharmacy $j \in A_i$, I define the latent utility w_{ij} as the minimum of the reservation value r_{ij} and the realized utility u_{ij}:

$$w_{ij} = \min\{r_{ij}, u_{ij}\}. \tag{6}$$

To derive a tractable expression for the distribution of w_{ij}, I adopt a specific parametric form for the distribution of effective search costs. Following Moraga-González et al. (2023), I assume:

$$F^{\tilde{c}}(\tilde{c}) = \frac{1 - \exp\left(-\exp\left(-H_0^{-1}(\tilde{c}) - \mu_{ij}\right)\right)}{1 - \exp\left(-\exp\left(-H_0^{-1}(\tilde{c})\right)\right)}, \tag{7}$$

where μ_{ij} is the location parameter for the search cost distribution.

Under this specification, the induced distribution of w_{ij} follows a Type I Extreme Value distribution with location parameter $\delta_{ij} - \mu_{ij}$:

$$F_{ij}^{w}(w) = \exp\big(-\exp\big(-(w - (\delta_{ij} - \mu_{ij}))\big)\big). \tag{8}$$

This closed-form result relies on the particular choice of the effective search cost distribution and is formally derived in Proposition 1 of Moraga-González et al. (2023).

Then, we can specify the latent utility of pharmacy j for patient i as:

$$w_{ij} = (1 - D_{ij})(\delta_{ij} - \mu_{ij}) + D_{ij}\delta_{ij} + \xi_{ij}, \tag{9}$$

$$w_{i0} = \xi_{i0}, \tag{10}$$

where δ_{ij} is the deterministic component of utility from Equation (1), and μ_{ij} is the location parameter for the search cost distribution. A positive value of μ_{ij} is required for $F^{\tilde{c}}(\tilde{c})$ to be a proper distribution. I parameterize μ_{ij} using a log-exp functional form:

$$\mu_{ij} = \log\big(1 + \exp(\lambda_0 + Z_{ij}\lambda)\big), \tag{11}$$

where Z_{ij} includes observed search cost shifters that vary by consumer and/or pharmacy. These may include distance from the patient's home ZIP code, patient demographics, and pharmacy chain affiliations.

The conditional choice probability that patient i selects pharmacy j is:

$$s_{ij} = \frac{\exp(\kappa_{ij})}{1 + \sum_{j \in A_t} \exp(\kappa_{ij})}, \tag{12}$$

where $\kappa_{ij} = (1 - D_{ij})(\delta_{ij} - \mu_{ij}) + D_{ij}\delta_{ij}$. As discussed earlier, pharmacies without buprenorphine are never chosen and are excluded from estimation.

In sum, this discrete choice framework yields a closed-form logit model, despite the underlying sequential search structure. Availability enters as a constraint on the choice set, and search costs are embedded in the utility index via μ_{ij}. The resulting model is computationally tractable and estimable by maximum likelihood, without requiring auxiliary data on search sequences or moments that separately identify preferences and search costs. In this sense, the estimation procedure is even faster than that of Moraga-González et al. (2023), despite being based on a discrete choice model, as it does not require additional moments on search behavior for identification.

D. Estimation and Identification

I estimate the model via maximum likelihood. The log-likelihood function is:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} \sum_{j \in \{A_{it}, 0\}} Y_{ij} \log(s_{ij}), \tag{13}$$

where $Y_{ij} = 1$ if patient i fills their buprenorphine prescription at pharmacy j, and $Y_{ij} = 0$ otherwise. The parameter vector θ includes the price coefficient α, the preference parameters β, and the search cost parameters λ.

To reduce computational burden, I restrict each consumer's choice set to pharmacies within 25 miles for urban ZIP codes and 50 miles for rural ZIP codes. This restriction not only accelerates estimation but also helps remove problematic observations, such as patients who may have moved but failed to update their recorded ZIP code.

Identification: Identification boils down to separating the components of utility, δ_{ij}, from those of search cost, μ_{ij}. The model is identified through two main sources of variation.

First, I exploit asymmetries in how w_{ij} is constructed for default and non-default options. For the default pharmacy, I assume that patients always search it which implies that its effective search cost is zero. As a result, the default's utility depends only on δ_{ij}. In contrast, the utility of non-default pharmacies reflects both δ_{ij} and μ_{ij}. This structure provides an exclusion restriction: variation between the default and the outside option (as it is normalized to zero) identifies δ_{ij}. Given the the combined effect of $\delta_{ij} - \mu_{ij}$ are identified through variation in observed choices like a standard logit, I can identify μ_{ij} through differencing.

For instance, consider the constant term: let β_0 be the coefficient on the constant in δ_{ij}, and λ_0 the corresponding coefficient in μ_{ij}. A change in β_0 affects the utility of default options but leaves the utility of the outside option unchanged. By comparing the default option to the outside option, we can identify β_0. Given that the total effect of the constant is identified, we can then back out λ_0 by differencing. This logic generalizes to any covariate that enters both specifications, allowing separate identification under appropriate variation.

Second, if the utility specification δ_{ij} and the search cost specification μ_{ij} include excluded covariates, then the coefficients on covariates that enter only one of the two components can be identified without relying on additional assumptions or moment conditions. For example, in my specification, the distance between a consumer's residence and a pharmacy enters only the search cost equation and not the utility function.

Although μ_{ij} follows a parametric log-exp functional form (Equation 11), this choice imposes minimal constraint in practice. For moderate values (e.g., $\lambda > 3$), the approximation $\log(1+\exp(\lambda_0)) \approx \lambda_0$ holds closely. For example, $\log(1+\exp(3)) = 3.05$. In my estimation sample, the average μ_{ij} is 7.31. Thus, functional form is not the primary source of identification.

Even in settings without a closed-form solution for reservation values, the model remains identified. The key insight is that the consumer always search the default option, so its realized utility is directly observed—analogous to the outside option. For a consumer to reject other pharmacies, the realized utility from the default must exceed the minimum of reservation values and realized utility of all alternatives. Since those reservation values depend on both preferences and search costs, while the default's utility depends only on preferences, this comparison introduces identifying variation.

Correctly specifying the default option is essential. I define the default pharmacy as the one where the patient most frequently filled prescriptions prior to the index visit. For non-controlled substances, providers typically transmit prescriptions to the patient's designated pharmacy on file. A consistent fill history strongly suggests intentional selection. Misclassifying the default—e.g., by assuming it is the nearest pharmacy—would bias estimates. If patients are more likely to fill prescriptions at their true default than at the nearest pharmacy, conditional on availability, this would overstate search intensity and understate true search costs.

VI. Results

This section I first shows the estimated coefficient via the estimation procedure and what the interpretations are and second show the simulated search behavior from the estimated model. In Appendix D, I discuss the internal validity of the results.

A. *Estimated Coefficients*

Table 1 reports the estimated coefficients from the preference and search components of the model. In the estimated preference parameters ($\hat{\delta}$), a higher value reflects greater utility derived from pharmacy and consuming buprenorphine i.e., a greater likelihood of filling the prescription. In contrast, higher values in the search cost parameters ($\hat{\mu}$) indicate greater barriers to search.

Price and Travel Distance: Patients are generally not price-sensitive, with a small but statistically significant negative coefficient on out-of-pocket price. Medicaid recipients, however, are substantially more price-sensitive, consistent with lower incomes in this population. Search costs increase with travel distance, both from the patient's residence and from their default pharmacy. This effect is more pronounced in urban areas, where each additional mile traveled from the residence or default pharmacy corresponds to a greater increase in disutility. Quantitatively, each additional mile of travel imposes an effective search cost of approximately \$0.62 from the patient's residence and \$0.32 from the default pharmacy. These values represent 2.9% and 1.6% of the average out-of-pocket price of buprenorphine, respectively.[20] While these figures may appear modest, they imply far greater search burdens relative to price than in other markets. For comparison, Moraga-González et al. (2023) estimate that in the European car market, traveling one kilometer imposes an average cost of €148. Given an average vehicle price of €19,917, this amounts to only 1% of the product's value per mile traveled.

Provider Characteristics: Coefficients on provider characteristics, when entering through the utility function, should not be interpreted as prescribing behavior. Instead, they capture how provider attributes shape the perceived value of treatment. For example, patients assigned to female providers exhibit lower utility, potentially reflecting patient-side bias or differences in how treatment is communicated. In contrast, patients matched with more experienced providers or those specializing in addiction medicine report significantly higher utility, consistent with higher treatment quality or better alignment with patient needs. Provider characteristics also enter the search cost equation. One interpretation is that more experienced providers may help reduce patient uncertainty about buprenorphine availability. For example, they might direct patients

[20]Estimates are scaled by the share of patients on Medicaid and Medicare, and distances are population-weighted based on urban ZIP code distributions.

to better-stocked pharmacies, thereby lowering effective search costs. However, the estimates do not support this mechanism: experience is not associated with lower search costs

Health History: Health history variables reveal important heterogeneity in both preferences and search costs. Patients whose OUD diagnosis appears earlier in the coding hierarchy (i.e., more likely to be the primary diagnosis) exhibit higher utility from buprenorphine and face lower search costs. However, we observe what could be interpreted as adverse selection: patients with more severe health histories (i.e., higher past opioid use, mental illness, and substance use disorder) derive lower utility from treatment. This suggests that those who need buprenorphine most may perceive it as less valuable or be less responsive to treatment, posing a concern for equity and effectiveness. Interestingly, the relationship reverses in the search cost estimates: sicker patients face lower search costs. One possible explanation is that patients with multiple comorbidities needs fill multiple prescriptions and may already be familiar with pharmacy availability through other drugs, thus reducing marginal search costs. A greater number of diagnosed conditions also predicts lower search frictions, potentially for similar reasons.

Demographics: Racial and socioeconomic disparities are evident. Black patients derive lower utility from buprenorphine and face higher search costs. Older patients have higher treatment preferences but also higher search costs, possibly due to mobility. Female patients show slightly lower preference for treatment, but also lower search costs. Medicaid and Medicare recipients derive lower utility and face higher travel-related barriers. Patients living in higher-income areas derive higher utility but encounter higher search costs, potentially due to lower pharmacy density or higher opportunity cost.

Pharmacy Attributes: Most chain brands (e.g., CVS, Walgreens) show no significant effects in either the preference or search cost parameters. This is partly because the effects are absorbed by an indicator for affiliation with the patient's default pharmacy (e.g., if the default pharmacy is CVS, all CVS locations receive a value of 1 for this variable). Patients filling prescriptions at pharmacies affiliated with their default location derive higher utility and face lower search costs, likely reflecting established relationships and greater familiarity. Rite Aid is an exception: patients derive higher utility and also face higher search costs. This may reflect a chain-wide policy to stock buprenorphine and serve OUD patients more consistently.

Table 1— Estimated Coefficients

Preference Coefficients in δ			Search Coefficients in μ		
Variable	Estimate	SE	Variable	Estimate	SE
Out-of-Pocket Price	-0.005	2.7e-7	Distance from Residence	0.044	6.5e-5
×Medicaid	-0.408	0.002	×Urban	0.107	8.6e-5
×Medicare	-0.006	5.0e-7	Distance from Default	0.039	4.8e-5
			×Urban	0.039	6.4e-5
			Urban	0.036	0.027
Provider Characteristics					
Female Provider	-0.118	0.002	Female Provider	0.082	0.002
log(Experience)	0.043	4.0e-5	log(Experience)	0.045	4.0e-5
Addiction Medicine Specialist	0.025	0.004	Addiction Medicine Specialist	-0.006	0.004
× log(Past Opioid Consumption)	-0.033	2.6e-4	× log(Past Opioid Consumption)	-0.055	3.3e-4
× log(Past Mental Illness)	-0.002	0.019	× log(Past Mental Illness)	-0.004	0.022
× log(Past Substance Use Disorder)	0.000	0.012	× log(Past Substance Use Disorder)	-0.005	0.012
Health History					
OUD First Occurrence Position	-1.376	8.8e-4	OUD First Occurrence Position	0.469	0.003
# of All Conditions	0.026	1.2e-4	# of All Conditions	-0.061	1.2e-4
log(Past Opioid Consumption)	-0.314	5.4e-5	log(Past Opioid Consumption)	-0.242	7.4e-5
log(Past Mental Illness)	-0.035	0.004	log(Past Mental Illness)	-0.025	0.005
log(Past Substance Use Disorder)	-0.038	0.002	log(Past Substance Use Disorder)	-0.019	0.003
Demographics					
Black	-0.034	0.008	Black	0.026	0.007
Age	0.160	1.0e-4	Age	0.014	1.3e-4
Age Squared	-0.002	1.4e-8	Age Squared	-0.000	1.9e-8
Gender	-0.040	0.002	Gender	-0.045	0.002
Medicaid	-0.103	0.006	Medicaid	0.050	0.002
Medicare	-0.059	0.007	Medicare	0.032	0.008
Above High School	0.009	0.186	Above High School	0.026	0.328
log(Income)	0.126	0.010	log(Income)	0.313	0.008
Unemployment	0.005	0.878	Unemployment	-0.003	1.580
Poverty	0.013	0.168	Poverty	-0.005	0.160
Pharmacy Attributes					
Same Affiliation as Default	0.094	0.030	Same Affiliation as Default	-0.086	0.034
CVS	-0.041	0.056	CVS	0.035	0.060
Walgreens	-0.122	0.032	Walgreens	0.099	0.035
Rite Aid	0.169	0.029	Rite Aid	-0.151	0.031
Walmart	0.040	0.032	Walmart	-0.030	0.038
Albertson's	-0.030	0.031	Albertson's	0.044	0.033
Fred Meyer	-0.027	0.032	Fred Meyer	0.019	0.036
Bartell	-0.005	0.033	Bartell	0.020	0.036
Regional Chain	-0.010	0.037	Regional Chain	0.009	0.040
Constant	0.021	0.998	Constant	0.019	0.912

Note: Table 1 presents coefficient estimates obtained via maximum likelihood. Columns 1–3 display preference parameters, while columns 4–6 report search parameters. Heteroskedasticity-robust standard errors are computed using the Huber–White sandwich estimator.

Overall, the results reveal significant heterogeneity in both utility and search costs. Disadvantaged populations—such as Black patients and those with more severe OUD histories—face a dual burden: they derive lower utility from buprenorphine and encounter higher barriers to access. This disparity is especially troubling given their elevated need for treatment.

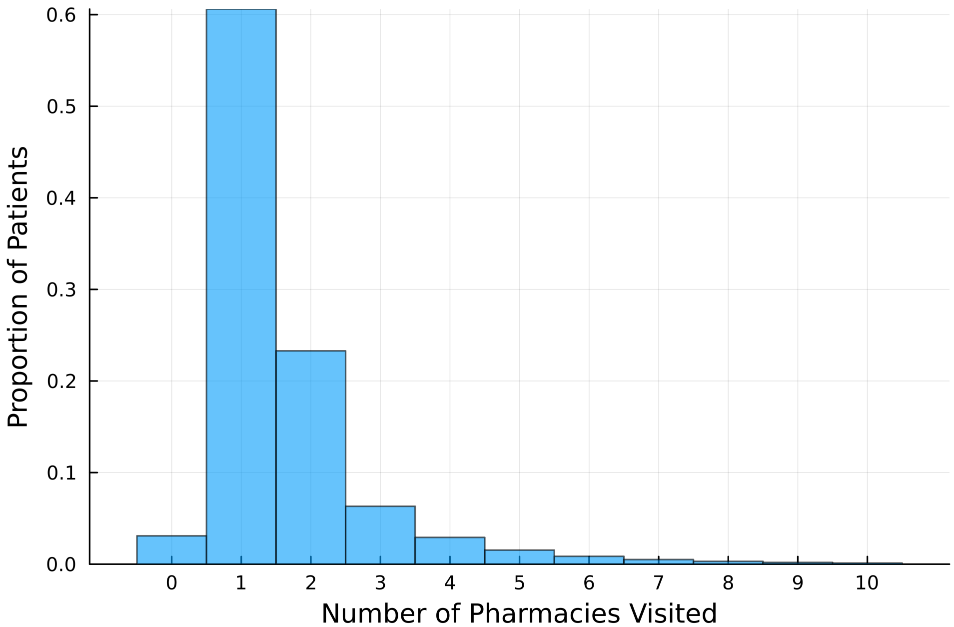
B. Patient Search Behavior

Although the model is not estimated using direct observations of search behavior, it generates predicted search patterns based on the estimated parameters. For each patient, I simulate utility draws from a Type I Extreme Value distribution with location parameter $\hat{\delta}_{ij}$, and draw effective search costs from the distribution in Equation 7, using the estimated location parameter $\hat{\mu}_{ij}$. I repeat this process 100 times per patient. Using Equation 5, I compute the reservation value for each option. Patients are then assumed to follow the Weitzman rule: they visit pharmacies in descending order of reservation values and stop once the realized utility exceeds the reservation value of the next-best option.

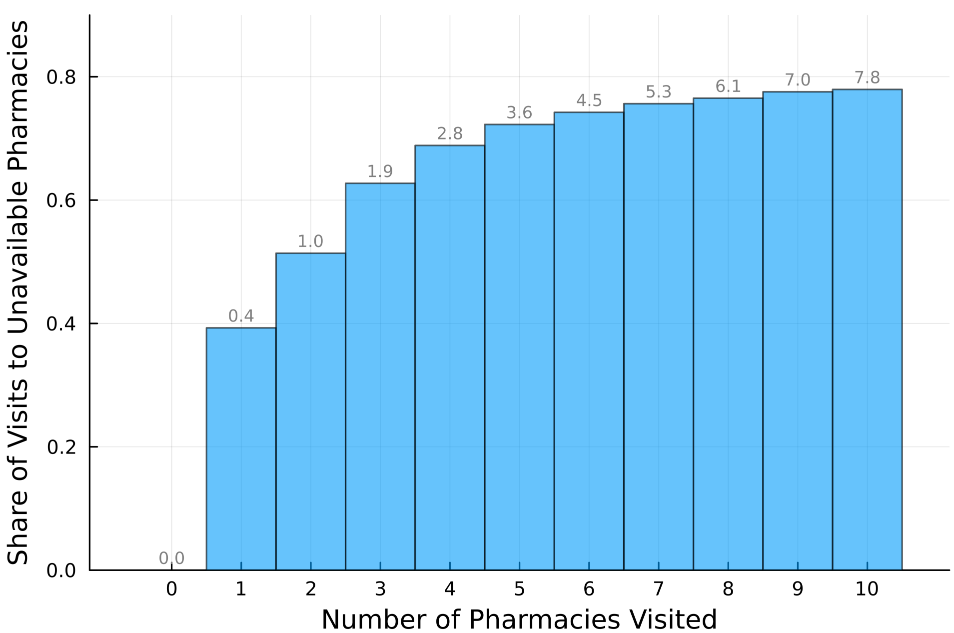
I focus on two key dimensions of search behavior: (i) the number of pharmacies visited and (ii) the incidence of *suboptimal searches*—defined as searches that result in visiting a pharmacy without buprenorphine. While such visits do reveal availability information, they ultimately do not expand the patient's choice set.

The model predicts that patients rarely search more than twice, as shown in Figure 3a. A small share of patients conduct no search at all, this largely driven by those without a default pharmacy. If a patient has a default pharmacy, it is always searched. The predicted distribution of search frequency is consistent with prior findings in other high-stakes settings. For example, Ambokar and Samaee (2019) show that in the mortgage refinancing market, 59% of U.S. borrowers make only one inquiry, and about 80% make fewer than two. This degree of inaction is comparable to the behavior observed in this context.

Figure 3b examines the extent to which patients visit pharmacies that do not have buprenorphine in stock. Patients are grouped by the total number of pharmacies visited, and for each group, the figure plots the average share of visits made to pharmacies without supply. For example, among patients who visited two pharmacies, one visit on average was to a pharmacy



(a) Number of Searches



(b) Number of Suboptimal Searches

Figure 3. Predicted Consumer Search Behaviors

Note: This figure presents predicted patient search behavior based on the estimated model. Panel (a) shows the distribution of the number of pharmacies visited. Panel (b) reports the average share of visits made to pharmacies without buprenorphine in stock, conditional on the total number of pharmacies visited. Search behavior is simulated using estimated utility and search cost parameters. For each simulated patient, realized utilities and reservation values are drawn, and the Weitzman rule is applied to determine the sequence and number of searches.

without buprenorphine, meaning that 50 % of their searches were unsuccessful. The share of unsuccessful visits increases with the total number of pharmacies visited. Among patients who visited only one pharmacy, 40 % encountered a location without supply. Among those who visited ten pharmacies, 78 % of visits were to locations that lacked buprenorphine. This pattern suggests that patients who search more widely do so not because they are more willing to search, but because they are more likely to encounter pharmacies without the medication.

VII. Counterfactuals

As discussed earlier, patients seeking buprenorphine face substantial information frictions. There is no mechanism to learn which pharmacies have the medication in advance. Pharmacies cannot openly advertise buprenorphine availability, leaving patients to rely on physical visits to determine availability. This section evaluates counterfactual policies designed to reduce these frictions by providing patients with indirect access to inventory information, without requiring pharmacies to disclose stock status publicly. Each intervention aims to improve treatment uptake at a fraction of the cost of mandating universal availability.

In the second part of the analysis, I examine the potential impact of electronic prescribing. During the study period, prescriptions for controlled substances were typically handwritten and could not be transmitted in advance. With electronic prescribing, physicians can transmit prescriptions directly to pharmacies, allowing availability to be confirmed in advance. How effective is this change in improving access? And what trade-offs might arise—for instance, if switching pharmacies becomes more difficult once a prescription is sent?

A. Information Policies

I examine three counterfactual policies that provide certainty about pharmacy availability:

1) **Universal Availability Mandate.** This benchmark scenario mandate that all pharmacies are required to carry buprenorphine. By eliminating uncertainty, this policy minimizes effective search costs. In addition, it expands the choice set as all pharmacies stock the drug. While useful as an upper bound on policy effectiveness, its implementation may be infeasible due to operational and financial constraints.

2) **Perfect Information via Providers.** In this scenario, the state maintains a real-time database of pharmacy-level availability that prescribers can access and share with patients at the point of care. This approach preserves pharmacy discretion, as inventory is not advertised directly to patients. The intervention reduces effective search costs by eliminating uncertainty but does not increase the number of pharmacies stocking buprenorphine. Patients only search pharmacies that carry buprenorphine.

3) **Partial Information via Informal Networks.** Even in the absence of a centralized inventory system, prescribers may form informal agreements with a small number of local pharmacies—e.g., the five closest—to reliably stock buprenorphine for their patients. In this scenario, the prescriber shares availability information only for these pharmacies. Effective search costs fall for the subset of pharmacies in the network but remain unchanged elsewhere. Patients are free to visit any pharmacy, but they know with certainty that at least some pharmacies will carry buprenorphine.

All three policies reduce information frictions by increasing certainty about which pharmacies carry buprenorphine. Under a universal availability mandate, patients believe that every pharmacy stocks the medication. In the informal network scenario, patients are certain that a subset of nearby pharmacies—e.g., the five closest—will have buprenorphine available. These interventions shift patients' beliefs about availability, altering the belief parameters ϕ_{ij}.

I assume that patients form rational expectations about local availability to circumvent the problem that beliefs are not separately identified in the model. Let $\hat{\phi}_i$ denote patient i's perceived probability that a randomly selected pharmacy within their choice set has buprenorphine in stock. For instance, if ten pharmacies are within reach and three carry buprenorphine, then $\hat{\phi}_i = 0.3$. Under this framework, the effective search cost is scaled by availability beliefs: $\tilde{c}_{ij}/\hat{\phi}_i$, where $\tilde{c}_{ij}$ is the baseline effective search cost for pharmacy j.

To simulate search and purchase behavior, I draw 100 realizations from the adjusted search cost distribution $F_{\tilde{c}}(\tilde{c}_{ij}/\hat{\phi}_i)$ for each patient. Given these simulated search costs and the estimated utility component $\hat{\delta}_{ij}$, I compute the reservation value using Equation 5. The latent utility w_{ij} is then calculated as the minimum of the reservation value and the realized utility, where the latter is drawn from a Type I Extreme Value distribution with the location paramter, $\hat{\delta}_{ij}$. For

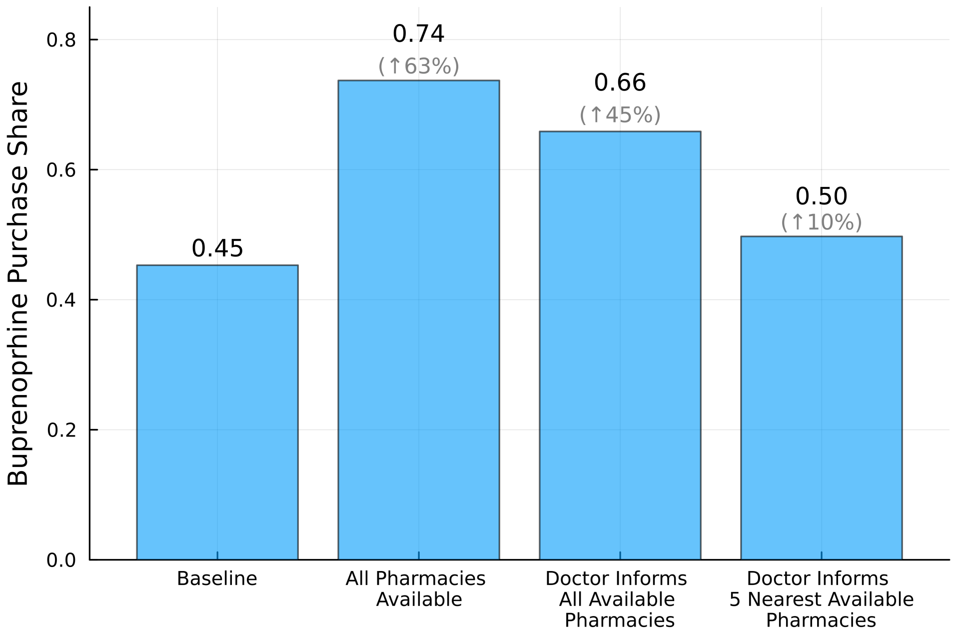


Figure 4. Buprenorphine Purchase Counterfactuals

Note: This figure is generated by simulating each patients' w_{ij} values by simulating search cost draw from the distribution of $F_{\tilde{c}}(\tilde{c}_{ij}/\hat{\phi}_i)$. Then to obtain the population share purchasing buprenorphine under three counterfactual scenarios: (i) all pharmacies offer buprenorphine, (ii) doctors have full knowledge of pharmacy availability, and (iii) doctors know five nearby pharmacies that offer the medication. The baseline reflects actual purchase shares observed in the data. The number on the top of each bar indicates percentage increase compare to the baseline scenario under that scenario.

purchase behavior, patients select the pharmacy with the highest w_{ij}. For search behavior, I apply the Weitzman rule: patients visit pharmacies in descending order of reservation values, stopping once the realized utility at a visited pharmacy exceeds the reservation value of the next-best alternative.

Figure 4 displays the predicted share of patients who successfully obtain buprenorphine under each policy scenario. If all pharmacies offered buprenorphine, the purchase rate would rise to 74%—comparable to a commonly dispensed medication such as levothyroxine. This provides external validation for the model's assumptions regarding patient beliefs. Mandating universal availability raises purchase rates by 63% relative to baseline, but such a policy may be financially or logistically infeasible.

From a state perspective, a more practical alternative is to equip prescribers with real-time information on pharmacy availability. This policy does not expand the choice set but substantially reduces search costs by eliminating uncertainty. It increases the predicted purchase share by 45%—about 71% of the effect achieved under universal availability. This suggests that a primary barrier to treatment is not the supply of buprenorphine per se, but the informational frictions patients face when trying to access it.

Even in the absence of system-wide coordination, smaller-scale interventions can yield substantial benefits. If providers maintain informal relationships with five pharmacies known to dispense buprenorphine and communicate this information to patients, treatment uptake increases by 10%. Although patients may still face uncertainty at other locations, the presence of a few known options lowers search costs and improves access. This intervention can be implemented at the individual provider level, offering a low-cost, decentralized alternative to broad mandates. A similar pattern emerges for consumer surplus, as shown in Figure E1.

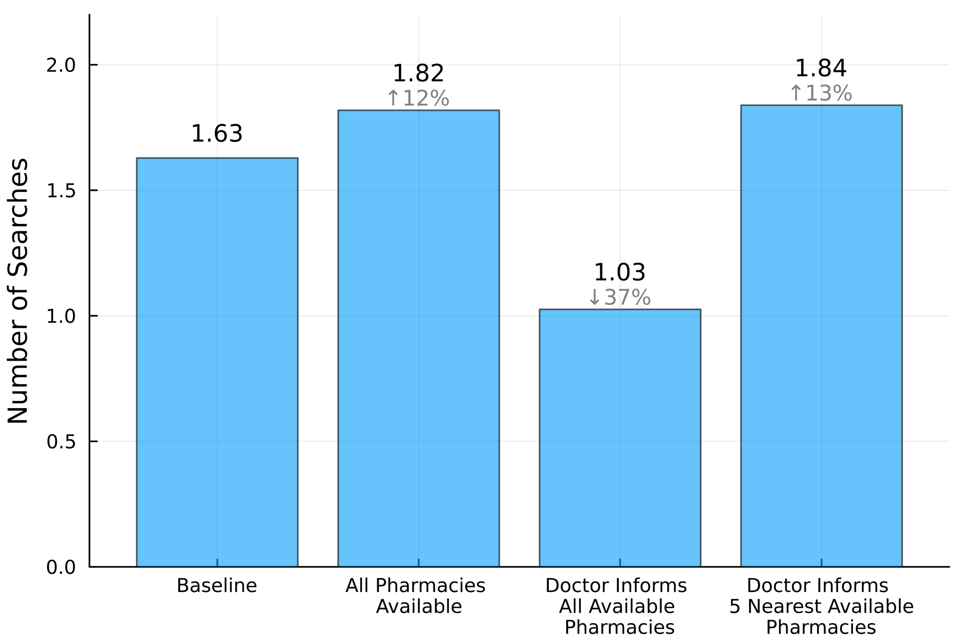


Figure 5. Number of Searches Counterfactuals

Note: This figure is simulated similarly to Figure 4, but it shows the predicted number of pharmacies searched by patients under each policy scenario. The baseline reflects actual search behavior observed in the data.

Figure 5 shows how each policy scenario affects patient search behavior. Mandating universal availability increases search activity by 12%. While this policy lowers effective search costs across all pharmacies and expands the choice set, the increase in search is modest. This shows that most patients search primarily for availability—once they find a pharmacy with buprenorphine, few continue searching. In contrast, when providers inform patients about availability at all pharmacies, patients avoid locations without supply—including their default pharmacy if it lacks buprenorphine—reducing total searches by 37%. The five-pharmacy information scenario leads to a similarly modest increase in search—about 13%—comparable to the universal availability mandate. This suggests that ensuring reliable availability at a small subset of pharmacies can guide patients just as effectively as system-wide stocking, at least in terms of search behavior. Once patients identify a pharmacy with known supply, further search is rarely necessary.

B. Electronic Prescribing

By 2025, all U.S. states will require electronic prescriptions (e-prescriptions) for controlled substances, including buprenorphine. This policy aims to reduce diversion and improve traceability by linking each prescription to a specific patient, provider, and pharmacy. In doing so, it addresses one of the early drivers of the opioid crisis, unregulated prescribing and dispensing by rogue actors.

While the enforcement benefits of e-prescription have received substantial attention, its implications for patient access to treatment have been less studied. For controlled substances, e-prescriptions cannot be transferred between pharmacies without the provider issuing a new prescription. Thus, If the designated pharmacy is out of stock, the patient must contact the prescriber to issue a new prescription.[21] This added burden is especially problematic for medications like buprenorphine, which are not uniformly available across pharmacies.

At the same time, e-prescription offers a distinct advantage: it eliminates ex-ante uncertainty. Under a paper-based system, patients often must visit the pharmacy in person to determine whether buprenorphine is available. In contrast, e-prescriptions are transmitted directly, and the pharmacy notifies the patient of fulfillment status. This removes the need for physical visits

[21]This only applies to controlled substance, it does not apply to other medicaiton.

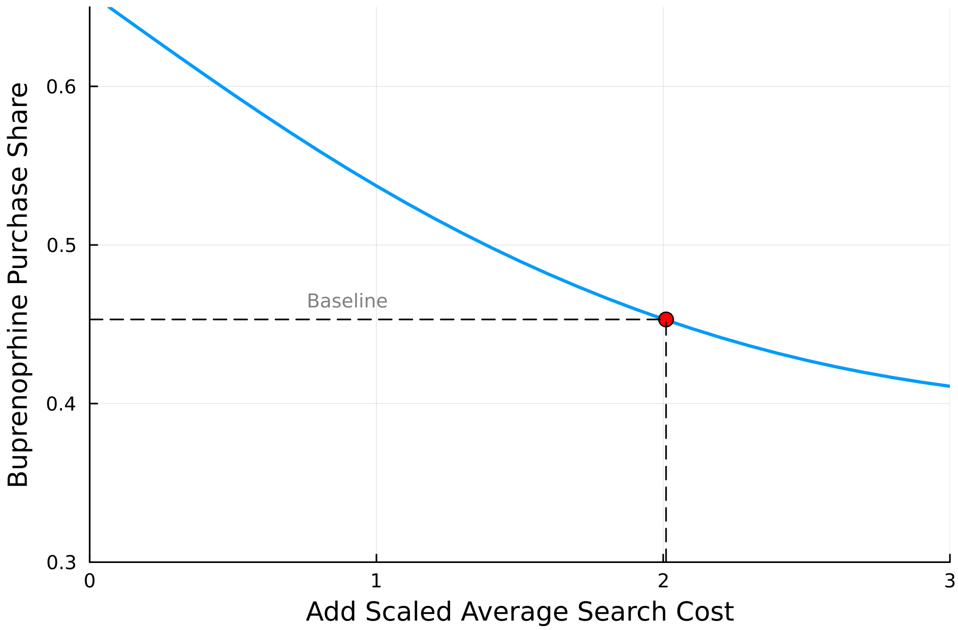


Figure 6. Trade-Offs Under E-Prescription

Note: This figure shows what happens when a patients face additional average search costs. How much increases the additional search costs need to be in order for the e-prescription policy to be worse than the baseline scenario. The baseline reflects actual purchase shares observed in the data. Addtional search costs are added into search cost location parameters μ_{ij}, such that the effective search cost becomes $\mu_{ij} + s\bar{\mu}$, where s is the scaling factor and $\bar{\mu}$ is the average search cost. After doing this, it draws from $F_{\tilde{c}}(\tilde{c}_{ij}/\hat{\phi}_i)$ to simulate the search costs then formulate the reservation values and realized utility.

solely to check for availability, thereby reducing informational frictions in the search process.

To quantify this trade-off, I model e-prescription as a combination of two opposing forces: (i) a reduction in uncertainty and (ii) an increase in search costs if the prescription must be redirected. Although the exact burden of re-contacting a provider is unknown, I assess how much search costs would need to increase to offset the informational benefit of certainty. Let s denote the additional burden imposed by contacting a provider to rewrite a prescription, expressed as a multiple of the average baseline search cost $\bar{\mu}$. Therefore, search cost location parameter becomes $\mu + s\bar{\mu}$. As before, uncertainty is captured by the average perceived availability $\hat{\phi}_i$. Follow the previous procedure, I simulate the search costs by drawing from the distribution $F_{\tilde{c}}(\tilde{c}_{ij}/\hat{\phi}_i)$. The reservation values and realized utility are then formulated as before.

Figure 6 shows how predicted buprenorphine purchase rates vary with the scaling factor s.

The baseline reflects observed purchases under the paper-based regime. When $s = 0$, the predicted uptake matches the "perfect information via providers" scenario discussed previously. As s increases, uptake declines, reflecting the additional cost of coordinating with providers to redirect prescriptions when a pharmacy lacks inventory.

Importantly, for the costs of e-prescription to outweigh its informational benefits—that is, for predicted purchases to fall below the baseline—the required burden must exceed twice the average search cost. This is unlikely in practice. Even accounting for delays and provider inaccessibility, the marginal effort of contacting a doctor to issue a new prescription is unlikely to be twice more costly than physically visiting multiple pharmacies. Therefore, the e-prescription policy, on net, is likely to improve patient access to buprenorphine by reducing the informational frictions that currently suppress treatment uptake.

VIII. Conclusion

As the opioid epidemic shifts from prevention to recovery, the policy focus has increasingly turned toward expanding access to effective treatment. Buprenorphine, a key medication for opioid use disorder, remains underutilized despite clinical consensus on its efficacy. Even among patients who obtain a prescription, many fail to initiate treatment. This paper develops a framework to understand how patients search for buprenorphine under uncertainty. Consistent with prior work, I find that most patients search only once. But unlike other settings, the challenge here is compounded by limited availability: patients often needs to search multiple pharmacies to find buprenorphine.

The core friction lies in the lack of information about pharmacy inventory. Patients cannot verify buprenorphine availability without visiting pharmacies, and pharmacies are reluctant to openly advertise their stock to avoid attracting unwanted attention. This paper shows that even modest interventions that inform patients about inventory at the point of care can substantially reduce search costs and improve uptake. Looking ahead, the shift toward mandatory electronic prescribing for controlled substances may further alleviate this barrier by eliminating the need for in-person verification, thus reducing search frictions and improving access.

Data Construction

A1. Patient Identification

The objective of this section is to identify patients who initiated buprenorphine treatment for OUD. Ideally, a patient's initiation is observed as a medical claim indicating an outpatient visit for OUD, followed by a corresponding pharmacy claim for a buprenorphine prescription. However, two challenges complicate this process: (i) buprenorphine can be prescribed without an explicit OUD diagnosis, and (ii) OUD diagnoses may lead to alternative treatments such as methadone, without generating buprenorphine pharmacy claims.

To address these issues, I apply the following data processing strategy. First, I exclude all patients with any evidence of prior OUD-related care (identified via ICD-9/10 diagnosis codes in medical claims) or buprenorphine prescriptions (identified via NDC codes specific to medications for opioid use disorder in pharmacy claims) before April 1, 2014. I focus exclusively on outpatient visits, removing encounters in emergency or institutional settings, and restrict to medical claims involving providers who prescribed buprenorphine during the same calendar year. This ensures the sample includes only new episodes of care likely associated with buprenorphine initiation.

Among these patients, I classify the first outpatient medical claim with an OUD diagnosis as a potential treatment initiation. If this visit is followed by a buprenorphine prescription fill within 14 days, I classify the patient as plausibly matched.

For patients who have a buprenorphine prescription without a preceding medical claim meeting the above criteria, I search for the closest outpatient visit within 14 days of the fill date. Preference is given to visits involving the same prescriber as recorded in the pharmacy claim, and among those, to the visit closest in time. This step helps address cases where the medical claim lacks an explicit OUD diagnosis, but the prescriber is known to have issued buprenorphine.

Finally, for patients with a qualifying OUD-related medical visit but no timely pharmacy match, I check for sustained follow-up with the same provider. If the patient returned to the same provider at least three times within the following 90 days, I infer that the care episode likely reflects a different treatment plan (e.g., methadone or non-pharmacologic intervention), and exclude these cases to avoid ambiguity.

This process yields three mutually exclusive groups of patients:

1) Matched OUD initiators: Patients whose first OUD-related medical visit is followed by a buprenorphine fill within 14 days. (22% of the first time patients)
2) Pharmacy-first initiators: Patients with a buprenorphine prescription who are matched to a proximate outpatient visit with the same prescriber, even if the medical claim lacks an OUD diagnosis. (22% of the first time patients)
3) Unmatched medical visits: Patients with OUD-related outpatient visits who do not initiate buprenorphine and do not show sustained provider follow-up suggestive of alternative treatment. (56% of the first time patients)

A2. Inventory Construction

To make the problem tractable, I adopt several simplifying assumptions when constructing pharmacy-level buprenorphine inventory. First, I aggregate across formulations and strengths. Buprenorphine is commonly dispensed either as a monotherapy or in combination with naloxone, most often in 2mg, 8mg, or 12mg doses. While substitution between brand-name and generic products is generally straightforward, clinical substitution between formulations—such as switching from buprenorphine alone to buprenorphine/naloxone—requires medical judgment and may not always be appropriate. Despite these differences, I aggregate all formulations into total milligrams of buprenorphine, treating them as interchangeable. This abstraction ignores strength-specific constraints—for example, pharmacies may not split high-dose tablets to fulfill low-dose prescriptions—and likely overstates the availability of buprenorphine.

Second, the shipment data from ARCOS and the sales data from APCD are not directly comparable. ARCOS captures all shipments to pharmacies, whereas the APCD includes only pharmacy transactions for Washington residents covered by insurance, excluding both cash payments and out-of-state patients. On average, APCD sales account for approximately 40% of total shipments. To assess whether a pharmacy has inventory available for a given patient, I evaluate the pharmacy's stock on the relevant date: the pharmacy claim date if available, or otherwise the medical claim date. For each pharmacy within the patient's choice set, I calculate the difference between cumulative shipments over the prior seven days (scaled by 0.403 to reflect the share of sales captured in APCD) and cumulative APCD sales over the same window. A pharmacy is considered to have sufficient stock if the resulting estimate exceeds the patient's inferred need on that date. When a pharmacy claim is observed, I use the actual strength and duration of that claim to determine the patient's need. When no pharmacy claim is available, I impute demand as a 14-day supply of 8mg buprenorphine/naloxone—the most common treatment pattern observed in the data.

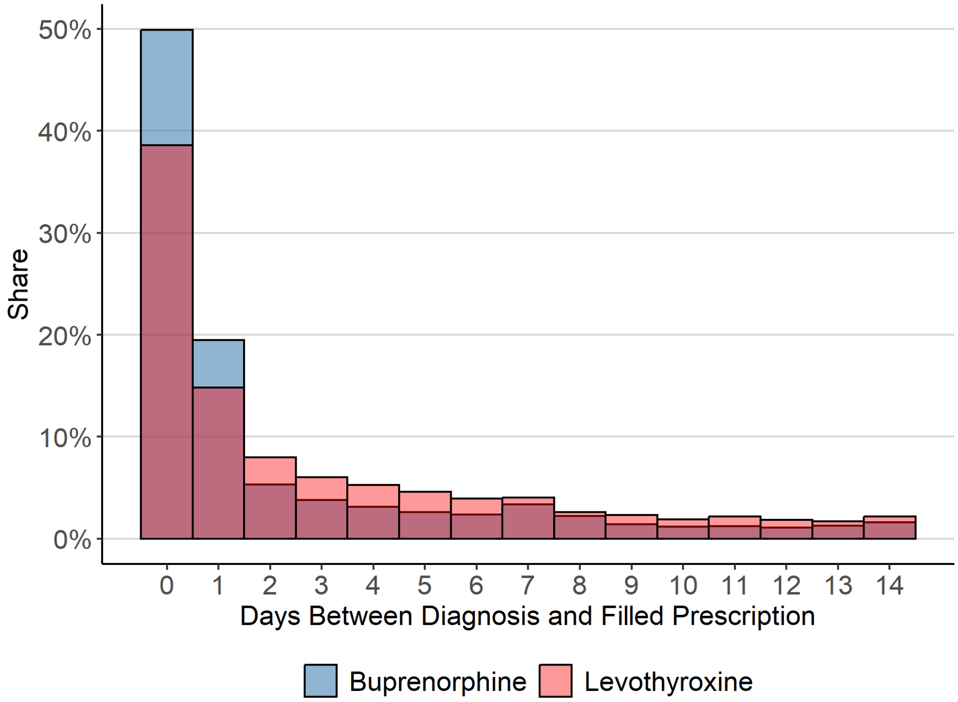


Figure B1. Number of Days Between Doctor Visits and Prescription Filled

Note: This figure displays the distribution of days between the first OUD-related medical visit and the first buprenorphine prescription fill, and between the first hypothyroidism-related visit and the first levothyroxine prescription fill. Patients medical conditions are sourced from WA-APCD.

Additional Stylized Facts

B1. Time to Fill a Prescription After Diagnosis

Access to treatment depends not only on whether a prescription is written, but also on how quickly patients are able to fill it. For some medications, patients may wait before filling a prescription, particularly if the drug is not urgently needed. For buprenorphine, however, the timing of initiation is critical. Patients must begin treatment at the onset of withdrawal, and delays can increase the likelihood of relapse. As a result, even short search frictions can carry meaningful clinical consequences.

To examine delays in access, I compare the time between diagnosis and prescription fill for two drugs: buprenorphine and levothyroxine. I restrict attention to first-time users of each medication. The timing measure is defined as the number of days between the first diagnosis-related medical visit and the first fill of the corresponding prescription.

Figure B1 presents the distribution of fill times. Most patients in both groups fill their prescriptions within a few days. Among OUD patients, nearly 70% obtain buprenorphine within one day of diagnosis, compared to 55% of hypothyroidism patients who fill levothyroxine within the same window. The more rapid uptake of buprenorphine reflects its urgency in managing withdrawal, but also underscores the importance of pharmacy availability. When the default pharmacy does not carry buprenorphine, even brief delays in search may disrupt treatment initiation and risk relapse. To ensure that these differences are not driven by underlying differences in patient populations, I condition on prior opioid exposure: both samples are restricted to individuals with at least four prior opioid prescriptions. Results are similar when further conditioning on patients who eventually fill a buprenorphine prescription, though the sample size is smaller.

B2. Search Patterns Following Unavailability at the Default Pharmacy

This section presents stylized facts consistent with patients engaging in additional search when buprenorphine is unavailable at their default pharmacy. While I do not observe the search process directly, I examine subsequent purchase behavior to infer patterns.

I focus on patients who ultimately filled a prescription after encountering unavailability at their default pharmacy. For each such case, I calculate two distances for the pharmacy where the prescription was filled: the distance to the patient's residential ZIP code and the distance to the default pharmacy. If patients always check availability at the default pharmacy first, then the observed purchase can be interpreted as the result of continued search. Proximity to home reflects baseline preference for convenience, while proximity to the default pharmacy captures behavior consistent with search initiated after discovering unavailability.

Figure B2 shows the distribution of these two distances. Both are skewed toward shorter values, indicating that most patients fill prescriptions close to home and close to the default pharmacy. However, the distribution is more concentrated near zero for the distance to the default pharmacy. This suggests that while home proximity remains important, the location

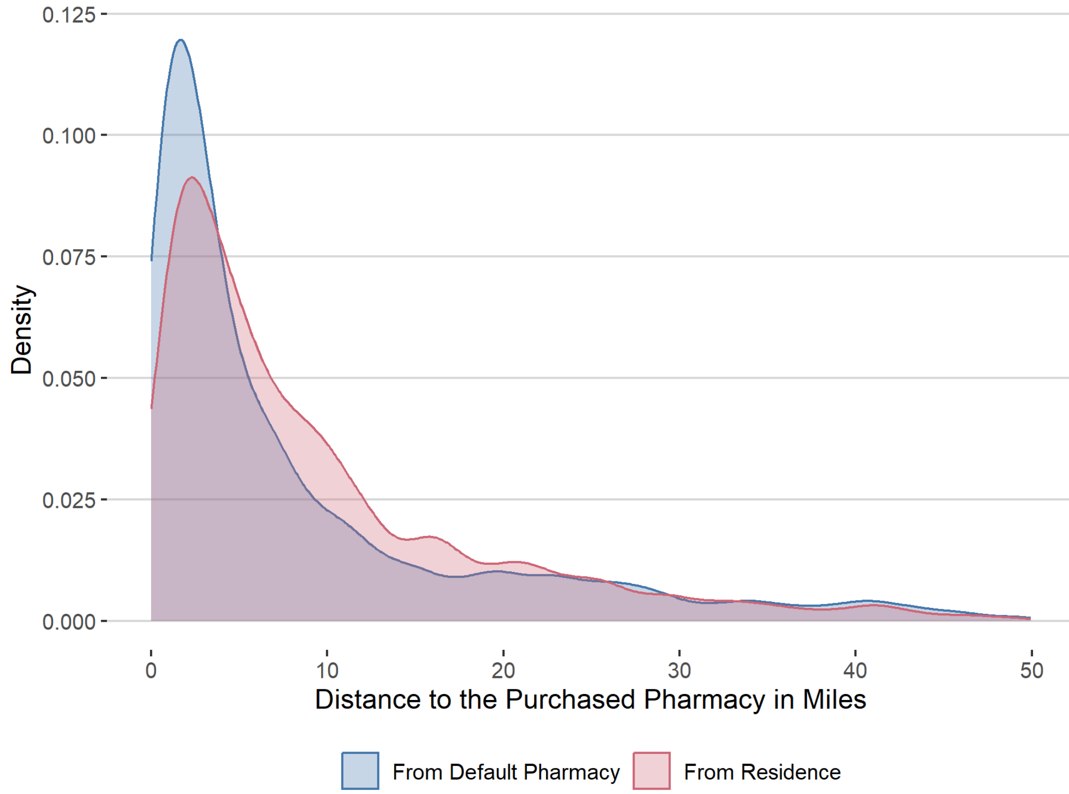


Figure B2. Distance to Default and Residential ZIP Code for Purchased Pharmacy

Note: This figure shows the distribution of distances from the purchased pharmacy to the default pharmacy and the patient's residential ZIP code, conditional on the default pharmacy being unavailable. The sample includes patients who ultimately filled a buprenorphine prescription elsewhere.

of the default pharmacy also shapes the search path. This implies that patients continue their search from that point, rather than starting from home alone. These patterns justify a search-based model, as distance plays a clear and significant role in consumer choice.

B3. Health Outcomes

The paper's focus on increasing buprenoprhine take-up rate, but to what extend taking buprenoprhine would improve the health outcomes? It is not clear to the literature, evidence largely builds on observational study and clincial evidences. However, the paper's has a unique design that allows to estimate the effect of buprenorphine treatment on health outcomes. The problem with directly estimating patients with OUD that whether take or not take buprenorphine is that subject strongly to selection bias. Patients who take buprenorphine are likely to be more health-conscious, and thus may achieve the same outcomes without medication. To address this, I can use an instrument for this endogenous treatment, in that, patients are more likely to take buprenorphine if the default pharmacy has buprenophrine available, but the availability itself should not directly affect health outcomes except through treatment uptake. Further, together I can use a difference-in-differences (DiD) design to controls for fixed unobservables, which led to a more creidble identification.

First, like the whole paper I focus on the first-time OUD patients with buprenoprhine prescription. The treatment group consists of patients who receive buprenoprhine, while the control group includes only those who never recevived buprenoprhine after the buprenoprhine prescritpion.[22] DiD speicifcaion as following,

$$y_{it} = \beta \text{Buprenorphine Treatment}_{it} + \alpha_i + \gamma_t + \text{Doctor}_i + \text{ZIP}_i + \epsilon_{it} \tag{B1}$$

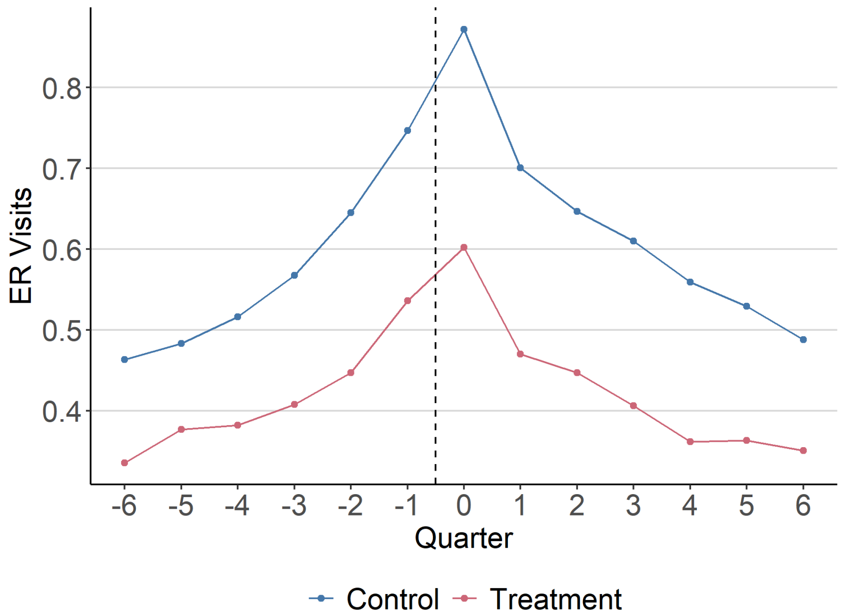
where y_{it} represents the number of emergency room visits per quarter, Buprenorphine Treatment$_{it}$ is a binary indicator for treatment, and α_i and γ_t are individual and time fixed effects. I further control for doctor and ZIP code fixed effects.

To address endogeneity concerns, I instrument for buprenorphine treatment using its availability at the default pharmacy. Patients are more likely to initiate treatment when buprenorphine is available at their default pharmacy, but availability itself should not directly affect health outcomes except through treatment uptake. The instrumental variable regression is:

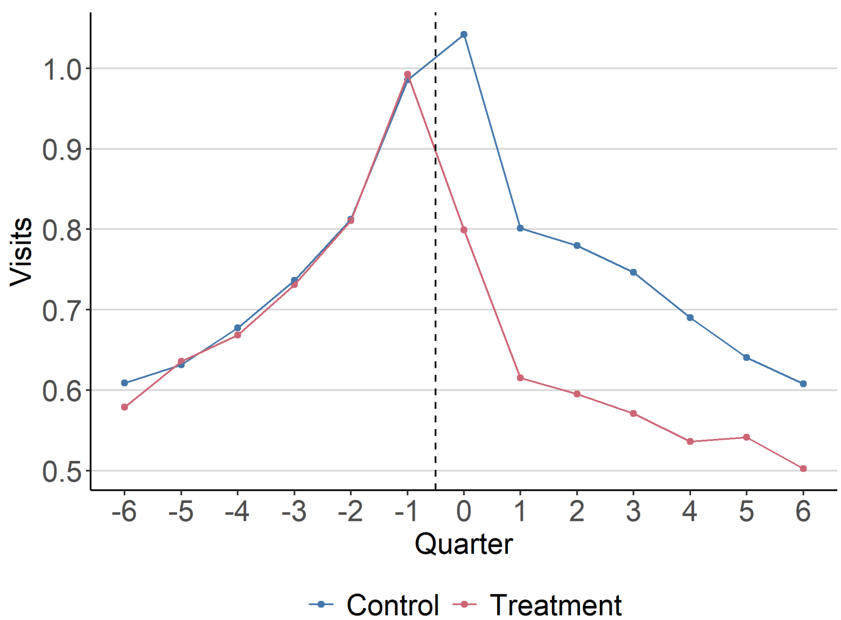
$$\text{Buprenoprhine Treatment}_{it} = \pi \text{Default Availability}_{it} + \tilde{\alpha}_i + \tilde{\gamma}_t + \widetilde{\text{Doctor}}_i + \widetilde{\text{ZIP}}_i + \eta_{it} \tag{B2}$$

Figure B3 presents ER visit trends for treatment and control groups. The raw trends (Figure B3a) reveal several key patterns. First, patients do not immediately get OUD treatment after an

[22] Later-treated patients are excluded from the control group to prevent bias from differential health trends.



(a) Raw Trends



(b) Partial Trends (60th percentile to 90th percentile)

Figure B3. Emergency Room Visits Per Quarter Trends by Treatment Groups

Note: This figures shows the trends in emergency room visits for patients recieving buprenoprhine prescription with taking buprenoprhine (treatmnet) and chose not too (control group). The emergency room visits are identified within the medical claims from APCD data, the emergency room visits are idenfied using place codes, that speicifc the location of the emergency room. For multiple claims within the same date, it counts as one. Panel a shows the raw trends and Panel b shows the trends for patients between the 60th and 90th percentiles of pre-treatment ER visit frequency.

ER visit—there is a buildup process before they enter care. Second, receiving an OUD diagnosis is the first step toward recovery, and ER visits decline sharply after diagnosis, regardless of whether the patient starts buprenorphine treatment. Finally, patients who eventually receive buprenorphine already have lower ER visit rates before treatment. This last point has important implications. If the full sample are used directly, the estimated effect of buprenorphine may be underestimated, particularly when reductions in ER visits are more pronounced for those starting from a high baseline.[23]

To address this concern, I ensure that patients and patients are comparable between treatment and control groups. For example, if I only focus on those between the 60th and 90th percentiles of pre-treatment ER visit frequency, as shown in Figure B3b, I can ensure that treatment and control groups are more similar at baseline. In light of these, I stratify patients into quintiles based on pre-treatment ER visits to ensure that treatment and control groups are comparable, mitigating concerns about the initial baseline.

Figure B4 presents estimated treatment effects from DiD and instrumented difference-in-differences (DiD-IV) regressions. Across all quintiles, most estimates show statistically significant reductions in emergency room visits. In many cases, these declines exceed 20% relative to the pre-treatment mean for the treated group.

The DiD-IV estimates are consistently larger in magnitude, though not statistically different from the DiD estimates. The largest differences arise in the bottom two quintiles, where DiD estimates are close to zero while DiD-IV identifies substantial reductions in emergency room visits. This reflects the fact that DiD-IV scales the DiD estimate by the first-stage effect of the instrument (i.e., divides by β in Equation B2).

The DiD-IV specification captures an average causal response among compliers—patients whose treatment uptake depends on whether buprenorphine is available at their default pharmacy. It yields a properly weighted average of treatment effects for this subgroup. In contrast, the standard DiD estimate reflects a mixture of compliers and always-takers—patients who would obtain buprenorphine regardless of pharmacy availability. Because always-takers are likely more

[23] A useful analogy is weight loss treatments: Suppose drug A is given to severely overweight individuals, while drug B is taken by those who are only moderately overweight. If weight loss is greater for those taking drug A, this does not necessarily mean it is the more effective treatment—it could simply reflect differences in initial weight.

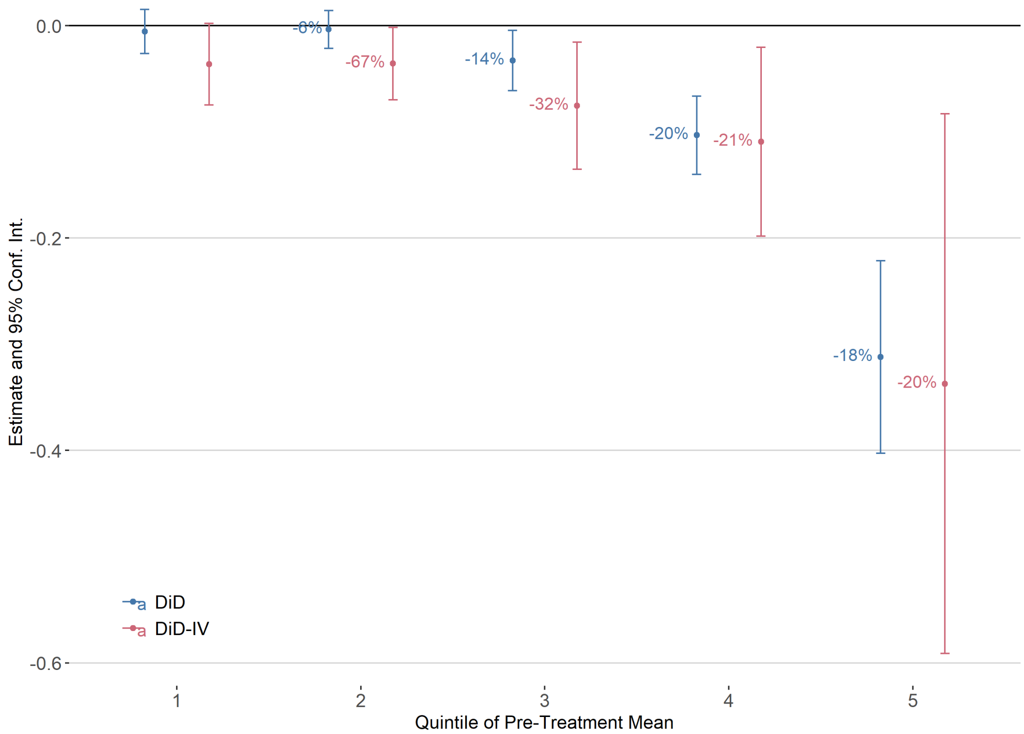


Figure B4. Taking Buprenoprhine Effects on Emergency Room Visits

Note: This figure presents the estimated effects of taking buprenorphine on emergency room visits on each quintile of pre-treatment ER visits. The DiD estimates are directly obtained through estimating Equation B1 and the DiD-IV estimates are obtained through estimating the the IV Equation using buprenoprhin avialalbilty as an instrument for taking buprneoprhine and then plugging the predicted value into the DiD Equation. The cofidence interval 95% is clustered at the patient level.

motivated to seek treatment, their average treatment effect is smaller. As a result, the DiD estimate is smaller than DiD-IV estimates.

Proof

Theorem 1—Eventual Purchase: *Let* $w_j \equiv \min\{\mathbf{1}\{i \in A\}u_j + \big(1 - \mathbf{1}\{i \in A\}\big)(u_0 - \iota), r_j\}$ *for each* j*. Given* u_0*, the consumer purchases product* j *if and only if* $w_j > u_0$ *and* $w_j > w_k$ *for all* $k \neq j$*.*

Proof: Sufficiency: If $w_j > u_0$, product j is available (if unavailable, $w_j < u_0$). Given product j is available, she purchases a product j because she is willing to visit at least one seller ($r_j > u_0$) and make a purchase ($u_j > u_0$). It remains to show that if $w_j > w_k$ when product j is available, then product k is not chosen.

- **Case 1**: Suppose product k is unavailable ($\mathbf{1}\{k \in A\} = 0 \implies w_k < u_0$), she has no incentive to visit seller k or purchase product k. I only need to consider when product k is available.
- **Case 2**: Suppose $r_k \leq u_k$, then $w_k = r_k^*$. The consumer visits seller k only after seller j because $r_k \geq w_j > r_k$. However, once she visits seller j, she has no incentive to visit seller k because $u_j > r_k$.
- **Case 3**: Suppose $r_k > u_j$, which implies that $w_k = z_k$. In this case, even if she visits seller j, she either recalls a previous product ($u_j > z_k$) or continues to search ($r_j > z_k$) and finds a better product ($u_j > z_k$).

Necessity: If $w_i < u_0$, then seller j is neither visited ($r_j < u_0$) nor product j is purchased ($\mathbf{1}\{i \in A\}u_j < u_0$), regardless of availability.

If $w_j < w_k$ for some $k \neq j$, and product j is unavailable, product j cannot be chosen ($w_j < u_0$). If j is available, $w_j < w_k$ implies product k is also available as $0 < w_j < w_k$. By the same logic as above (case 2 and case 3), the consumer does not purchase product j. Q.E.D.

Internal Validation

Figure D1 compares predicted and observed buprenorphine purchases, conditional on whether the default pharmacy has the medication in stock, on three broad category (default pharmacy, non-default pharmacy and no purchase at all). These three broad category are not moments

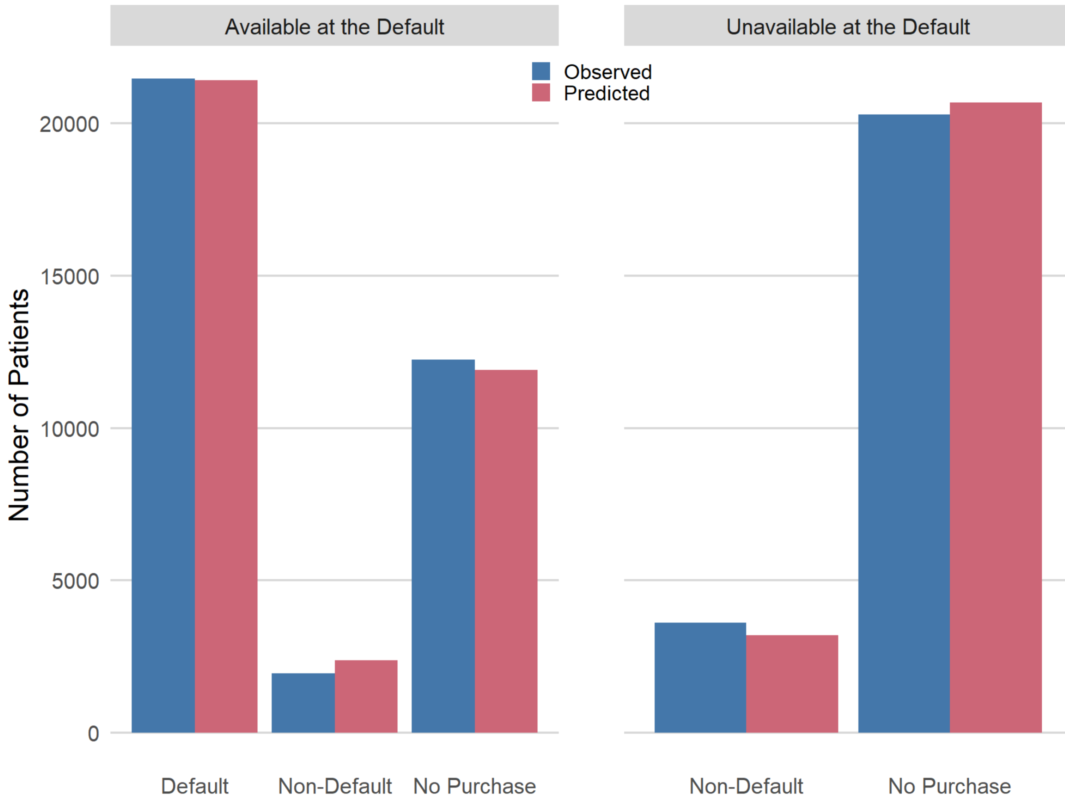


Figure D1. Internal Validation

Note: Fiugre D1 shows the observed and predicted number of patients purchase at default, non-default, or no purchase at all under two different scenarios, buprenoprhine is avaiable at the default pharmacy and whether unavaiable at the default pharmacy. The predicted number of patients purchase is aggregating the predicted purhcase probablity from individual to pharmacy to the pharmacy level using estimated coefficient from Table 1 in Equation 12.

directly used in the estimation. This exercise boosts the confidence in the model that later would generate belief The predictions align well with the observed data. The largest discrepancy—at most 3%—occurs in cases where buprenorphine is unavailable at the default option and is purchased at a non-default pharmacy.

Additional Tables and Figures

Table E1— Summary Statistics

Variable	Mean	St. Dev.	Min	P25	Median	P75	Max
Individual Variables							
OUD First Occurrence Position	2.37	2.26	1.00	1.00	1.00	3.00	15.00
Past Opioid Consumption (MGE)	14,885.33	45,679.43	0.00	0.00	0.00	3,300.00	1,991,675.00
Past Mental Illness Diagnoses	0.70	2.46	0.00	0.00	0.00	0.00	92.00
Past Substance Use Disorder Diagnoses	0.93	3.41	0.00	0.00	0.00	1.00	92.00
# of All Conditions	4.05	2.25	1.00	3.00	4.00	5.00	25.00
Black	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Age	41.85	14.57	0.00	30.00	39.00	53.00	90.00
Gender	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Medicaid	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Medicare	0.14	0.34	0.00	0.00	0.00	0.00	1.00
Above High School	0.90	0.06	0.00	0.88	0.91	0.94	1.00
Income	35,167.69	12,107.95	3,594.00	27,798.00	32,703.00	38,942.00	189,150.00
Unemployment	0.06	0.02	0.00	0.04	0.06	0.07	1.00
Poverty	0.13	0.06	0.00	0.08	0.12	0.16	1.00
Female Provider	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Provider Experience	8.84	3.28	0.00	7.00	10.00	11.00	14.00
Addiction Medicine Specialist	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Urban	0.92	0.28	0.00	1.00	1.00	1.00	1.00
Pharmacy Variables							
CVS	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Walgreens	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Rite Aid	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Walmart	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Albertsons	0.17	0.37	0.00	0.00	0.00	0.00	1.00
Fred Meyer	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Bartell	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Regional Chain	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Individual-Pharmacy Variables							
Price	21.33	78.19	0.00	0.00	8.25	8.30	595.80
Distance from Default	15.52	9.43	0.00	8.42	14.52	21.16	50.00
Distance from Residence	15.07	8.26	0.02	8.90	14.78	20.48	50.00

Note: This table presents summary statistics for the main variables used in the analysis. The variables are grouped into individual characteristics, pharmacy characteristics, and individual-pharmacy level variables. The mean, standard deviation, minimum, 25th percentile (P25), median, 75th percentile (P75), and maximum values are reported for each variable.

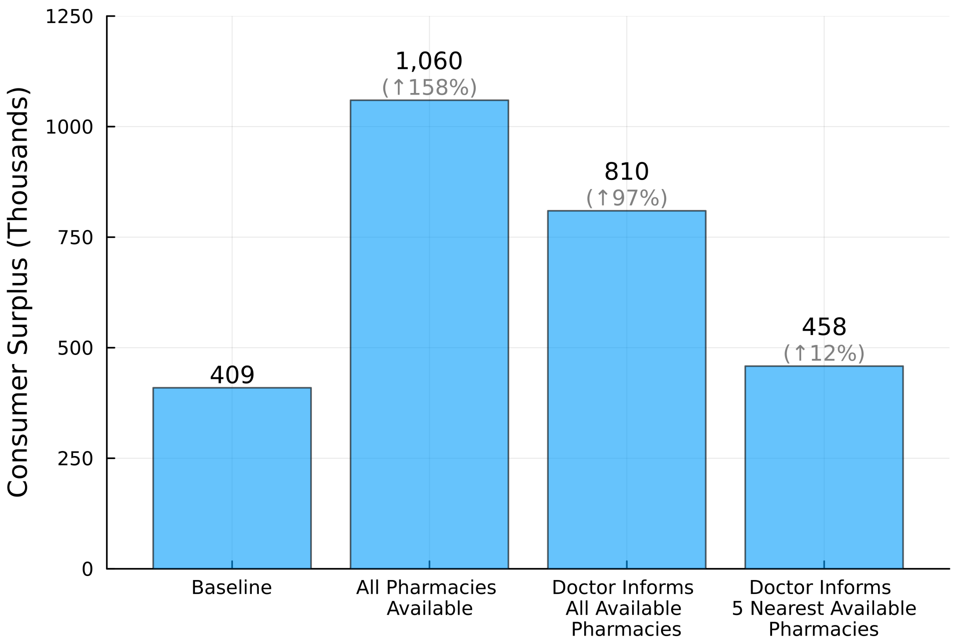


Figure E1. Consumer Surplus Counterfactuals

Note: This figure is simulated in a manner similar to Figure 4. Consumer surplus is calculated as the difference between realized utility and cumulative search costs, scaled by the price coefficient.

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