Cutting Red Tape: Administrative Simplification and Treatment Capacity

Yiyu Xing*

July 10, 2024

Abstract

Excess administrative expenses impose a strain on the U.S. healthcare system. Yet, little is known regarding how these administrative requirements affect facilities' provision of medical services. I empirically assess this question by drawing on the staggered adoption of state laws restricting prior authorization (PA) requirements for substance abuse treatments (SAT) in commercial health plans. Using multiple datasets, I find specialty care facilities are more likely to provide low-intensity (i.e., outpatient) SAT services while decreasing the provision of high-intensity ones (i.e., intensive outpatient, partial hospital, inpatient). I further corroborate supporting evidence for one plausible mechanism: lowering administrative hassles can expand both facilities' and health providers' treatment capacity. To capture welfare implications, I document the fact that imposing PA restrictions can reduce the suicide rate due to SUD issues. This paper thus highlights a novel source of costs associated with healthcare administrative processes: beyond imposing direct paperwork costs, they substantially restrain organizational treatment capacity.

Keywords: substance abuse treatment, prior authorization, health insurance, administrative hassle

*Yiyu Xing: School of Medicine, University of California, Los Angeles. E-mail: nkxingyy@gmail.com. I am indebted to my advisor Nicolas Ziebarth for always providing incredible feedback, inspiring discussions, and generous support. I am also grateful to Duha Altindag, John Chung, Ia Vardishvili, and Chris Vickers for sharing thoughtful comments and suggestions. I also thank the participants and discussants from the 2023 APPAM conference and the 2024 EEA conference. All errors are my own.

1 Introduction

Central to the ongoing debates in the U.S. healthcare system is how to balance cost containment with the provision of high-quality services. Among many other issues, excess administrative spending is a critical concern, with prior estimates indicating that it accounts for approximately 20%to 34% of healthcare expenditures (Dunn et al., forthcoming).[1] A noteworthy feature of some administrative processes (e.g., cost control process) is that they present a delicate trade-off between mitigating consumer moral hazard in service utilization (Brot-Goldberg et al., 2023) and restraining facilities' treatment capacity. On the one hand, demonstrating and verifying medical necessity is essential to preventing over-utilization of healthcare services (Cutler, 2020), reducing unnecessary medical spending, and enhancing quality (GAO, 2018).[2] On the other hand, the imposition of these administrative processes can create sizable burdens on providers, hindering them from allocating resources efficiently. For example, prior authorization, quality limits, and step therapy are common cost control processes that can create barriers and lead to negative health outcomes among patients, by delaying or denying access to treatments and increasing administrative costs for providers, who must navigate complex and often inconsistent rules and regulations across different plans.[3]

In this paper, I aim to add some empirical evidence along this line of discussion and investigate whether simplifying the administrative process would affect the provision of behavioral healthcare services. To this end, I exploit the staggered rollout of state laws restricting the use of prior authorization in private health plans for substance abuse treatment (SAT) and explore if the provision of various SAT services is affected. Health plans routinely require physicians to obtain approval for a prescribed health service or medication in order to control costs and oversee coverage decisions. This process, named "prior authorization requirement," can impose a unique barrier for individuals seeking substance use disorder (SUD) treatment by delaying the initiation of care when an individual needs treatment, which places the patient at risk of continued substance use, medical complications, overdose, and death.(Weber, 2020). Starting in 2016, 18 states enacted laws to limit private insurers from imposing prior authorization requirements on a SUD service or medication.

[1] Billing and coding costs, physician administrative activities, and insurance administrative costs are all primary drivers of these expenses (Chernew and Mintz, 2021).

[2] See https://www.gao.gov/assets/gao-18-341.pdf, last accessed July 10, 2024.

[3] For a detailed discussion regarding how prior authorization restrains providers' capacity of treatment, see https://www.ama-assn.org/practice-management/prior-authorization, last accessed July 10, 2024.

Because the provision of SAT services hinges on the pairwise interactions between patients, private insurance companies, and providers, and whether and how restricting PA affects the supply of SAT are both theoretically ambiguous. For example, among many other competing channels, the removal of PA requirements can trigger both adverse selection and moral hazard along a number of dimensions, thereby creating plausibly exogenous *demand shocks* to healthcare facilities. In the meantime, as shown in Dunn et al. (forthcoming), adding administrative ordeals in health plans may induce selective contracting between providers and insurers: Administrative burdens created by prior authorization can increase the marginal cost per treatment episode and deter providers. At the same time, prior authorization could add more general administrative burdens to facilities by tightening the capacity constraint in terms of providing treatment and allocating medical resources. Taken together, it is essential to rely on data to investigate the consequences of restricting PA on providers' decisions and responses.

In the empirical portion of this paper, I employ a stylized staggered difference-in-differences framework and assemble a variety of data sources to test relevant hypotheses. I start with checking the direct effect of PA restrictions on the supply of SAT services of different intensities. Using detailed facility-level data drawn from the National Survey of Substance Abuse Treatment Services (N-SSATS), I document three pieces of evidence: First, when restricting the use of prior authorization in private plans, the likelihood of providing any types of outpatient services significantly increases by 3.5 percentage points or 5.7 percentage points. Second, among all facilities providing any outpatient SAT services, the likelihood of providing intensive outpatient SAT services has declined by 5.4 percentage point. Third, following the PA restriction, there is a statistically significant decrease (3.4 or 5.0 percentage points) in the propensity to provide SAT services in an inpatient setting (hospital and residential SAT services). Overall, these results point to a redirection in providing high-intensity care to low-intensity care.

I then turn to empirically test several potential channels (mentioned in section 3 and section 4). First, I exploit client-level data in the Treatment Episode Data Set (TEDS) to check if simplifying the administrative process can substantially change the composition of on-site penitents. To do so, I first collapse both the admission data and the discharge data to the state-year cells and find there are no changes along these two margins, indicating PA restrictions do not affect the aggregate number of

patients within all SAT facilities. I then analyze if introducing PA restrictions induces any changes associated with key characteristics of both the newly admitted and newly discharged. Again, no statistically significant results are documented in this exercise. Overall, these two pieces of evidence rule out the possibility that PA restrictions significantly change the composition of within-facility patients, and further suggest the observed shift in providing SAT services is not primarily driven by either adverse selection and moral hazard in the private insurance market (i.e., patients w/ higher risks of developing SUDs are more likely to get covered by private plans), or the moral hazard at the admission margin (i.e., conditional on being covered, marginal patients are incentivized to utilize more low-cost SUD services).

In the second test, I ask if the observed shift in provision towards low-intensity care is a result of *ex-post* moral hazard along the margin of treatment (i.e., conditionally on getting admitted, patients with higher background risk are more likely to continue the treatment, or say, less likely to voluntarily drop out of the program). Extracting information for the discharge set of the TEDS (TEDS-D), I constructs a coarse measure of *ex-post* moral hazard — whether the discharge is because of voluntary decisions/intentions. My preliminary result show this proxy is not getting significantly affected by PA laws, thereby ruling out the channel of demand shocks due to moral hazard along the margin of treatment.

Moving on to explore the potential supply-side driving forces, I begin by showing that the aggregate numbers of SAT facilities providing inpatient and outpatient services are insignificantly influenced by the passage of PA laws, suggesting no changes in the local market structure. I then search for any evidence of selective contracting between facilities and private insurers. To this end, I use information from the N-SSATS to create an indicator for whether the facility accepts private/public plans/patients with no insurance respectively.[4] Results indicate that although simplifying PA processes does not affect the propensity to accept a private plan, the law creates some positive spillovers to the public insurance market.

Eventually, I highlight one potential mechanism through which simplifying the administrative pro-

[4] Admittedly, one caveat here is that I cannot explicitly examine whether other critical dimensions of a private plan has changed due to the PA restriction, given the limited scope of my data. For example, the reimbursement rate associated with a private plan can increase/decrease, or the patient has shifted from one private plan to another within the same treatment episode in response to these PA restrictions.

cess can affect the provision of SAT services: Limiting the use of PA can relax facilities' capacity constraint, thereby enabling them to reallocate medical resources. Consistent with this conceptual premise, I find that following the PA law, there is a significant decline in the likelihood of experiencing normal and severe facility-induced medical delay by 25.6% and 18.6% respectively, among patients within an outpatient setting. This additional evidence along with my main results thus emphasizes when simplifying the administrative process, healthcare facilitates' treatment capacity has indeed been expanded.

This paper can contribute to a small yet growing strand of literature which emphasizes the consequence of administrative processes in the healthcare sector. Two recent papers addresses both the benefits and costs: Brot-Goldberg et al. (2023) study the key trade-off (moral hazard vs. administrative burden) for prior authorization restriction policies in Medicare Part D, and find the cost savings resulting from PA likely exceed beneficiaries' willingness to pay for foregone drugs. Dunn et al. (forthcoming) quantify one of many potential costs associated with healthcare billings: More aggressive use of claim denials reduce the willingness of providers to contract with insurers. My work contribute by quantifying a novel dimension of the costs induced by administrative processes: The (over)use of prior authorization requirements may largely limit healthcare facilities' treatment capacity and trigger medical delays.

Broadly speaking, my paper can add values to another strand of literature in public finance, addressing the role of administrative ordeals facing potential program beneficiaries. These ordeals may improve program targeting (see e.g., Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019). In other contexts, program complexity deters beneficiaries' participation (e.g., Currie et al., 2001). My paper contributes to this line of literature by showing beyond the context of safety net programs, administrative processes and costs can harm consumers welfare, by limiting the access to healthcare services.

The rest of this paper proceeds as follows: section 2 provides the institutional background. Section 3 sketches some theoretical channels to motivate the empirical analysis. Section 4 specified the primary empirical strategies. Section 5 describes a number of datasets enabling to me to implement the empirical analyses; section 6 presents the main results. Section 7 describes and tests relevant mechanisms.

2 Institutional Background

In this section, I briefly discuss the institutional details regarding prior authorization *per se* and how recent state legislation aims to restrict the use of such administrative requirements.

2.1 Prior Authorization for Substance Use Disorder Services

Prior authorization (PA) is a process requiring health care providers to obtain pre-treatment approval from health plans before a prescription medication or medical service is delivered to the patient (American Medical Association).[5] Health insurance companies typically require PA for certain medical procedures, treatments, and drugs that are likely to trigger high costs or high abuse potentials.[6] In particular, insurers claim that prior authorization requirements are necessary to protect patients from unsafe prescribing decisions and limit rapidly increasing prescription drug expenditures.[7]

Originating from the 1960s and getting widely adopted since the 1990s, prior authorization requirements have been utilized in both private and public health plans.[8] [9] Common types of care requiring PA include prescription drugs, durable medical equipment, diagnostic radiology, surgical procedures, inpatient stays, and behavioral health treatments. In the context of substance use disorder services and medications, the presence of prior authorization requirements is more frequent than many other medical procedures (Weber, 2020). According to Nguyen et al. (2022), commercial insurers impose PA requirements on buprenorphine: with 23% of formularies having at least one buprenorphine product with prior authorization requirements in 2017. In 2008, the Mental Health Parity and Addiction Equity Act barred the discriminatory use of prior and continuing authorizations.

Conceptually, the presence of *prior authorization* is akin to an administrative hassle (Brot-Goldberg et al., 2023). Indeed, according to a national survey conducted by the American Medical Association (AMA):

[5] See https://www.ama-assn.org/practice-management/sustainability/prior-authorization, last access on July 10, 2024.
[6] https://fixpriorauth.org/resources
[7] See https://www.statnews.com/2021/01/01/prior-authorization-whos-choosing-americans-medications-doctors-or-insurers/, last accessed on July 10, 2024.
[8] In the appendix, I describe how a PA request works in detail.
[9] https://www.priorauthtraining.org/the-evolution-of-prior-authorizations/, last accessed on July 10, 2024.

> Among all patients with PA in one's treatment, 94% experience delayed access to necessary care due to PA, and 80% report that PA can at least sometimes lead to treatment abandonment ... Physicians and their staff spend an average of almost two business days each week completing PAs, nearly 35% of physicians have staff who work exclusively on PA, and 88% of physicians describe the burden associated with PA as high or extremely high ... 64% of physicians report that PA has led to ineffective initial treatments, 62% of physicians report that PA has led to additional office visits, and 46% of physicians report that PA led to immediate care and/or ER visits (i.e., highly intensive treatment).

Intuitively, the adverse events due to PA might not be too surprising in the context of substance use disorder (SUD): Addiction typically affects the parts of the brain responsible for motivation and decision-making, creating narrow and shifting windows in which a patient is motivated to engage in treatment. Consequentially, requesting and obtaining prior authorization can impose delays in the initiation of care, which can lead to serious consequences for the patient, including failing to return for subsequent appointments, resuming substance use, medical complications, overdose, and even death (Weber, 2020).

2.2 State-Level Restrictions on Prior Authorization

In response to the opioid epidemic, several states have removed some prior authorization requirements and aim to improve the efficacy of accessing and delivering substance abuse treatment (SAT) (Weber, 2020). As of April 20, 2020, 18 states have enacted laws that restrict the use of prior authorization for SUD treatment in private health plans. Of course, the legal languages vary substantially across different states: Some states have adopted a range of standards in limiting prior authorization for at least one type of SUD medications, some require any FDA-approved SUD medication on the plan's formulary or preferred drug list to be covered without prior authorization, and others limit prior authorization for specific time periods within a treatment episode, or limit prior authorization requests to one per year (Weber, 2020). In terms of the general SUD services, a number of states restrict the use of prior authorization for inpatient and/or outpatient services delivered by state-licensed/certified providers/facilities, while others limit prior authorization only for services

involving medication-assisted treatment (MAT), such as behavioral therapy and counseling (Weber, 2020).

3 Conceptual Model

In this section, I provide a conceptual framework, which closely follows Harris, Liu and McCarthy (2020) to illustrate how an exogenous shock on facilities' capacity, which is induced by the prior authorization (PA) restriction, can influence the provision of medical treatment.

3.1 Set-up

Throughout the analysis, I assume a typical *behavioral healthcare facility* is the key decision maker instead of the individual physician as Harris, Liu and McCarthy (2020). The primary reason to do so is two-fold: First, in the setting of substance abuse treatment (SAT) services, various types of healthcare professionals can jointly deliver such services, including psychiatrists, psychologists, social workers, advanced practice psychiatric nurses, certified prevention specialists, addiction counselors, etc.[10] Second, the primary data source I relied on in the empirical portion reflects facilities' decisions instead of individual providers' responses. When discussing the alternative channels, I also show there is little evidence that imposing PA restrictions can influence individual providers' prescribing behavior.

In the context of SAT service, I define "*treatment capacity*" as the aggregate, facility-level time available to meet with patients, which is the product of time available per provider to meet a patient's needs of care and the number of providers available within a facility.[11] Essentially, I assume imposing a restriction on the use of PA for SAT services is equivalent to an exogenous expansion of facilities' treatment capacity. It's reasonable to conceptualize PA as a treatment capacity constraint, because on the supply side, capacity and financial constraints within the specialty SUD treatment delivery system limit the ability of providers to increase access to newly insured individuals (Andrews et al., 2015). For instance, many specialty SUD treatment facilities fail to provide open slots and allocate time to admit new patients (Carr et al., 2008; Jones et al., 2015). Meanwhile, this assump-

[10] See here, for example, https://www.samhsa.gov/workforce, last accessed July 10, 2024.

[11] For simplicity, I ignore the teamwork of the medical workforce, the substitution/complementarity between different healthcare professionals, etc.

tion is also consistent with my empirical findings: state-level PA restrictions reduce the likelihood of experiencing involuntary medical delay among patients in an outpatient setting; such involuntary medical delay is primarily driven by "programs' capacity issue."

As suggested in prior research (Harris, Liu and McCarthy, 2020), this conceptual framework also accommodates a key stylized fact of medical services where labor is the primary input and the quality of the service provided is a function of time with the customer: a reduction in the treatment capacity is equivalent to a proportional increase in the arrival rate of patients to a typical facility. I also assume the likelihood of providing a specific type of service is the *extensive* margin of healthcare provision. Put differently, if the optimal amount of time a facility provides to meet patients' demands is positive, facilities will provide the service.[12]

3.2 Facilities' Problem

As shown in Harris, Liu and McCarthy (2020), individuals are assumed to arrive following a Poisson process, with the mean arrival rate denoted as λ over a unit of time normalized to one. Service time per facility is assumed to be distributed exponentially, with a mean service time μ. The primary goal in this setting for facilities is to ensure that a patient's needs for care are met by choosing both the intensive (i.e., the amount of time) and extensive (i.e., whether to provide or not) margins of SAT service.[13]

Mathematically, a typical facility minimizes the loss function in each period with respect to the average time spent with each patient. The function can be decomposed into two parts: First, the disutility from spending less time on average with existing patients; second, the disutility from leaving new patients unseen.

$$U(\mu|\gamma,\lambda) = \underbrace{f(\gamma-\mu)}_{\text{loss from spending less time with admitted patients}} + \underbrace{g(\lambda-\frac{1}{\mu})}_{\text{loss from not admitting new patients}} \tag{1}$$

where γ is the fixed amount of time one facility can spend, and the number of new, unseen patients

[12] Due to the data limitation, it's not feasible to check the intensive margin (i.e., the number of hours spent on service) empirically.

[13] For simplicity, I do not assume behavioral healthcare facilities can choose the price endogenously.

is $(\lambda - \frac{1}{\mu})$. $f()$ and $g()$ are both decreasing and convex.

For simplicity, we can assume $f()$ and $g()$ are exponential functions, and the loss function would be expressed as

$$U(\mu|\gamma,\lambda) = -exp(\alpha(\gamma-\mu)) - exp(\beta(\lambda - \frac{1}{\mu})) \tag{2}$$

where α captures the disutility from spending less time than ideal with existing patients; β captures the disutility from leaving new patients unseen. As mentioned above, the facility's decision is to choose the optimal amount of time μ to minimize the loss. As a result, if we take the derivative with respect to μ, the first-order condition would be:

$$\alpha \times exp(\alpha(\gamma-\mu^*)) - \frac{\beta}{\mu^{*2}} \times exp(\beta(\lambda - \frac{1}{\mu^*})) = 0 \tag{3}$$

Based on equation (3), when $\lambda \leq \frac{1}{\gamma}$, the optimal amount of time allocated to medical treatment would be $\mu^* = \gamma$. This is simply because the provider's time constraint is not binding. Intuitively, when the arrival rate of patients is sufficiently low (or, say, the treatment capacity is sufficiently high), facilities can freely allocate time to each patient without incurring any disutility from turning new patients away. When $\lambda > \frac{1}{\gamma}$, the facility would choose the optimal μ^* as shown above.

3.3 Comparative Statics

In this framework, I conceptualize a prior authorization restriction as an exogenous, positive shock on facilities' treatment capacity (or, equivalently, a negative shock on the arrival rate of patients, λ). Put differently, the imposition of PA restrictions will increase the (aggregate) time available at the facility level.

Based on the implicit function theorem, the comparative statistic is captured by the following equation:

$$\frac{d\mu^*}{d\lambda} = \frac{\frac{\beta^2}{\mu^2} \times exp(\beta\lambda - \beta/\mu)}{\frac{\beta(2\mu-\beta)}{\mu^4} \times exp(\beta\lambda - \beta/\mu) - \alpha^2 \times exp(\alpha\gamma - \alpha\mu)} \tag{4}$$

Overall, the direction and the magnitude of adjusting μ^* with respect to λ hinge on several gradients: the preference parameters α (which captures how facilities value the treatment of existing patients) and β (which captures how facilities value the treatment of unseen, new patients), the current capacity to start with $(\gamma - \mu)$, and the value of the arrival rate of patients λ. As shown in Harris, Liu and McCarthy (2020), there are several key takeaways from this equation:

Initial treatment capacity $(\gamma - \mu)$: the change in μ^* with respect to the shock in treatment capacity (i.e., changes in λ) hinges on the initial level of time available within a facility $(\gamma - \mu)$. In particular, Harris, Liu and McCarthy (2020) found the numerical solution: an increase in λ is associated with a decline in μ^*. The negative relationship suggests the increasing marginal disutility of $(\gamma - \mu)$ dominates.[14] This is a reasonable prediction: If the facility is crowded in the first place, it's more challenging to reallocate time and labor to accommodate new patients and offer new medical services.

Preference parameters (α and β): when a facility values seeing new patients (β) more than spending the ideal level of time with each patient (α), $\frac{\mu^*}{\lambda} < 0$. Intuitively, this indicates if a facility cares about ensuring more patients can get proper medical services on time, an expansion in treatment capacity would lead to an increase in the time allocated to providing new SAT services. Mathematically, this means β and α satisfy the following condition:

$$(\beta\lambda - \beta/\mu)^{\frac{\beta(2\mu-\beta)}{\mu^4}} < (\alpha\gamma - \alpha\mu)^{\alpha^2} \tag{5}$$

In Figure 2 of Harris, Liu and McCarthy (2020), they show that numerically, the magnitude of the decline in μ^* is larger when α is a smaller portion of β.

Initial arrival rate of patients (λ): according to Figure 2 shown in Harris, Liu and McCarthy (2020), as the initial value of λ keeps increasing, $\frac{d\mu^*}{d\lambda}$ approaches to zero. The numerical solution

[14] Recall g() is a convex function.

should not be surprising: if the number of patients is extremely high and the facility is overcrowded in the first place, the facility has neither incentives nor capacity to reallocate time and labor to deal with new patients.

Taking together, the effects of an exogenous increase in treatment capacity (or, say, an exogenous decline in the arrival rate of patients) on the time and effort allocated to the provision of medical treatment is theoretically ambiguous:

First, when the arrival rate is sufficiently low (i.e., $\lambda \leq \frac{1}{\gamma}$), the facility does not need to adjust one's allocation of time they spend with each patient because the time constraint is not binding at all.

Second, when the initial λ is close to its capacity (i.e., $\lambda > \frac{1}{\gamma}$), a decreased arrival rate would result in a surge in μ^*, representing the increased provision of healthcare services.

Third, if a facility has an extremely large amount of patients to begin with, changes in the arrival rate barely have any effects on the optimal time μ^* because providers are not willing to spend extra time with any patient.

Note that there are two broad categories of settings, which provide high-intensity services and low-intensity services respectively. The exogenous shock induced by the PA removal does not necessarily affect a facility's decision along this margin in the same way.

4 Alternative Theoretical Mechanisms

This section briefly discusses several alternative potential channels through which a PA restriction can affect the provision of healthcare services. Overall, the provision of SAT services hinges on pair-wise interactions among patients/consumers, private insurance companies, healthcare professionals, and facilities.

Besides the treatment capacity story mentioned above (section 3), removing PA requirements from commercial plans can (1) trigger substantial changes in the commercial health insurance market *per se* with adverse selection and moral hazard, (2) *ex-post* moral hazard in utilizing healthcare services among existing, admitted patients, (3) strategic contracting between healthcare facilities and commercial plans through network formation, (4) changes in prescribing behaviors of healthcare

professionals (i.e., physicians and other providers) due to financial incentives, and (5) changes in local market structure.

4.1 Adverse Selection and Moral Hazard in Insurance Market

As a first-order effect, restricting the use of prior authorization in private health plans would plausibly increase the intensity of asymmetric information regarding one's health conditions between consumers and insurers, thereby triggering both adverse selection (i.e., when individuals who have a choice among insurance plans select their plan, those who are more likely to require SUD care tend to choose more generous plans) and moral hazard (i.e., when insured individuals bear a smaller share of their medical care costs, they are likely to consume more care). Specifically, an insurance company is now strictly restrained from requesting detailed information about the patient's medical history and treatment progress.

In a new equilibrium (of the insurance market), removing PA requirements can thus change one's coverage status of SAT services in a health plan and the utilization of SUD treatment services. This is because the plan covers more and/or such a plan attracts individuals with greater underlying health needs. In either case, we would expect these first-important effects in the commercial insurance market will result in an increased demand for SUD treatment along the admission margin,[15] mechanically driving up the provision of such services.

4.2 Ex-post Moral Hazard of Existing Patients

The second alternative explanation for changes in the provision of SAT services concerns ex-post moral hazard among existing patients. Similar to the argument in section 4.1, patients who are admitted by a facility are less likely to terminate their treatment voluntarily because of a more generous plan without checking medical necessity. Again, this induced increase in medical demand can lead to a mechanical surge in providing SAT services. Treatment facilities eventually find themselves providing care to patients who may not benefit significantly from continued treatment but remain enrolled due to improved insurance coverage and reduced administrative barriers.

[15] For example, being covered by more generous plans will induce patients to use more unnecessary SAT services.

4.3 Facilities' Selective Contracting with Insurers

PA restrictions can also change providers' decisions through selective contracting with private insurers: the more burdensome and restrictive the PA process, the more likely providers are to limit their contracting with insurers that require PA for certain treatments or services. The underlying mechanism is akin to the argument from Dunn et al. (2021) that more aggressive use of claim denials reduces the willingness of providers to contract with insurers. Theoretically, as an administrative ordeal, prior authorization would increase the marginal cost per treatment. This increasing marginal cost may encompass providers' efforts in reviewing paperwork, back-and-forth confirmations with insurers, resubmitting, etc. In turn, the selection in contracting with insurers can substantially alter the scope of services provided on-site.

In this regard, with *less-stringent* PA requirements in place, one may expect that providers are more inclined to accept private plans. One noteworthy caveat, however, is that due to the limitations of my data and methodology, other margins related to the network formation and bargaining over reimbursement rates between providers and insurers (see, for example, Ho and Lee (2017)) are beyond the scope of this paper. Taking these margins into account could largely complicate the analysis: For example, if the restriction of PA substantially changes the reimbursement rates of private plans, then providers may strategically admit and/or discharge consumers due to financial incentives. In order to shed light on some welfare effects, future research should address such issues with detailed claim/client-level data and/or structural models.

4.4 Physicians' Diagnostic and Prescribing Behaviors

Another noteworthy channel through which PA restrictions influence the provision of such behavioral healthcare services is relevant to physicians' financial incentives. A large line of literature investigates how changes in reimbursement rates or other general changes in medical prices influence providers' diagnostic, prescribing, and treatment choices (see, e.g., Gruber and Owings, 1996; Dafny, 2005; Clemens and Gottlieb, 2014; Alexander, 2020). Prior work found that physicians/providers tend to prescribe more services in response to either an increase or a decrease in the related reimbursement rates. The typical explanation is that when the price of a service is lowered, physicians will prescribe more of the service in order to make up for the lower unit price to maintain

an income target; when the price of a service is raised, physicians will have an incentive to prescribe more of that service to increase his/her income.

In the context of prior authorization, this provider-induced demand theory can rationalize changes following the restriction: For example, if administrative hassle is valued as an implicit tax per treatment, the removal of such a tax would largely increase the price of medical services, thereby driving up/down physicians' diagnostic incentives.[16] Particularly, one may expect more profound changes in SUD treatment based on medication, *medication-assisted treatment* (MAT). This is simply because MAT requires doctors, nurse practitioners, or physician's assistants who meet certain qualifications to treat opioid patients with drugs approved by the FDA for the treatment of opioid dependence: buprenorphine, methadone, and naltrexone.

4.5 Changing Local Market Structure

The last but not the least influential factor is related to the local market structure of behavioral healthcare facilities. All structural factors mentioned above (i.e., facilities' treatment capacity constraint, the interplay between consumers and insurers, the increased demand due to ex-post moral hazard among existing patients, facilities' strategic contracting with insurers, and physicians' diagnostic/prescribing behaviors) can induce the aggregate-level provision of SAT services, which in turn would alter the incentive of individual facilities to offer relevant SAT services. From the empirical perspective, prior research found the impact of competition (market structure) on the provision, quality, and cost of medical services is quite mixed (see, for example, Kessler and Geppert, 2005; Karlsson, 2007; Gaynor, Moreno-Serra and Propper, 2013).

5 Empirical Strategy

The main objective of this paper is to examine whether restricting the use of prior authorization requirements affects the provision of substance abuse treatment. Throughout the analysis, I focus on measuring the probability of providing different types of healthcare services. I leverage the phase-in

[16] Of course, it is empirically challenging to clearly tell apart changes in providers' incentives and changes in demand for relevant services. I will elaborate on how I separate these two channels in data in section 8.

of state laws restricting the use of PA as a quasi-experiment and employ the following staggered difference-in-difference (DID) model to identify the causal effect:

$$y_{ist} = \alpha + \beta PALimit_{st} + X_{ist}^{'}\gamma + \rho_{st} + \eta_t + \psi_s + \varepsilon_{ist} \tag{6}$$

where i denotes facilities, s represents states, and t indexes years. y_{ist} is the key outcome of interest, the likelihood of offering a variety of SUD services in facility i located in state s in year t. $PALimit_s$ is an indicator whether there is a state law restricting the use of PA for SAT services in state s in year t. X_{ist} is a set of facility-specific controls, and ρ_{sc} represents a collection of state-specific control. I also include state fixed effects (ψ_s) and and η_t are patent subclass and year fixed effects, respectively. Therefore, β would identify the impact of PA restrictions on the provision of facilities.

Of course, the key assumption of this difference-in-differences model is that controlling for state and year-fixed effects, changes in key outcomes would have been comparable among different states in the absence of prior authorization laws. To directly test this assumption, I estimate a stylized event study model as follows in equation 2:

$$y_{ist} = \alpha + \sum_{i=-5}^{4} \beta_{t+i} Treat_{st} \times year_{t+i} + \rho_{st} + \eta_t + \varepsilon_{ist} \tag{7}$$

where $year_{t+i}$ is a set of indicators denoting whether a year is the i^{th} year before or after the enactment of the PA law. In this specification, the estimate associated with one year prior to the treatment is normalized to zero. This way, $\beta_P t + i$ also captures the dynamic effects of restricting PA.

Another threat to identification is the reverse causality issue. For example, one might imagine that states enacting restricting laws are also those with a higher level of demand for SUD treatment and/or a smaller amount of specialty facilities providing behavioral health services in the first place. If changes in PA restrictions are correlated with underlying legal, economic, political, or social trends, it would be challenging to use such variation to isolate the effects of restrictions on healthcare provision. In subsequent analysis, I corroborate the evidence that the provision of SAT services does not differentially change in years prior to changes in PA restrictions. Meanwhile, I also provide supplementary analyses by testing whether other changes in political, social, and economic features predict PA restriction changes.

Eventually, a growing strand of work emphasizes the sensitivity of a staggered difference-in-differences specification: the traditional staggered difference-in-differences estimation cannot fully capture the dynamic treatment effects with staggered adoption and heterogeneous treatment effects (Goodman-Bacon, 2021; Sun and Abraham, 2021). I am still in the middle of checking the robustness of my results using such alternative specifications (e.g., Callaway and Sant'Anna, 2021; Wooldridge, 2023).

6 Data

This section summarizes the data assembled from multiple resources and provides motivational evidence. To implement the empirical analysis, I collect data on (1) the timing of adopting the state-level limits on substance abuse treatment (SAT) in private health insurance, and (2) measures of the facilities' capacity of providing various types of treatments and the probability of participating the private health insurance market. I then describe how to construct each measure, enabling me to conduct the empirical analysis in turn.

6.1 Adoption of PA Limits on Substance Abuse Treatment

To obtain information on the state laws restricting the use of prior authorization in substance abuse treatment (SAT), I mainly rely on the report from the Legal Action Center (LAC) and collect policy data on the Westlaw legal library.[17] In particular, the LAC report provides a helpful starting point but lacks the detailed information needed for the empirical analysis. As a supplement, I investigated changes in PA limits for each state over time via text mining to construct a panel policy database including the timing of change, the type of service/medication covered, and the During the sample period (2012-2020), there are 18 states enacting laws to restrict private insurers from imposing prior authorization requirements on a SUD service of medication. Of course, there is substantial variation in the state legal language regarding the content of PA limits. At a higher level of generalization, I exploit the variation in timing for the baseline estimation. Table A1 in the appendix lists the corresponding states, the effective dates of PA limits, and a summary of these laws.

[17] See https://www.lac.org/assets/files/Prior-Authorization-Spotlight-FINAL-use-this-one.pdf and https://legal.thomsonreuters.com/en/westlaw for the LAC report and Westlaw legal library, last accessed on July 10, 2024.

6.2 National Survey of Substance Abuse Treatment Services

The primary data source enabling me to implement the empirical analysis is the National Survey of Substance Abuse Treatment Services (N-SSATS), a national annual survey of specialty SAT facilities.[18] The N-SSATS is widely used to study SUD treatment outcomes by economists (see for example, Markowitz and Grossman, 2000; Carpenter, 2007; Popovici, Maclean and French, 2017; Hamersma and Maclean, 2021, etc.). The sampling frame for the N-SSATS is the Inventory of Behavioral Health Services (I-BHS), including a registry of the universe of SAT facilities known to the Substance Abuse and Mental Health Services Administration (SAMHSA). Data collection for the N-SSATS occurs between late March and early December each year, during which time surveys are sent to all facilities on the I-BHS. New facilities that are discovered by SAMHSA during this period and also included in the N-SSATS and subsequently placed on the I-BHS for the following year. Facilities fill out questionnaires of services they provide, counts of clients currently receiving treatment, and counts of beds dedicated to SAT clients (if applicable).[19]

To measure the treatment capacity of an SAT facility, this paper exploits two categories of outcomes in the N-SSATS: *the probability of providing inpatient/outpatient services*, and *the propensity to participate in the private health insurance market*. Specifically, a specialty SAT facility included in N-SSATS can be a hospital or other facility with an SAT program offering any of the following services: outpatient, inpatient, and residential/rehabilitation treatment; detoxification; opioid treatment; and halfway-house services. N-SSATS does not include SUD treatment providers that exclusively treat incarcerated patients. Providers included in N-SSATS often provide other services (e.g., mental healthcare); a requirement for inclusion is that the provider offers specialty SUD treatment, not that this treatment is the provider's primary focus (Hamersma and Maclean, 2021).

6.3 Annual Reports for N-SSATS

Besides the detailed, facility-level data derived from the N-SSATS, I also complement my analysis by digitizing the annual reports of the N-SSATS and collecting state-level information. The primary reason for conducting this exercise is to measure the likelihood of providing early-stage interventions

[18]The dataset is available here https://www.datafiles.samhsa.gov/dataset/national-survey-substance-abuse-treatment-services-2020-n-ssats-2020-ds0001, last accessed July 10, 2024.

[19]The reference date for residential and hospital inpatient beds and client counts was March 30/31.

for SUD among these specialty facilities. Due to confidential concerns, such information is not publicly available in the annual N-SSATS.

Specifically, I construct the annual number of facilities offering a variety of assessment and pre-treatment services as a proxy for the propensity to provide early interventions. These services include brief intervention, screening for SUD, comprehensive assessment and diagnosis, and outreach services for each state; thus, the unit of this analysis is state-year. Figure 6 presents a snapshot of the annual survey for the N-SSATS.

6.4 Treatment Episode Data Set

Another primary data source I relied on in this paper is the Treatment Episode Data Set (TEDS), which compiles client-level data for substance abuse treatment admissions from state agency data systems. State data systems collect data from facilities about their admissions to treatment and discharges from treatment.[20]

The TEDS is one component of a broader data inventory maintained by SAMHSA to track both the quantity and quality of specialty SUD treatment within the U.S. The TEDS includes information on approximately two million admissions to specialty SUD treatment each year, and contains nearly the universe of specialty SUD treatment facilities that receive financing from the state or federal government, are certified by the state to provide specialty SUD treatment, or are tracked for some other reason. Thus, TEDS reflect admissions financed by multiple payers (e.g., self-payment, private insurance, Medicaid, Medicare). TEDS is commonly employed within the policy literature to study SUD treatment (Anderson, 2010; Dave and Mukerjee, 2011; Pacula et al., 2015; Powell, Pacula and Jacobson, 2018) and is used by the Federal government to estimate the costs of SUD treatment to the U.S. economy (Office of National Drug Control Policy 2012).

In particular, the TEDS is composed of two parts: the Admission set (TEDS-A) and the Discharges set (TEDS-D). The former one contains records on admissions of people aged 12 and older, and includes information on admission demographics (for example, age, sex, race/ethnicity, employment status) and substance use characteristics (for example, substances used, age at first use, route of use,

[20]This data set is available here https://www.datafiles.samhsa.gov/dataset/teds-d-2020-ds0001-teds-d-2020-ds0001 and https://www.datafiles.samhsa.gov/dataset/treatment-episode-data-set-admissions-2020-teds-2020-ds0001, last accessed July 10, 2024.

frequency of use, number of prior admissions). Another noteworthy feature is that TEDS-A records represent admissions rather than individuals, as a person may be admitted to treatment more than once. By contrast, the TEDS-D contains records on discharges of people aged 12 and older, and includes information on admission demographics (for example, age, sex, race/ethnicity, employment status) and substance use characteristics (for example, substances used, age at first use, route of use, frequency of use, number of prior admissions).

7 Main Results

In this section, I present my main results relating to various measures of the provision of healthcare services based on equation 1 and discuss how to interpret the magnitude, as well as the implications.

7.1 Effects of Any Restriction

In Table 2, I report the coefficient estimates for β, which captures the impacts on SAT provision. The key outcome of interest in the first two columns is the probability of solely providing low-intensity SAT services, relative to only offering high-intensity SAT services. In column (3) and column (4), I focus on the probability of offering both low-intensity and high-intensity services, compared to only providing low-intensity ones. Eventually, in the last two columns, the dependent variable is the likelihood of providing both, relative to only offering services in a high-intensity setting. In all odd-numbered columns, the sample includes all specialty care facilities, while in the even-numbered, the sample is composed of facilities accepting commercial plans.[21]

Based on results from Table 2, we can see that following the PA restriction, the probability of only offering low-intensity service significantly increases by 8.8 percentage points (relative to only providing high-intensity ones). This is equivalent to an increase of 13.79% (=8.8/63.8). The point estimates in column (3) and column (4) indicate that the imposition of PA restrictions leads to a decline in the probability of offering both low- and high-intensity SAT services (relative to offering only low-intensity ones). However, these negative effects are sensitive to the specification: Among facilities accepting private plans, the negative effect is statistically insignificant. Finally, I focus on the likelihood of providing both types of SAT services (relative to solely providing high-intensity

[21] I also found the probability of accepting commercial plans does not change among these specialty care facilities.

SAT services) in the last two columns: it increases significantly by at least 4.3 percentage points (or 5.95%).

Overall, the coefficient estimates in this round of regressions suggest restricting the use of PA in commercial plans would incentivize more specialty care facilities to offer low-intensity SAT services. This surge reflects two patterns: First, facilities shift from only providing high-intensity SAT services to low-intensity ones (or say, the number of facilities only offering low-intensity SAT increases compared to that of those only offering high-intensity ones). Second, facilities also shift from only offering high-intensity services to providing both types. Put differently, the number of facilities with both SAT services increases compared to that of those only offering high-intensity ones.

7.2 Heterogeneous Effects by the Type of Restrictions

As shown in Table 1, there are two primary types of restrictions: PA restriction on general SAT services and PA restriction on SAT medication. Meanwhile, there are various PA restrictions on SAT services in Medicaid. In Table 3, I examine the heterogeneous effects by the type of these restrictions. The specification is quite similar to equation (6):

$$y_{ist} = \alpha + \beta_1 ServiceRestriction_{st} + \beta_2 MedRestriction_{st} + \beta_3 MedicaidRestriction_{st} + X_{ist}^{'}\gamma + \rho_{st} + \eta_t + \psi_s + \varepsilon_{ist} \tag{8}$$

where $ServiceRestriction_{st}$ refers to the PA restriction on general SAT services in commercial plans in state s and year t, $MedRestriction_{st}$ represents the PA restriction on SAT medication in commercial plans within state s and year t, and $MedicaidRestriction_{st}$ denotes an indicator for a PA restriction in Medicaid for SAT services.

My results are shown in Table 3. Based on estimates from the first and second rows, the significant effects associated with PA restriction primarily come from the restriction on general SAT services. For example, imposing general PA service restrictions is associated with a significant increase in the probability of solely offering low-intensity services by 8.4 percentage points (13.17%) and another increase by 3.5 percentage points (4.84%) in the probability of offering both types (compared to only offering high-intensity SAT services). Interestingly, I also find the presence of PA restrictions

within Medicaid for SAT services would increase the provision of low-intensity services (by 14.8 percentage points, or 23.2%, related to solely providing high-intensity SAT services).

7.3 Threats to Identification

As I mentioned in section 5, there could be various concerns regarding my identification strategy. I address some of them in this section in turn.

Event-study specification: I first estimate the event-study specification shown in equation (7) and plot the coefficient estimates in Figure (6) to Figure (8). Overall, there is no obvious reason to believe that the assumption of parallel trends is violated. At the same time, among all three exercises, I find the PA restriction is associated with positive effects on the provision of low-intensity services for at least four years. The likelihood of offering both types (compared to offering low-intensity) significantly declined, while the probability of providing both types would increase relative to the probability of offering only high-intensity ones for at least four years.

Alternative DID Specifications: one critic for the staggered difference-in-differences model is that Goodman-Bacon (2021). To take care of this issue, I use Callaway and Sant'Anna (2021) to demonstrate the robustness of my main estimates. In Table 4, we can see the increased provision of low-intensity SAT services is still statistically significant (as shown in column (1) and column (2)) by 6.9% (=4.4/63.8*100%).

Policy Endogeneity: Another concern relevant to my identification strategy is policy endogeneity. For example, one may argue the high mortality rate due to SUDs and/or the lack of SAT services provision partially contribute to the enactment of these PA restrictions. To alleviate the concern, I took two exercises: First, I follow Johnson, Lavetti and Lipsitz (2023) and test whether states' social and economic characteristics predict PA law changes. In particular, I collect information from the University of Kentucky Center for Poverty Research's National Welfare Data (University of Kentucky Center for Poverty Research, 2018) on state population, unemployment rates, state GDP, minimum wage, the number of Medicaid beneficiaries, the level of SNAP benefits, and the level of TANF benefits.[22] I also collect data on mortality rate due to "mental and behavioral disorders due

[22] See https://cpr.uky.edu/resources/national-welfare-data, last accessed July 10, 2024.

to psychoactive substance use" from the CDC WONDER online databases .[23][24]

In Table 5, I present my point estimates regarding the enactment of any PA restriction on SAT, PA restrictions on general services of SAT, and PA restrictions on medication of SAT, respectively. The results suggest that the only two factors contributing to the enactment of PA laws are state-level minimum wages and the level of state population (though sensitive to the specification). Higher minimum wages lead to an increase in the probability of enacting such PA restrictions, while states with more residents are less likely to impose these restrictions. Intuitively, these findings are reasonable: higher levels of minimum wage have the potential to prevent individuals from SUDs. Meanwhile, the correlation between the state-level death count due to SUDs and the enactment of PA restrictions is not statistically significant, indicating the reverse causality concern should be minimal. In the main analysis, I include both the level of state population and the state minimum wage to attenuate this endogeneity issue.

As for the second exercise, recall in Figure (6), Figure (7), and Figure (8), I showed that there is little evidence suggesting that the provision of SAT services does not differentially change in years prior to a PA law change.

7.4 Suggestive Evidence on the Provision of Early Interventions

Of course, besides offering traditional SAT services, facilities also have the option to provide some early interventions, including assessment and pre-treatment services, education and counseling services, etc. Such services are crucial to prevent the development of SUDs. For example, according to the SAMHSA, screening can quickly "assess the severity of substance use and identify the appropriate treatment level" and brief intervention "focuses on increasing insight and awareness regarding substance use and motivation toward behavioral change." By providing these early interventions, facilities can help individuals at risk for developing SUDs avoid the need for more intensive and costly treatments in the future.

Turning to this margin, I rely on information hand-collected from the 2012/5-2020 annual reports

[23] According to UCD-ICD-10 Codes, the causes of mortality due to SUDs are captured by F10-F19 (mental and behavioral disorders due to psychoactive substance use) .

[24] See https://wonder.cdc.gov/, last accessed July 10, 2024.

for N-SSATS and construct four relevant measures: the provision of brief intervention, the provision of screening services for SUDs, the provision of comprehensive assessments, and the provision of outreach services.[25] Results in Table 4 then display some suggestive evidence: From column (1), one can directly tell that with a PA restriction in place, the propensity to offer brief intervention services increases by 63.3 percentage points at the state level. Similarly, the propensity to provide other early-stage interventions increases, although these estimates are relatively imprecise based on the coarse data.

8 Discussing Mechanisms

In this section, I empirically unravel several potential mechanisms at play (mentioned in section 3 and section 4) to explain why there are changes in the provision of SAT services. To be concrete, I test whether the observed shift in providing SAT services is a result of (1) an expansion in treatment capacity at the facility-level, (2) changes in the quantity and composition of patients receiving SAT services, (3) increased demand for SAT services due to moral hazard among on-site patients, (4) changes in providers' prescribing behaviors, (5) facilities' willingness to accept private plans, and (6) changes in the local market structure of behavioral healthcare facilities.

8.1 Facility-Level Treatment Capacity

8.1.1 Increased Provision of Low-Intensity Service

As shown in section 3, I begin by arguing the primary channel associated with the *increased* provision of low-intensity SAT services stems from an expansion in treatment capacity (i.e., time and labor available within a facility).

To test this hypothesis, I extract client-level information from the TEDS-A and construct three measures of facility-induced medical delays: an indicator for *any delay* ("whether there are any days waiting before receiving treatments"), an indicator for *normal delay* ("whether there is at least one week waiting before receiving treatments"), and another indicator for *severe delay* ("whether there

[25] For a detailed description of these early-stage interventions, see https://www.ncbi.nlm.nih.gov/books/NBK571017/, last accessed July 10, 2024.

are at more than two weeks waiting before receiving treatments") among the newly admitted.[26] Particularly, such information regarding the waiting time is designed to indicate the number of days from the first contact or request for a substance use treatment service until the client was admitted and the first clinical substance use treatment service was provided. This measure is intended to capture the number of days the client must wait to begin treatment because of program capacity, treatment availability, admissions requirements, or other program requirements and should not include time delays caused by client unavailability or client failure to meet any requirement or obligation.

Table 6 presents the corresponding results. In columns (1) and (2), I focus on all admissions to an inpatient setting (i.e., residential care, hospitalization, and intensive outpatient care), while turning to new admissions to an outpatient setting in columns (3) and column (4). In all odd-numbered columns, the outcome of interest is the indicator for *normal delay*, and the dependent variable is an indicator for *severe delay* in the even-numbered columns. Across all specifications, one can see that when enacting a PA law, there is a significant drop in the propensity to experiencing both *normal delay* (by 4.2 percentage points or 25.6%) and *severe delay* (by 1.8 percentage points, or say, 18.56%) in an outpatient setting. In contrast, little evidence shows the probability of medical delay due to facilities' treatment capacity changes in an inpatient setting: the declines (-0.005 and -0.001) are statistically insignificant. Mapping these results to the documented changes in the provision of SAT services (section 7), it implies that relaxed capacity constraints mainly drive the shift from high-intensity care to low-intensity care: Without the administrative burden associated with PA, facilities can better reallocate medical resources from high-intensity to low-intensity services.

8.1.2 Decreased Provision of High-Intensity Serivce

Turning to the *decreased* provision of high-intensity treatment, I further argue there are three channels: (1) mechanical shift of patients, (2) reallocation of medical resources (within facilities), and (3) facilities' dynamics (i.e., entry and exit).

[26] Of course, there could be selection along the margin of admission — for example, some patients may be directly deterred by the long waiting time and thus seek other outside options. With this selection bias, my analysis would *underestimate* the true effect. For example, deterred patients may have more severe substance use disorders subject to more stringent PA requirements or face greater barriers to treatment access, making them more vulnerable to delays in care. If this is the case, then the effect of PA restrictions on waiting times for treatment may be larger for patients who are not deterred by long waiting times than for those who are. Failing to account for this selection bias could lead to underestimating the true effect.

Mechanical shift of patients: I should first highlight the observed decline in high-intensity SAT provision could reflect a mechanical change in patients. Patients who experienced delays in the outpatient setting were initially placed in an inpatient setting (due to worsening health outcomes); when the removal of PA can expand facilities' treatment capacity and admit patients on time, those who were "mistakenly" placed in an inpatient setting got the chance to receive less intensive one. In other words, this mechanical reduction in demand for high-intensity services thus explains the pattern in my data.[27]

Ideally, one can implement empirical exercises to test this channel using individual-level data in TEDS-A. If the mechanical shift story holds (or at least dominates), one would expect (1) the aggregate number of patients getting admitted to high-intensity settings would decline and/or (2) the likelihood of being transferred from low-intensity to high-intensity would decrease among existing patients.[28] Admittedly, I don't have some administrative patient-facility matching data, so it's extremely hard to examine medical transfers across facilities at this point. I thus run the following regression to investigate the admission margin:

$$\frac{\#\text{newly admitted patients}_{st}}{100,000\text{pop}_{st}} = \alpha + \beta PARestriction_{st} + X_{st}^{'}\gamma + \psi_s + \eta_t + \varepsilon_{st} \tag{9}$$

The outcome of interest is the number of newly admitted patients to (high-intensity or low-intensity or all) facilities per 100,000 state residents. X_{st} includes various state-level controls. Others are identical to those in equation (6). Therefore, β captures the causal effects of imposing PA restrictions. Regressions are all weighed by the state population per year.

In Table 7, I present my main results regarding how the aggregate number of admissions responds to the PA law change, by the type of policies and by the setting of SAT services. In odd-numbered columns, the coefficient estimates capture the impact of imposing any PA restriction; in even-numbered columns, I separately examine the effects of PA services restrictions and PA medication restrictions. In the first two columns, I focus on all types of admissions and in the rest of the

[27] Of course, to provide more rigorous evidence for this argument, I will keep assembling more administrative data, especially regarding individual-level information about medical transfers.

[28] Of course, it would be empirically challenging to disentangle the demand-side and supply-side factors. However, as I argue and show in the subsequent analysis, the aggregate number of facilities providing high-intensity services does not change following a PA restriction, suggesting patients' access to such services is unchanged. As a result, if there is any change along the admission margin, there's a good chance that it reflects a mechanical shift story.

columns, I check admissions to the low-intensity setting (column 3-column 4) and admissions to the high-intensity setting (column 5-column 5), respectively. Although the estimates here are less precise, the takeaway is that there is little evidence suggesting the presence of a PA restriction will substantially reduce the size of new patients receiving such services, especially the high-intensity ones. The findings here thus indicate the observed reduction in high-intensity SAT provision is probably not driven by an immediate, mechanical surge in the corresponding demand.

Reallocation of medical resources: The second channel I argue is regarding the reallocation of available medical resources within a facility. With the amount of demand for SAT services fixed, removing PA relaxes facilities' treatment capacity constraints, thereby enabling facilities to reallocate limited hours per provider and/or the number of healthcare workers across departments and settings (i.e., from high-intensity ones to low-intensity ones). Put differently, the presence of administrative hassles (e.g., prior authorization) distorts the efficient allocation of medical resources in the first place.

Facilities' dynamics: Besides any changes within facilities, it's also possible to argue that the increased provision of low-intensity SAT service and the declined provision of high-intensity services represent changes along the extensive margin: firms' dynamics. This alternative story is plausible due to several reasons. For example, if the removal of PA leads to a significant expansion (reduction) in the network between insurers and facilities, new specialty care facilities might be incentivized to enter. Meanwhile, if removing these administrative costs can largely decrease the general entry barrier, a surge in new entrants would also be expected.

At this stage, I clearly don't have precise measures of providers' time allocation, the number of healthcare providers, and detailed facility identifiers over time in the current datasets. To tackle this issue, I am talking to staff from the Substance Abuse and Mental Health Services Administration (SAMHSA) and plan to submit a FOIA request to access facility identifiers if it's feasible. This way, it would enable me to directly distinguish any within-facility shift (from high- to low-intensity services) and changes in firms' dynamics. In the meantime, I am looking into a dataset, the National Sample Survey of Registered Nurses (NSSRN, 2008, 2018, and 2022), which provides rich information regarding registered nurses' location, industry, occupation, work time, earnings, and demographic characteristics.

8.2 Quantity and Composition of Patients

To empirically and explicitly identify a variety of alternative demand/supply-side factors mentioned in section 4 is an extremely challenging task: both the coverage status of SAT services in a health plan and the admission/discharge decisions are equilibrium outcomes, hinging on the interplay among consumers, healthcare facilities, and private insurers. Due to the lack of detailed claim-level data and/or a structural model, I turn to conduct a two-stage test and directly check if removing such administrative hassles induces any changes in the composition of patients on site. This exercise enables me to identify/rule out some channels beyond the margin of treatment within facilities: For example, if there is little evidence showing that both the aggregate number and the key characteristics of on-site patients are affected by a PA restriction, one can somewhat be assured that neither changes in insurance coverage status nor *ex-post* moral hazard at the admission margin should be primary drivers of results documented in section 7.[29]

To be concrete, exploiting client-level data from both the TEDS-A and the TEDS-D, I first explore whether the aggregate number of both admissions and discharges among these SAT facilities change significantly, following a prior authorization restriction. In the second stage, I then examine if there are any changes in a number of key characteristics (demographic information, pre-existing health conditions, and the coverage status of various plans) associated with the newly admitted and discharged. Drawing on evidence from these two exercises allows me to infer whether restricting PA substantially alters the composition of current patients getting treated within SAT facilities.

Changes in the aggregate number of admissions and discharges: To implement the first-stage analysis, I rely on the TEDS-A/D and collapse these data to the state-year cells. In other words, I construct a panel documenting the aggregate number of new admissions/discharges of SAT facilities for each state per year. To avoid some institutional complications related to the criminal justice system, I drop all observations referred by any police official, judge, prosecutor, probation officer, or other person affiliated with a federal, state, or county judicial system.[30] I then estimate a regression

[29] Again, due to the lack of information regarding the reimbursement rates and/or premiums, my results in this subsection cannot directly rule out the following possibility: the content of a private plan may change among these on-site patients (i.e., a higher level of premiums, a decline in the reimbursement rate, etc.), thereby affecting providers' financial incentives to treat.

[30] Including this set of admissions in the primary sample may reflect not only patients' willingness to get treated but also responses from the criminal justice system. See, for example, https://nida.nih.gov/sites/default/files/podat_1.pdf for a detailed description of how the criminal justice system plays a role in SUD, last accessed July 10, 2024.

specification similar to equation (9). The outcomes of interest include both the aggregate numbers of new admissions and discharges.

In Table 8, I repeat the exercise shown in section 8.1.2 and again, find little evidence that the enactment of PA laws could significantly affect the aggregate number of discharges from SAT facilities. Taken together, I argue there is little strong evidence that the introduction of PA restrictions in the private insurance market influences the aggregate number of patients of these behavioral healthcare facilities.

Changes in key characteristics of the newly admitted and discharged: In the second stage, I turn to assess if introducing PA restrictions would alter a number of key characteristics associated with newly admitted and discharged patients. Table 9 shows relevant point estimates: None of these key features are affected significantly by the law, indicating that there are little changes among the stock of patients within facilities in terms of one's demographic characteristics, pre-existing conditions, and insurance coverage status. These estimates further mitigate the concern that the redirection in providing SAT services is partially a result of changes in the private insurance market. Instead, this shift towards low-intensity care is likely to be driven by the interaction between providers and patients who are already within one's treatment program.

8.3 Ex-post Moral Hazard Among Existing Patients

Recall in section 4, I mention that besides the margin of getting admitted, moral hazard can also take place among some marginal patients who are already getting treated. To be concrete, the PA law may increase information asymmetry about a patient's condition because the insurance company is now restrained from requesting detailed information about the patient's medical history and treatment progress. It can thus trigger another type of *ex-post* moral hazard, resulting the increased incentives to keep utilizing available resources, although they may not be medically necessary.

A central question relevant to this channel is to what extent we should be concerned about *ex-post* moral hazard in behavioral healthcare services in the first place. *A prior,* I would argue medical services targeting SUDs are less likely to suffer from *ex-post* moral hazard issues.

First, both policymakers and researchers worry about the *underutilization* of SAT services rather than

the *overutilization*.[31] This unique pattern could be largely attributed to demand-side psychological factors, including public stigma, self-stigma, and structural stigma (Allen, Nolan and Paone, 2019).

Second, based on some descriptive evidence, the concern about overutilizing SAT services is also minimal. I collect data from the National Survey on Drug Use and Health (NHDUH): According to the 2021 data, 94% of people aged 12 or older with a substance use disorder did not receive any treatment. Among this population, nearly did not think they needed treatment. In this regard, it reinforces the idea that instead of having incentives to use unnecessary treatment, other factors (e.g., social, cultural, psychological, etc.) may hinder people from taking up treatment targeting SUDs.

Using data from the TEDS-D, I construct a relatively "coarse" measure to capture the existence of moral hazard along the treatment margin: whether one has been discharged due to a voluntary dropout. Specifically, this type of dropout includes clients choosing not to complete one's treatment program, with or without specific advice to continue treatment. In Table 10, I find that the propensity to drop out of a treatment program voluntarily has slightly declined in the presence of PA restrictions among all patients discharged from these facilities by 2.2 percentage points (column (1)). However, when turning to those actually covered and discharged with commercial plans (as shown in the even-numbered columns), the effects are positive and statistically insignificant. Therefore, it is less likely that my results shown in section 7 are primarily attributed to a sizable change in moral hazard at the treatment margin.

8.4 Providers' Prescribing and Diagnostic Behaviors

According to the provider-induced demand theory (Arrow, 1978), any changes in the medical price would alter providers' financial incentives, thereby influencing one's prescribing and diagnostic behaviors. If removing PA requirements can largely change the price of each SAT treatment, one would expect my main results to reflect a redirection in providers' treatment decisions. To empirically test this hypothesis, I restrict my attention to medication-assisted treatment (MAT) for two primary reasons:

[31] For example, recent research has identified that less than half (41%) of all people treated for OUD in the United States receive methadone or buprenorphine through substance use disorder (SUD) treatment programs. When the source of referral to a treatment program is the criminal justice system (i.e., coercive), the proportion of people receiving MAT drops to just under 5% (Krawczyk et al., 2017).

First, insurer requirements for prior authorization of MAT are historically widespread, with prior authorization requirements being one of the most frequently cited buprenorphine prescribing barriers in studies of clinicians (Barbara Andraka-Christou and Stein, 2023). For SAT services, the presence of prior authorization requirements is more frequent than many other medical procedures (Weber, 2020). [32]

Second, prescribing MAT solely relies on licensed healthcare providers (i.e., physicians, physician assistants (PAs), or nurse practitioners who have completed mandatory training and obtained specific authorization from SAMHSA). In contrast, other SUD counseling and individual/group therapy are jointly provided by various professionals.[33] In this vein, focusing on MAT enables me to better capture individual providers' decisions instead of opinions from a joint team.

Prior work typically argues empirical tests for models of physician-induced demand are remarkably challenging because it is difficult to separate the demand and the supply sides — overuse of medical procedures or drugs could also reflect consumer demand and/or physicians' belief about consumer demand (Currie, Lin and Meng, 2014). To tackle this issue, I use information from the 2012-2020 TEDS-D to examine whether imposing a PA restriction affects (1) the likelihood of providing low-intensity MAT services (as a proxy for firms' decisions), (2) the actual utilization of low-intensity MAT services (as a proxy for the equilibrium outcome), and (3) the probability of voluntarily drop out from outpatient MAT services as a proxy for consumers' demand.

The corresponding results are presented in Table 11 and 12. Starting with Table 11, I show the heterogeneous effects of PA restrictions by the type of low-intensity services. The outcome of interest in the first two columns is the probability of offering low-intensity regular SAT services (i.e., counseling and behavioral therapy); the dependent variable is the likelihood of providing low-intensity medication-assisted treatment. In column (1) and column (3), I include all discharges from the specialty care facilities regardless of whether and how one is insured. In column (2) and column (4), I restrict my attention to those discharges paid by private plans. The point estimates in Table 11 suggest that imposing PA restrictions on commercial plans would significantly increase

[32] According to Nguyen et al. (2022), commercial insurers impose PA requirements on buprenorphine: with 23% of formularies having at least one buprenorphine product with prior authorization requirements in 2017.

[33] To name a few, such professionals include clinical social workers, professional counselors, mental health counselors, marriage and family therapists, clinical alcohol and drug counselors, peer specialists, and many others.

the provision of low-intensity regular SAT services and the provision of low-intensity medication-based SAT. Given MAT services are more likely to reflect individual providers' incentives, I argue the exercise demonstrates the surge in low-intensity service provision (shown in section 7) might result from both an expansion in treatment capacity and a significant change in providers' financial incentives.

To further corroborate some evidence, I continue with another exercise in Table 12. In the first two columns, the dependent variable is a dummy variable for being admitted to an outpatient MAT program. In the last two columns, the dependent variable is the likelihood of dropping out of an outpatient MAT program. In column (1) and column (3), I include all discharges from the specialty care facilities regardless of whether and how one is insured. In column (2) and column (4), I restrict my attention to those discharges paid by private plans. Interestingly, the coefficient in column (2) indicates having a PA restriction leads to a decline in the admission margin, conditional on having private plans. This finding suggests in equilibrium, the utilization of MAT services decreases. The coefficient estimate in column (4) means having PA restrictions incentivizes consumers to drop out and reduce the demand for such services. Taken together, I would argue these two patterns highlight the increased provision of MAT services in an outpatient setting cannot be fully attributed to substantial increases on the demand side.

Putting these results together (Table 11 and Table 12), I provide suggestive evidence that both an increase in the facility's treatment capacity and a surge in individual providers' financial incentives can explain the patterns we document in section 7. Due to the limitation of my current data, I cannot clearly disentangle these two mechanisms and thus encourage future work to keep pursuing this interesting topic using much more detailed claim data.

8.5 Facilities' Contracting with Private Plans

To test if the willingness to accept private insurance is a key margin where providers adjust decisions, I present the regression results in Table 12 regarding the propensity to accept various types of payments among SAT facilities. This exercise enables me to shed some light on whether changes in the provision of SAT services are driven by firms' selective contracting (mentioned in section 4).

In column (1) and column (2), I start with a baseline OLS regression where the key outcome of in-

terest is the propensity to accept private health plans as the primary method of payment. In columns (3) and (4), I turn to a specification with the dependent variable as an indicator equaling to one if an SAT facility is inclined to accept any public insurance plans (i.e., Medicare, Medicaid, and other state-funded plans). In the last two columns, I focus on the case where the dependent variable is the likelihood of accepting cash or other self-payment. Another noteworthy feature is that in all even-numbered columns, I check the robustness of my results by directly excluding states with a Medicaid prior authorization law in place.

Based on the estimated coefficients in column (1) and column (2), one can tell that the enactment of prior authorization restrictions has imposed insignificant effects on the propensity to accept private plans for a SAT facility. In contrast, when moving to the results in columns (3) and (4), it suggests that restricting the use of PA in private plans has created some positive spillovers on the participation in the public insurance market: the presence of PA laws is associated with a significant increase in the propensity to participate in the public insurance market by 2.6 - 4.6 percentage points. Conceptually, this spillover across different insurance markets may result from changes in firms' financial incentives following the PA restriction. For example, if PA requirements impose substantial administrative costs on healthcare facilities, removing these administrative costs may relax firms' capacity constraints and incentivize firms to accept low-margin consumers. This channel is quite relevant in the context of SAT services, given that public insurance reimbursement rates are generally lower than private plans.

8.6 Local Market Structure of Specialty Healthcare Facilities

Last but not least, I compile some aggregate-level data to test if changes in the local market structure (i.e., competition) can partially explain specialty facilities' decisions.[34] A long literature in healthcare has demonstrated that increased competition pressure can alter the provision, quality, and costs of medical services (see, for example, Kessler and Geppert, 2005; Karlsson, 2007; Gaynor, Moreno-Serra and Propper, 2013). The key concern here is that structural factors mentioned above in this section can all contribute to substantial changes in the market structure of specialty behavioral health facilities, further altering individual facility's provision decisions.

[34] Admittedly, without a structural model to explicitly disentangle various mechanisms, I cannot rule out this competition story for sure.

The empirical exercise I took here is to test if the number of facilities offering any SAT per 100,000 population within a state change following the PA restriction.[35] To do so, I aggregate all facilities reporting to the N-SSATS per year to the state-year level and re-scale it by the state population. All regressions are weighted by state population. I present my results in Table 14. The dependent variable of interest is the number of facilities offering relevant SAT services per 100,000 state population per year across all columns. Column (1) focuses on all such specialty care facilities offering any SAT service. In column (2), the variable of interest is the number of facilities solely offering low-intensity ones; the estimates in column (3) capture the impacts on the number of facilities providing only high-intensity service. Eventually, in the last column, I restrict my attention to the number of facilities offering both high- and low-intensity SAT services. Panel A presents my estimates for imposing any PA restrictions and Panel B shows the estimates for both the PA restriction on general SAT services and the PA restriction on medication-assisted treatment.

Overall, I observe some interesting patterns from the data. First, there is no significant effect on the aggregate number of facilities available within a state (column (1)), suggesting the null impact on the local market structure of such specialty care associated with a PA restriction. Second, consistent with the facility-level analysis shown in section 7, the number of facilities offering only low-intensity SAT services significantly went up in response to the PA law change by 0.277 units per 100,000 population (column (2)), while the number of facilities offering high-intensity SAT services dropped by 0.159 units per 100,000 population (column (3)). These two findings thus reinforce the fact removing PA can induce a shift in the provision of facilities (from high-intensity to low-intensity).

From Figure (17) to Figure (20), I plot my estimates from an event-study specification for four types of facilities respectively: facilities offering any SAT service (Figure (17)), facilities offering only low-intensity SAT service (Figure (18)), facilities offering only high-intensity SAT service (Figure (19)), and facilities offering both low- and high-intensity services (Figure (20)). Among these estimates, I only find some significant results in Figure (18) and Figure (19): removing PA requirements largely scaled up the provision of share of facilities solely providing low-intensity SAT and the impact here is persistent.

[35] This idea is consistent with Knowles (2022).

9 Welfare Implications

To close the discussion, I finally investigate some welfare implications related to the PA law change. Motivated by the descriptive evidence from the American Medical Association (AMA),[36] I compile state-level mortality rates due to SUDs to estimate the impacts of restricting PA requirements on health outcomes.

To identify deaths related to substance use disorders, I check the CDC Wide-ranging ONline Data for Epidemiologic Research (WONDER) system and exploit the ICD-10 code. In particular, I first define suicides due to all substance use disorders as follows: deaths caused by mental and behavioral disorders due to psychoactive substance use (ICD-10 F10-F19) and suicide (U03, terrorism intentional suicide; X60-X84, intentional self-harm; Y87, sequelae of intentional self-harm, assault, and events of undetermined intent).[37] I also construct the state-level mortality rate caused by drug and alcohol reasons.[38]

The estimates are presented in Table 15. In the first two columns, the dependent variable is the suicide rate due to SUDs per state year. In the last four columns, I focus on alcohol-induced deaths. The outcome of interest is the number of all deaths linked to alcohol-related issues per 100,000 population in column (3) and column (4); the dependent variable of interest is the number of deaths due to alcohol issues within medical facilities per 100,000 population in column (5) and column (6). Based on the results shown in Table 15, we can see that restricting the use of PA in commercial plans on the general SAT service leads to a significant decline in suicides due to SUDs (by 0.122 cases per 100,000 population), all alcohol-induced deaths (by 0.911 cases per 100,000 population), and alcohol-induced deaths within medical facilities (by 0.437 cases per 100,000 population).

An event-study specification as follows is estimated:

$$y_{st} = \alpha + \sum_{i=-5}^{4} \beta_{t+i} ServiceRestriction_s \times year_{t+i} + X_{st}^{'}\gamma + \rho_s + \eta_t + \varepsilon_{ist} \tag{10}$$

[36] See https://www.ama-assn.org/practice-management/prior-authorization/1-3-doctors-has-seen-prior-auth-lead-serious-adverse-event, last accessed July 10, 2024.

[37] Due to privacy protection, statistics from some states are suppressed. I show the availability of the suicide data in Figure 4.

[38] See for example, https://wonder.cdc.gov/mcd.html, last accessed July 10, 2024.

where $ServiceRestriction_{st}$ is an indicator for whether a state has ever had a PA restriction on general SAT services. The corresponding point estimates from the event-study specification are plotted in Figure 21, Figure 22, and Figure 23. Interestingly, the post-treatment estimates are statistically significant three years after the law change, suggesting the health improvement might take a while to be in effect.

10 Concluding Remarks and Future Work

This paper finds that restricting the use of prior authorization (PA), a widely used administrative practice in health plans, can significantly influence the provision of behavioral healthcare services. In response to a restriction on PA in commercial plans targeting substance abuse treatment (SAT) can increase the provision of low-intensity services (i.e., regular outpatient services) while decreasing the provision of high-intensity services (i.e., intensive outpatient service, partial hospital service, hospital inpatient service, and residential inpatient service).

I further corroborate evidence for two potential channels: First, the removal of PA largely expanded facilities' treatment capacity (i.e., time and labor available to patients), thereby increasing the provision of low-intensity medical services on time. Second, restricting the use of this administrative hassle also alters providers' (financial) incentives in prescribing, diagnosis, and treatment. In the meantime, my empirical results suggest the shift from high-intensity service to low-intensity one cannot be primarily attributed to noticeable changes in the private insurance market *per se*, *ex-post* moral hazard problems among existing patients, facilities' contracting with private insurers, and the changing market structure.

Going forward, I aim to compile more restricted data and empirically test other potential channels. Among many others, I am investigating potential explanations for the decline in providing high-intensity SAT service.

Mechanical Shift of Patients: Besides the tentative evidence mentioned in section 8.1.2, I also expect to assemble individual-level medical transfer records from SAMHSA (i.e., whether a patient is transferred from low-intensity (high-intensity) settings to high-intensity (low-intensity) settings). To my knowledge, the restricted N-SSATS includes such information and I plan to submit a FOIA

request to obtain the data.

Medical Resource Reallocation within Facilities: There are two potential ways to test this channel. First, I will look into the NSSRN data (2008, 2018, and 2022) to examine whether PA restrictions influence the work hours of registered nurses within behavioral healthcare facilities. Second, I will check with the SAMHSA if there is any information on the behavioral healthcare workforce within such facilities.

Facilities' Dynamics: As mentioned in section 8.1, I am discussing with staff from the SAMHSA regarding the availability of facility identifiers from 2015 and onwards. With the additional ID, I will be able to construct facility-level panel and track a facility's history in providing medical service over time. This way, I can tell apart the *medical resource realocation* channel and the *facilities' dynamics* channel.

References

Alexander, Diane. 2020. "How Do Doctors Respond to Incentives? Unintended Consequences of Paying Doctors to Reduce Costs." *Journal of Political Economy*, 128(11): 4046–4096.

Allen, Bennett, Michelle L. Nolan, and Denise Paone. 2019. "Article Commentary: Underutilization of Medications to Treat Opioid use Disorder: What Role does Stigma Play?" *Substance Abuse*, 40(4): 459–465. PMID: 31550201.

Anderson, D. Mark. 2010. "Does information matter? The effect of the Meth Project on meth use among youths." *Journal of Health Economics*, 29(5): 732–742.

Andrews, Christina, Amanda Abraham, Colleen M. Grogan, Harold A. Pollack, Clifford Bersamira, Keith Humphreys, and Peter Friedmann. 2015. "Despite Resources From The ACA, Most States Do Little To Help Addiction Treatment Programs Implement Health Care Reform." *Health Affairs*, 34(5): 828–835. PMID: 25941285.

Arrow, Kenneth J. 1978. "Uncertainty and the Welfare Economics of Medical Care." In *Uncertainty in Economics*. 345–375. Elsevier.

Barbara Andraka-Christou, Olivia Golan, Rachel Totaram Maggie Ohama Brendan Saloner Adam J. Gordon, and Bradley D. Stein. 2023. "Prior authorization restrictions on medications for opioid use disorder: trends in state laws from 2005 to 2019." *Annals of Medicine*, 55(1): 514–520. PMID: 36724766.

Brot-Goldberg, Zarek C, Samantha Burn, Timothy Layton, and Boris Vabson. 2023. "Rationing Medicine Through Bureaucracy: Authorization Restrictions in Medicare." National Bureau of Economic Research Working Paper 30878.

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021. "Difference-in-Differences with multiple time periods." *Journal of Econometrics*, 225(2): 200–230. Themed Issue: Treatment Effect 1.

Carpenter, Christopher. 2007. "Heavy Alcohol Use and Crime: Evidence from Underage Drunk-Driving Laws." *The Journal of Law and Economics*, 50(3): 539–557.

Carr, Carey J.A., Jiangmin Xu, Cristina Redko, D. Timothy Lane, Richard C. Rapp, John Goris, and Robert G. Carlson. 2008. "Individual and system influences on waiting time for substance abuse treatment." *Journal of Substance Abuse Treatment*, 34(2): 192–201.

Chernew, Michael, and Harrison Mintz. 2021. "Administrative Expenses in the US Health Care System: Why So High?" *JAMA*, 326(17): 1679–1680.

Clemens, Jeffrey, and Joshua D Gottlieb. 2014. "Do physicians' financial incentives affect medical treatment and patient health?" *American Economic Review*, 104(4): 1320–1349.

Currie, Janet, Jeffrey Grogger, Gary Burtless, and Robert F. Schoeni. 2001. "Explaining Recent Declines in Food Stamp Program Participation [with Comments]." *Brookings-Wharton Papers on Urban Affairs*, 203–244.

Currie, Janet, Wanchuan Lin, and Juanjuan Meng. 2014. "Addressing antibiotic abuse in China: An experimental audit study." *Journal of Development Economics*, 110: 39–51. Land and Property Rights.

Cutler, David M. 2020. "Reducing administrative costs in US health care." *The Hamilton Project Policy Proposal*, 9: 3–25.

Dafny, Leemore S. 2005. "How Do Hospitals Respond to Price Changes?" *American Economic Review*, 95(5): 1525–1547.

Dave, Dhaval, and Swati Mukerjee. 2011. "Mental health parity legislation, cost-sharing and substance-abuse treatment admissions." *Health Economics*, 20(2): 161–183.

Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy*, 11(4): 213–48.

Dunn, Abe, Joshua D. Gottlieb, Adam Hale Shapiro, Daniel J. Sonnenstuhl, and Pietro Tebaldi. 2021. "A Denial a Day Keeps the Doctor Away." University of Chicago, mimeo. Available online at https://users.nber.org/~jdgottl/BillingCostsPaper.pdf.

Dunn, Abe, Joshua D. Gottlieb, Adam Hale Shapiro, Daniel J. Sonnenstuhl, and Pietro Tebaldi. forthcoming. "A Denial a Day Keeps the Doctor Away." *Quarterly Journal of Economics*.

Finkelstein, Amy, and Matthew J Notowidigdo. 2019. "Take-Up and Targeting: Experimental Evidence from SNAP*." *The Quarterly Journal of Economics*, 134(3): 1505–1556.

Gaynor, Martin, Rodrigo Moreno-Serra, and Carol Propper. 2013. "Death by Market Power: Reform, Competition, and Patient Outcomes in the National Health Service." *American Economic Journal: Economic Policy*, 5(4): 134–166.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277. Themed Issue: Treatment Effect 1.

Gruber, Jonathan, and Maria Owings. 1996. "Physician Financial Incentives and Cesarean Section Delivery." *The RAND Journal of Economics*, 27(1): 99–123.

Hamersma, Sarah, and Johanna Catherine Maclean. 2021. "Do expansions in adolescent access to public insurance affect the decisions of substance use disorder treatment providers?" *Journal of Health Economics*, 76: 102434.

Harris, Matthew C., Yinan Liu, and Ian McCarthy. 2020. "Capacity constraints and time allocation in public health clinics." *Health Economics*, 29(3): 324–336.

Ho, Kate, and Robin S. Lee. 2017. "Insurer Competition in Health Care Markets." *Econometrica*, 85(2): 379–417.

Johnson, Matthew S, Kurt J Lavetti, and Michael Lipsitz. 2023. "The Labor Market Effects of Legal Restrictions on Worker Mobility." National Bureau of Economic Research Working Paper 31929.

Jones, Christopher M., Melinda Campopiano, Grant Baldwin, and Elinore McCance-Katz.

2015. “National and State Treatment Need and Capacity for Opioid Agonist Medication-Assisted Treatment.” *American Journal of Public Health*, 105(8): e55–e63. PMID: 26066931.

Karlsson, Martin. 2007. “Quality Incentives for GPs in a Regulated Market.” *Journal of Health Economics*, 26(4): 699–720.

Kessler, Daniel P, and Jeffrey J Geppert. 2005. “The Effects of Competition on Variation in the Quality and Cost of Medical Care.” *Journal of Economics & Management Strategy*, 14(3): 575–589.

Knowles, Matthew T. 2022. “How access to addictive drugs affects the supply of substance abuse treatment: Evidence from Medicare Part D.” *Health Economics*, 31(8): 1649–1675.

Krawczyk, Noa, Caroline E. Picher, Kenneth A. Feder, and Brendan Saloner. 2017. “Only One In Twenty Justice-Referred Adults In Specialty Treatment For Opioid Use Receive Methadone Or Buprenorphine.” *Health Affairs*, 36(12): 2046–2053. PMID: 29200340.

Markowitz, Sara, and Michael Grossman. 2000. “The effects of beer taxes on physical child abuse.” *Journal of Health Economics*, 19(2): 271–282.

Nguyen, Thuy D, Kao-Ping Chua, Barbara Andraka-Christou, W David Bradford, and Kosali Simon. 2022. “Trends in buprenorphine coverage and prior authorization requirements in US commercial formularies, 2017-2021.” Vol. 3, e221821–e221821, American Medical Association.

Pacula, Rosalie L., David Powell, Paul Heaton, and Eric L. Sevigny. 2015. “Assessing the Effects of Medical Marijuana Laws on Marijuana Use: The Devil is in the Details.” *Journal of Policy Analysis and Management*, 34(1): 7–31.

Popovici, Ioana, Johanna Catherine Maclean, and Michael T French. 2017. “Health Insurance and Traffic Fatalities: The Effects of Substance Use Disorder Parity Laws.” National Bureau of Economic Research Working Paper 23388.

Powell, David, Rosalie Liccardo Pacula, and Mireille Jacobson. 2018. “Do medical marijuana laws reduce addictions and deaths related to pain killers?” *Journal of Health Economics*, 58: 29–42.

Sun, Liyang, and Sarah Abraham. 2021. “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.” *Journal of Econometrics*, 225(2): 175–199. Themed Issue: Treatment Effect 1.

Turner, Ani, George Miller, and Samantha Clark. 2019. “Impacts of Prior Authorization on Health Care Costs and Quality.” *Center for Value in Health Care*.

Weber, E. 2020. “Spotlight on legislation limiting the use of prior authorization for substance use disorder services and medications.” *Legal Action Center. May*.

Wooldridge, Jeffrey M. 2023. “Simple approaches to nonlinear difference-in-differences with panel data.” *The Econometrics Journal*, 26(3): C31–C66.

Figures and Tables

Table 1. Limits on Prior Authorization in SAT

State	Effective Date	SUD Services	SUD Medication
Arizona	4/26/2018	A health care services plan must allow at least one modality of medication-assisted treatment to be available without prior authorization.*(ARIZ. REV. STAT. §20-3402(B))*	A health care services plan must allow at least one modality of medication-assisted treatment to be available without prior authorization. *(ARIZ. REV. STAT. §20-3402(B))*
Arkansas	4/12/2019		Except in the case of injectables, a healthcare insurer, including Medicaid, shall not require prior authorization in order for a patient to obtain coverage of buprenorphine, naloxone, naltrexone, methadone, and their various formulations and combinations approved by the United States Food and Drug Administration for the treatment of opioid addiction. *(ARK. CODE ANN. §23-99-1119)*
Colorado	5/16/2019		A health benefit plan subject to this subsection must provide coverage without prior authorization for a five-day supply of at least one of the FDA-approved drugs for the treatment of opioid dependence
Delaware	5/29/2017	Carriers may not impose prior authorization for the diagnosis and treatment of drug and alcohol dependencies, including inpatient treatment. (*DEL. CODE ANN. tit. 18, §§3343*)	
Illinois	1/1/2019	Prior authorization shall not be utilized for the benefits under this subsection. The substance use disorder treatment provider or facility shall notify the insurer of the initiation of treatment. *(IL ST CH 215 § 5/370c)*	
Maine	6/13/2019	A carrier may not require prior authorization for medication-assisted treatment for opioid use disorder for the prescription of at least one drug for each therapeutic class of medication used in medication-assisted treatment, except that a carrier may not impose any prior authorization requirements on a pregnant woman for medication-assisted treatment for opioid use disorder. *(PL 2019, c. 273, §2)*	A carrier may not require prior authorization for medication-assisted treatment for opioid use disorder for the prescription of at least one drug for each therapeutic class of medication used in medication-assisted treatment, except that a carrier may not impose any prior authorization requirements on a pregnant woman for medication-assisted treatment for opioid use disorder. *(PL 2019, c. 273, §2)*
Maryland	5/25/2017		An entity subject to this section may not apply a prior authorization requirement for a prescription drug: (1) when used for treatment of an opioid use disorder; and (2) that contains methadone, buprenorphine, or naltrexone.

Table 1. Limits on Prior Authorization in SAT

State	Effective Date	SUD Services	SUD Medication
Massachusetts	7/1/2016	Insurers (including state employee health plans) may not impose prior authorization or utilization review for up to 7 days on acute treatment services and clinical stabilization services. *(MASS. GEN. LAWS ch. 32A § 17N)*	
Missouri	8/28/2019		Health plans must cover buprenorphine tablets, methadone, naloxone, extended-release injectable naltrexone and buprenorphine/naloxone combination (and these dispensed when through an opioid treatment program), without prior authorization.
Montana	1/1/2020		A health insurance issuer may not impose prior authorization or step therapy requirements for an oral therapy prescription used to treat opioid use disorder. *(MONT. CODE ANN. § 33-32-215)*
New Hampshire	1/1/2017	When SUD services are covered, managed care plans may not require prior authorization for the first two outpatient visits in an episode of care for SUD. Prior authorization cannot be required for the first 24 hours of inpatient withdrawal management and clinical stabilization services.	
New Jersey	5/16/2017	Insurers may not require prior authorization for inpatient and outpatient SUD services for the first 180 days or visits of treatment during a year. Carriers are required to provide 28 days of inpatient treatment without retrospective or concurrent review and 28 days of intensive outpatient and partial hospitalization without any retrospective review.	Insurers may not require prior authorization for outpatient medications used to treat SUD.
New York*	6/22/2016 and 4/12/4018	authorization for inpatient treatment in in-network state-certified facilities and may not conduct concurrent review for the first 28 days of treatment. Insurers may not impose prior authorization on outpatient, intensive outpatient, outpatient rehabilitation, and opioid treatment in in-network state-certified facilities and may not conduct concurrent review for the first four weeks/28 visits.	

Table 1. Limits on Prior Authorization in SAT

State	Effective Date	SUD Services	SUD Medication
Oregon	10/6/2017		In reimbursing the cost of medication prescribed for the purpose of treating opioid or opiate withdrawal, an insurer offering a health benefit plan as defined in ORS 743B.005 may not require prior authorization of payment during the first 30 days of treatment. *(OR. REV. STAT. § 743B.425)*
Vermont	1/1/2020	A health insurance plan shall not require prior authorization for all counseling and behavioral therapies associated with medication-assisted treatment for a patient who is receiving medication-assisted treatment. *(VT. STAT. ANN. tit. 18, § 4754)*	A health insurance plan shall not require prior authorization for prescription drugs for a patient who is receiving medication-assisted treatment if the dosage prescribed is within the U.S. Food and Drug Administration's dosing recommendations. *(VT. STAT. ANN. tit. 18, § 4754)*
Virginia	3/21/2019		Require that no prior authorization be required for at least one drug prescribed for substance abuse medication-assisted treatment, provided that (i) the drug is a covered benefit, (ii) the prescription does not exceed the FDA-labeled dosages, and (iii) the drug is prescribed consistent with the regulations of the Board of Medicine
Washington	7/28/2019		For health plans issued or renewed on or after January 1, 2020, a health carrier shall provide coverage without prior authorization of at least one federal food and drug administration approved product for the treatment of opioid use disorder in the drug classes opioid agonists, opioid antagonists, and opioid partial agonists. *(WASH. REV. CODE ANN. § 48.43.760)*
West Virginia*	3/27/2018		The benefits for outpatient prescription drugs to treat substance use disorder shall be provided when determined medically necessary by the covered person's physician or psychiatrist without the imposition of any prior authorization or other prospective utilization management requirements. *(W. Va. Code, § 33-16-3cc)*

Note: Data are collected from Westlaw and the Legal Action Center (accessible at https://www.lac.org/resource/spotlight-on-legislation-limiting-the-use-of-prior-authorization-for-substance-use-disorder-services-and-medications). Particularly, New York and West Virginia enacted separated laws regarding outpatient and inpatient treatments.

Table 2. Effects of PA Limits on the Provision of SAT Services

	low vs. high		both vs. low		both vs. high	
PA restriction$_{st}$	0.088***	0.079***	-0.042***	-0.023	0.043**	0.054**
	(0.029)	(0.024)	(0.015)	(0.014)	(0.019)	(0.023)
state FE	✓	✓	✓	✓	✓	✓
other state SUD policies		✓		✓		✓
accepting private plans		✓		✓		✓
mean (pre-treatment)	0.638	0.670	0.597	0.650	0.723	0.790
# of obs.	59,720	37,508	107,070	77,156	86,070	62,345

Standard errors in parentheses

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

Notes: The dependent variables are the probability of only offering any low-intensity (i.e., outpatient) services relative to only offering any high-intensity (i.e., intensive outpatient, partial hospital, residential inpatient, and hospital-based inpatient) in columns (1) and (2), and the probability of offering both low- and high-intensity services relative to only providing low-intensity ones in column (3) and column (4). In column (5) and column (6), the dependent variable is the probability of offering both types of services relative to offering only high-intensity ones. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 3. Effects of PA Limits on the Provision of SAT Service

	low vs. high		both vs. low		both vs. high	
PA service restriction$_{st}$	0.084***	0.067***	-0.040**	-0.022	0.035**	0.045**
	(0.028)	(0.024)	(0.019)	(0.018)	(0.017)	(0.020)
PA medication restriction$_{st}$	0.029	0.044*	-0.007	0.003	0.025	0.038**
	(0.030)	(0.024)	(0.022)	(0.019)	(0.017)	(0.019)
Medicaid PA restriction$_{st}$	0.148***	0.249***	-0.050	-0.234***	0.066*	0.035
	(0.054)	(0.054)	(0.053)	(0.071)	(0.038)	(0.054)
state FE	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓
other state SUD policies		✓		✓		✓
accepting private plans		✓		✓		✓
mean (pre-treatment)	0.638	0.670	0.597	0.650	0.723	0.790
# of obs.	59,720	37,508	107,070	77,156	86,070	62,345

Standard errors in parentheses

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

Notes: The dependent variables are the probability of only offering any low-intensity (i.e., outpatient) services relative to only offering any high-intensity (i.e., intensive outpatient, partial hospital, residential inpatient, and hospital-based inpatient) in columns (1) and (2), and the probability of offering both low- and high-intensity services relative to only providing low-intensity ones in column (3) and column (4). In column (5) and column (6), the dependent variable is the probability of offering both types of services relative to offering only high-intensity ones. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 4. Effects of PA Limits on the Provision of SAT Services
(Callaway and Sant'Anna (2021))

	low vs. high		**both vs. low**		**both vs. high**	
PA restriction$_{st}$	0.044***	0.043***	-0.023**	-0.012	0.015	0.021*
	(0.012)	(0.015)	(0.010)	(0.011)	(0.010)	(0.011)
state FE	✓	✓	✓	✓	✓	✓
accepting private plans		✓		✓		✓
mean (pre-treatment)	0.638	0.670	0.597	0.650	0.723	0.790
# of obs.	59,720	37,508	107,070	77,156	86,070	62,345

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are the probability of only offering any low-intensity (i.e., outpatient) services relative to only offering any high-intensity (i.e., intensive outpatient, partial hospital, residential inpatient, and hospital-based inpatient) in columns (1) and (2), and the probability of offering both low- and high-intensity services relative to only providing low-intensity ones in column (3) and column (4). In column (5) and column (6), the dependent variable is the probability of offering both types of services relative to offering only high-intensity ones. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 4. Effects of PA Limits on the Provision of Early Interventions

	Brief Intervention	Screening	Comp Assessment	Outreach
PA limit$_{st}$	0.633**	0.653*	0.698*	0.528*
	(0.274)	(0.370)	(0.351)	(0.291)
state FE	✓	✓	✓	✓
year×division FE	✓	✓	✓	✓
state controls	✓	✓	✓	✓
Mean (pre-treatment)	4.871	5.718	5.598	3.644
N	441	294	294	294

Standard errors in parentheses

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

Notes: The dependent variables are the number of facilities offering brief intervention, screening for SUD, comprehensive assessment and diagnosis, and outreach services through column (1) to column (4). Data are obtained from the 2012-2020 Annual Reports for N-SSATS in column (1) and assembled from the 2015-2020 Annual Reports for N-SSATS in column (2)-column (4). State controls include ACA Medicaid Expansion, SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 5. Do Social and Economic Factors Predict the Enactment of PA Restrictions?

	Any PA Restriction	Service Restriction	Medication Restriction
log(population)	-2.993*	-2.914*	-0.168
	(1.730)	(1.627)	(1.644)
parity laws	-0.011	-0.017	-0.000
	(0.010)	(0.010)	(0.009)
log(# of SNAP recipients)	-0.060	-0.088	-0.215
	(0.275)	(0.245)	(0.202)
log(# of TANF recipients)	0.095	0.063	0.001
	(0.082)	(0.079)	(0.075)
log(state GDP)	0.921	0.458	0.162
	(0.667)	(0.537)	(0.583)
state unemployment rate	0.013	0.002	0.001
	(0.031)	(0.023)	(0.025)
state minimum wage	0.129***	0.073*	0.118***
	(0.039)	(0.037)	(0.039)
annual SUD deaths	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Observations	459	459	459

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the probability of enacting any PA restriction in state s and year t in column (1), the probability of enacting PA restrictions on general SAT services in column (2), and the probability of enacting PA restrictions on medication-assisted treatment (MAT) in column (3). State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level. Regressions are weighted by state population.

Table 6. Effects of PA Limits on Medical Delay (Due to Facilities' Capacity Issues)

	low-intensity			**high-intensity**		
	any delay	*normal delay*	*severe delay*	*any delay*	*normal delay*	*severe delay*
PA restriction$_{st}$	-0.100**	-0.044***	-0.018*	-0.021	-0.000	0.004
	(0.044)	(0.014)	(0.009)	(0.039)	(0.013)	(0.009)
state FE	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓
# of observations	2,487,244	2,487,244	2,487,244	3,227,149	3,227,149	3,227,149

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: In column (1), column (2), and column (3), the sample includes all patients admitted to a low-intensity (i.e., regular outpatient) setting. In column (4), column (5), and column (6), the sample includes all patients admitted to a high-intensity (i.e., intensive outpatient, partial hospital, residential inpatient, and hospital-based inpatient) setting. The dependent variables are the probability of experiencing any medical delay (any days prior to the treatment), normal medical delay (at least seven days prior to the treatment), and severe medical delay (at least two weeks prior to the treatment). Data are obtained from the 2012-2020 TEDS-A. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 7. Effects of PA Limits on the Number of Admissions to SAT Facilities

	any SAT services		low-intensity SAT		high-intensity SAT	
PA restriction$_{st}$	140.00	-	139.11	-	0.89	-
	(149.08)	-	(130.85)	-	(33.14)	-
PA service restriction$_{st}$	-	171.47	-	131.97	-	39.51
	-	(164.97)	-	(147.92)	-	(35.03)
PA medication restriction$_{st}$	-	244.24	-	251.41	-	-7.17
	-	(213.21)	-	(182.76)		(55.41)
state FE	✓	✓	✓	✓	✓	✓
year	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓
# of observations	459	459	459	459	459	459

Standard errors in parentheses

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

Notes: The dependent variables are the number of initial admissions to any SAT setting per 100,000 population in columns (1) and (2) and the number of initial admissions to a low-intensity setting per 100,000 population in column (3) and column (4). In column (5) and column (6), the dependent variable is the number of new admissions to a high-intensity setting. Data are obtained from the 2012-2020 TEDS-A. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level. Regressions are weighted by the state population.

Table 8. Effects of PA Limits on the Number of Discharges to SAT Facilities

	any SAT services		**low-intensity SAT**		**high-intensity SAT**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
PA restriction$_{st}$	79.12	-	82.03	-	-2.86	-
	(129.26)	-	(121.55)	-	(21.13)	-
PA service restriction$_{st}$	-	199.78	-	143.18	-	56.71**
	-	(173.03)	-	(157.03)	-	(25.71)
PA medication restriction$_{st}$	-	140.06	-	171.32	-	-31.38
	-	(187.03)	-	(173.74)		(29.57)
state FE	✓	✓	✓	✓	✓	✓
year	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓
# of observations	459	459	459	459	459	459

Standard errors in parentheses

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

Notes: The dependent variables are the number of initial discharges to any SAT setting per 100,000 population in columns (1) and (2) and the number of discharges to a low-intensity setting per 100,000 population in column (3) and column (4). In column (5) and column (6), the dependent variable is the number of discharges a high-intensity setting. Data are obtained from the 2012-2020 TEDS-A. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level. Regressions are weighted by the state population.

Table 9. Effects of PA Limits on the Composition of Patients

	male	black	high school	drug and alch	prior arrests	private ins	public ins	self-paid
Panel A. Admissions								
PA limit$_{st}$	0.001	-0.081	-0.005	-0.005	-0.004	-0.009	0.043	-0.035
	(0.006)	(0.004)	(0.009)	(0.016)	(0.006)	(0.011)	(0.031)	(0.029)
state FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓	✓	✓
N	10,432,043	10,432,043	10,581,019	11,558,253	10,090,998	5,166,925	5,166,925	5,166,925
Panel B. Discharges								
PA limit$_{st}$	0.005	-0.002	-0.000	-0.006	-0.005	0.006	-0.010	-0.007
	(0.007)	(0.007)	(0.009)	(0.013)	(0.005)	(0.010)	(0.020)	(0.012)
state FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓	✓	✓
N	10,015,460	9,782,326	9,315,549	10,018,717	8,461,177	3,397,226	3,397,226	3,397,226

Standard errors in parentheses

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

Notes: The dependent variables are the indicator for being male, black, with at least a high-school diploma, with issues in both alchol and drugs, with a history of prior arrests within 30 days, with coverage from a private plan/public plan/no plan through column (1) to column (8), respectively. Data are obtained from the 2012-2020 TEDS-A/D. State controls include ACA Medicaid Expansion, SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 10. Effects of PA Limits on Voluntary Dropout

	dependent variable: prob(voluntarily dropout)					
	All Discharges		*Low-Intensity*		*High-Intensity*	
Panel A. Any Restriction						
PA restriction$_{st}$	-0.022**	0.012	-0.014	0.031	-0.024**	0.014
	(0.010)	(0.016)	(0.016)	(0.024)	(0.011)	(0.012)
Panel B. Policy Heterogeneity						
PA service restriction$_{st}$	-0.035*	0.012	-0.031	0.017	-0.028	0.017
	(0.020)	(0.025)	(0.025)	(0.028)	(0.021)	(0.020)
PA medication restriction$_{st}$	0.006	-0.015	0.014	-0.003	-0.003	-0.009
	(0.023)	(0.023)	(0.029)	(0.022)	(0.024)	(0.017)
state FE	✓	✓	✓	✓	✓	✓
year	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓
sample	all	private	all	private	all	private
# of observations	8,088,908	364,827	3,156,893	117,905	4,931,275	246,889

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are the probability of voluntarily dropping out of a program (vs. completing a program). In column (1) and column (2), the sample includes all discharges of a specialty care facility. In column (3) and column (4), the sample includes all patients who initially receive low-intensity SAT services. In column (5) and column (6), the sample includes all patients who initially receive high-intensity SAT services. In odd-numbered columns, the sample includes all patients regardless of their method of payment. In even-numbered columns, the sample includes patients with private plans as the primary method of payment. Data are obtained from the 2012-2020 TEDS-D. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 11. Effects of PA Restrictions on Low-Intensity Regular SAT vs. MAT

	Regular SAT		Medication SAT	
PA restriction$_{st}$	0.035***	0.036***	0.056*	0.070**
	(0.012)	(0.012)	(0.032)	(0.035)
state FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
state controls	✓	✓	✓	✓
facilities accepting commercial plans		✓		✓
# of observations	106,513	73,825	53,930	39,121

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are the probability of offering regular low-intensity SAT service in column (1) and column (2) and are the probability of offering medication-assisted, low-intensity SAT services in column (3) and column (4). In odd-numbered columns, the sample includes all specialty care facilities. In even-numbered columns, the sample includes specialty care facilities accepting private plans. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 12. Effects of PA Limits on Outpatient Medication-Assisted Treatment (MAT)

	initial admission		voluntary dropout	
	(1)	**(2)**	**(3)**	**(4)**
PA restriction$_{st}$	0.005	-0.025**	0.005	0.088***
	(0.013)	(0.011)	(0.017)	(0.032)
state FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
state controls	✓	✓	✓	✓
paid by commercial plans		✓		✓
# of observations	7,839,817	323,450	630,002	12,629

Standard errors in parentheses

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

Notes: The dependent variables are the probability of getting admitted to an outpatient MAT program instead of other settings in column (1) and column (2) and the probability of voluntarily dropping out of a MAT program (vs. completing a MAT program) in column (3) and column (4). In odd-numbered columns, the sample includes all discharges regardless of the method of payment. In even-numbered columns, the sample includes discharges paid by commercial plans. Data are obtained from the 2012-2020 TEDS-D. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 13. Effects of PA Restrictions on the Participation in Insurance Market

	private plans	**Medicaid**	**Medicare**	**self-payment**
PA restrictions$_{st}$	-0.010	0.004	0.021*	0.003
	(0.014)	(0.014)	(0.011)	(0.006)
state FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
state controls	✓	✓	✓	✓
# of observations	114,382	114,212	113,561	115,029

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are the probability of accepting commercial plans, Medicaid payments, Medicare payments, and any cash or self-payments. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT parity laws, pain clinic regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and the effective state-level minimum wage. All standard errors are clustered at the state level.

Table 14. Effects of PA Restrictions on Local Market Structure

	DP: # of facilities per 100,000 pop			
	all facilities	*only low*	*only high*	*both types*
Panel A. any restrictions				
PA restrictions$_{st}$	0.184	0.277***	-0.159*	0.066
	(0.166)	(0.095)	(0.087)	(0.107)
Panel B. policy heterogeneity				
PA service restrictions$_{st}$	0.193	0.281**	-0.140*	0.052
	(0.211)	(0.130)	(0.078)	(0.111)
PA medication restrictions$_{st}$	-0.010	0.069	-0.096	0.016
	(0.259)	(0.154)	(0.098)	(0.179)
state FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
state controls	✓	✓	✓	✓
# of observations	459	459	459	459

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the number of all specialty care facilities per 100,000 population in column (1), the number of specialty care facilities only offering low-intensity SAT services per 100,000 population in column (2), the number of specialty care facilities only offering high-intensity SAT services per 100,000 population in column (3), and the number of specialty care facilities offering both high- and low-intensity SAT services per 100,000 population in column (4). In column (3) to column (6), all dependent variables are conditional on accepting private health insurance. In Panel A, the key independent variable is a dummy variable for whether there is a PA restriction in state s and year t. In Panel B, I take into account the policy heterogeneity. Data are obtained from the 2012-2020 N-SSATS. State controls include SAT Parity, Pain Clinic Regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and effective state minimum wage. All standard errors are clustered at the state level. Regressions are weighted by the state population.

Table 15. Effects of PA Restrictions on Mortality Rate Related to SUDs

	SUD suicide		*all alcohol-induced*		*alcohol-induced (medical facilities)*	
PA Restriction$_{st}$	0.019	-	-0.112	-	-0.098	-
	(0.069)	-	(0.407)	-	(0.167)	-
Service Restriction$_{st}$	-	-0.122*	-	-0.911**	-	-0.437**
	-	(0.061)	-	(0.422)	-	(0.181)
Medication Restriction$_{st}$	-	0.144	-	0.641	-	0.218
	-	(0.095)	-	(0.549)	-	(0.237)
state FE	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓
state controls	✓	✓	✓	✓	✓	✓
# of observations	279	279	459	459	459	459

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the number of deaths due to SUD-induced suicide per 100,000 population in column (1) and column (2), the number of deaths induced by alcohol use issues per 100,000 population in column (3) and column (4), and the number of deaths induced by alcohol use issues within medical facilities per 100,000 population in column (5) and column (6). In odd-numbered columns, the key independent variable is a dummy variable for whether there is a PA restriction in state s and year t. In even-numbered columns, I take into account the policy heterogeneity. Data are obtained from the 2012-2020 CDC WONDER system. State controls include SAT Parity, Pain Clinic Regulation, PDMP mandates, state unemployment rates, natural log of the population, natural log of the state GDP, and effective state minimum wage. All standard errors are clustered at the state level. Regressions are weighted by the state population.

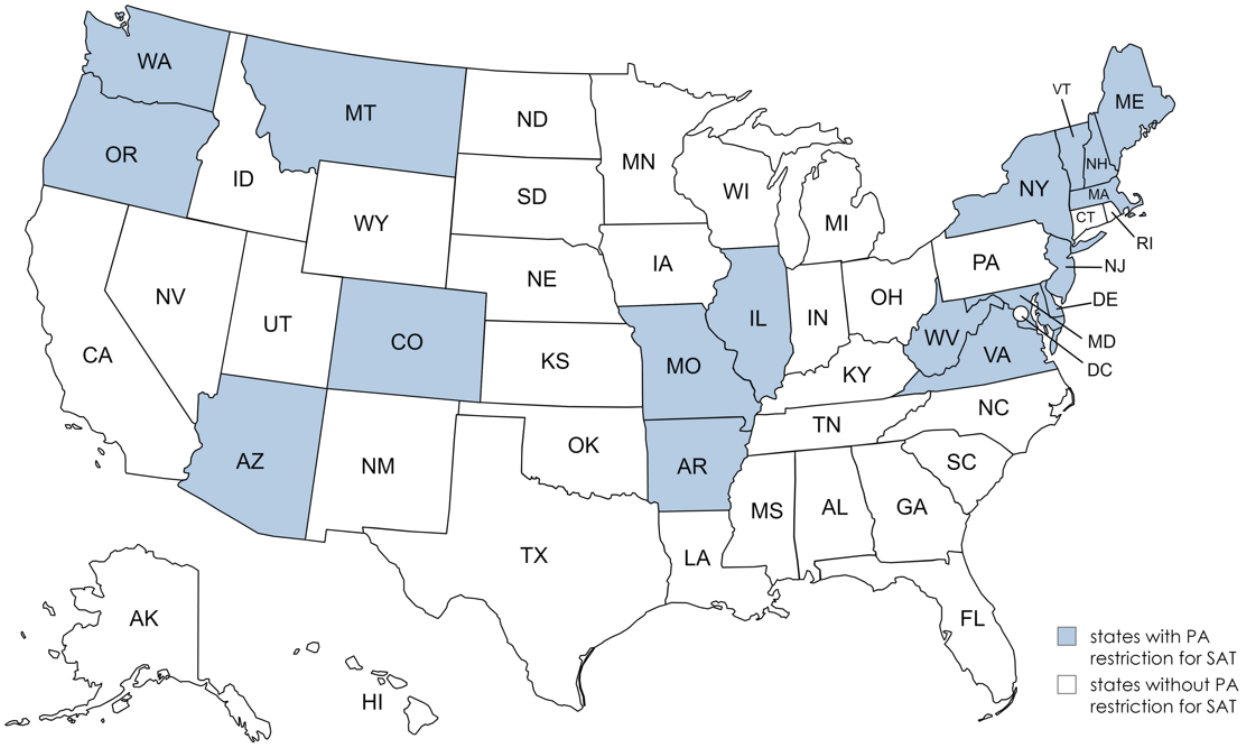


Figure 1: Distribution of State PA Restrictions on SAT in Commercial Plans

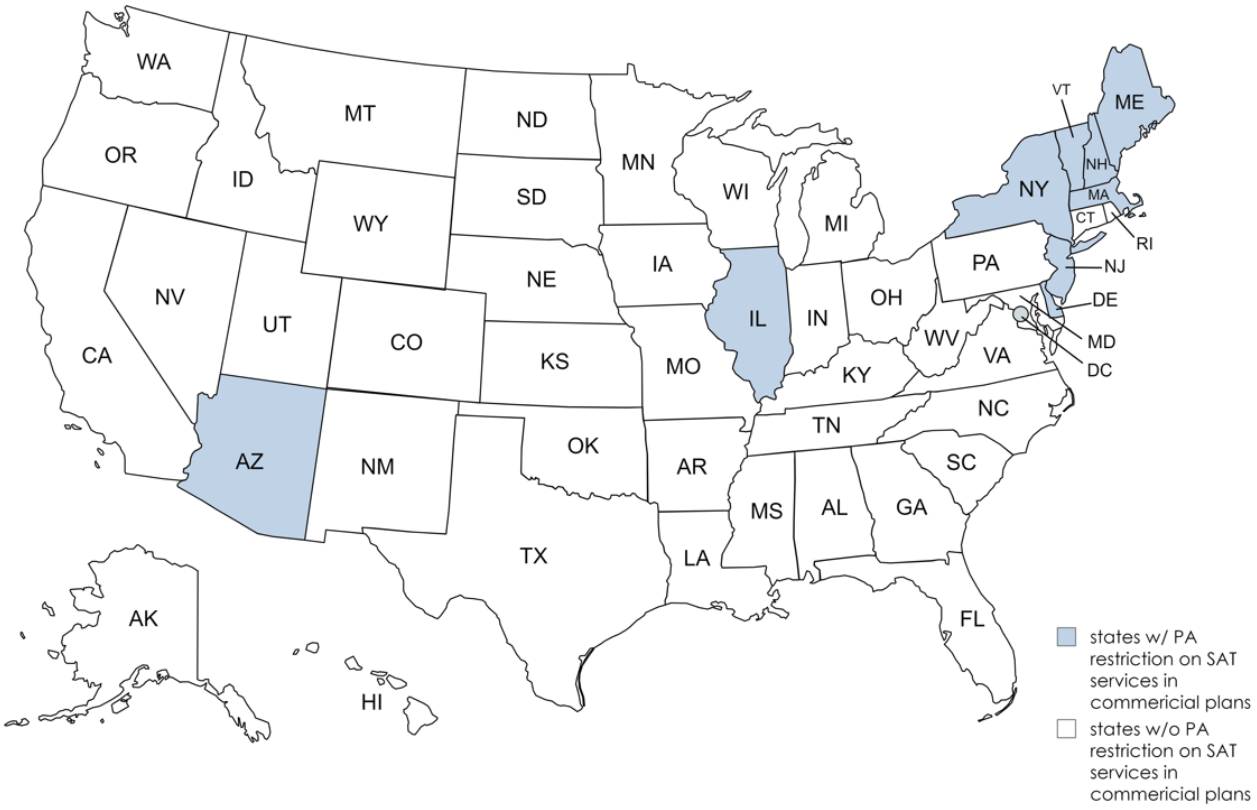


Figure 2: Distribution of State PA Restrictions on General SAT Service in Commercial Plans

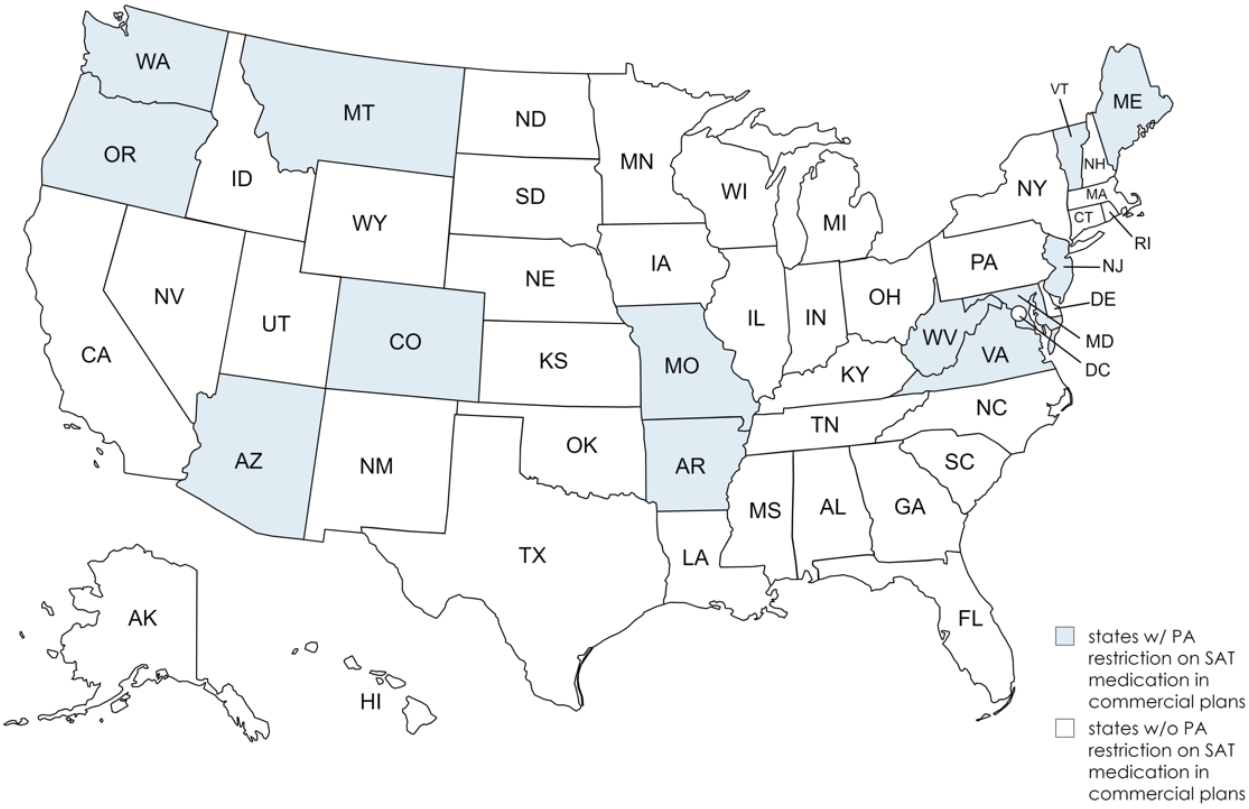


Figure 3: Distribution of State PA Restrictions on SAT Medication in Commercial Plans

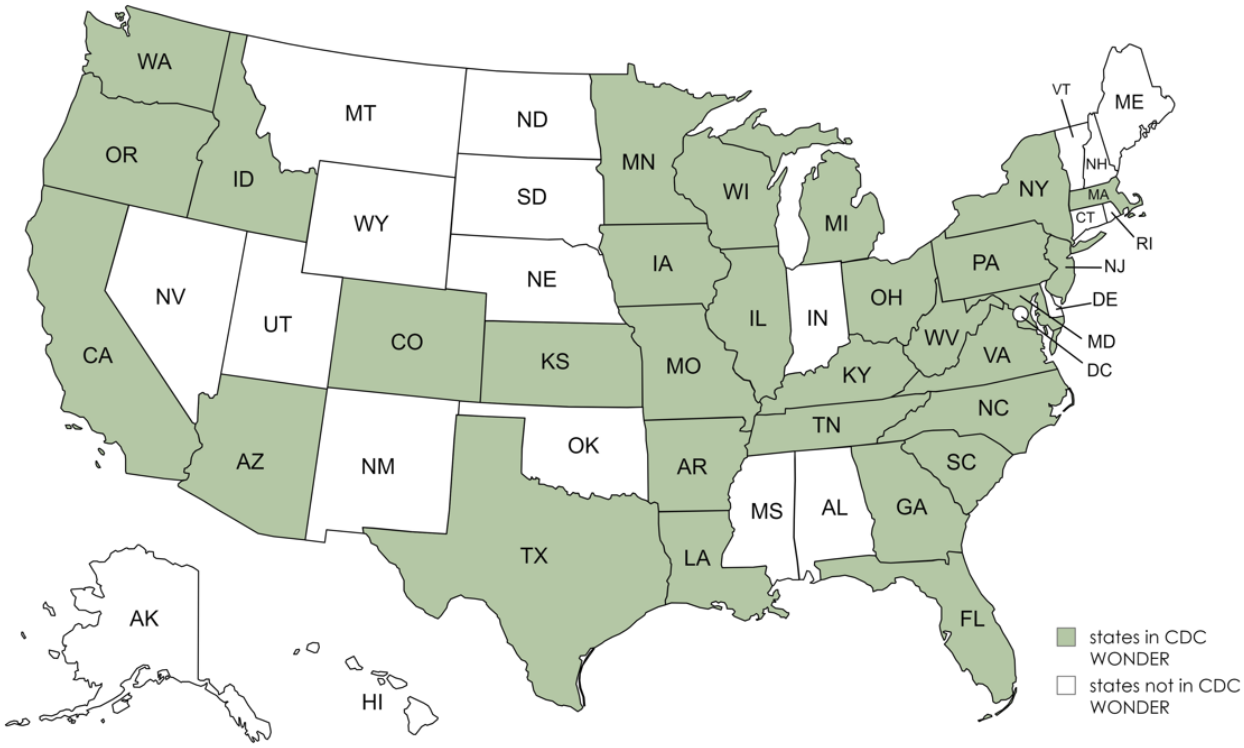


Figure 4: Availability of CDC WONDER States (SUD Suicide)

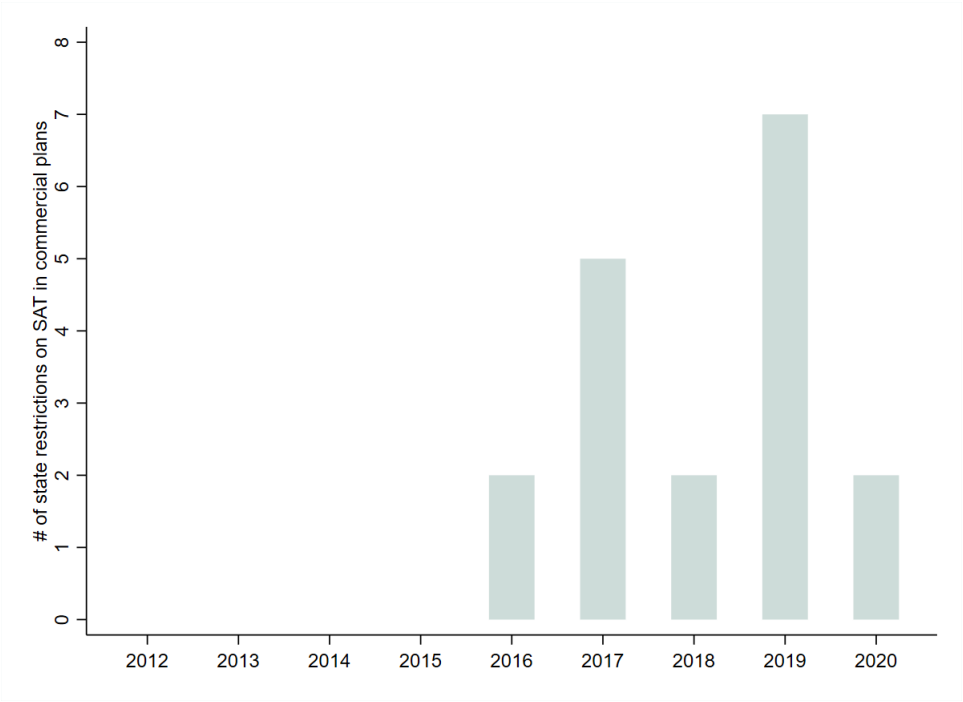


Figure 5: Evolution of State Laws Restricting PA on SAT in Commercial Plans

Table 6.6a. Type of assessment and pre-treatment services offered by facilities, by state or jurisdiction: Number, 2020

State or jurisdiction[1]	Total[2]	Assessment and pre-treatment services: Screening for substance abuse	Screening for mental health disorders	Comprehensive substance abuse assessment or diagnosis	Comprehensive mental health assessment or diagnosis	Screening for tobacco use	Outreach to persons in the community who may need treatment	Interim services for clients when immediate admission is not possible	Professional interventionist/ educational consultant	None of these assessment and pre-treatment services offered
Total	16,066	15,594	12,787	15,167	9,344	12,187	10,653	8,043	3,446	121
Alabama	155	153	95	141	55	104	129	101	28	2
Alaska	105	102	94	100	77	91	83	80	21	- -
Arizona	447	434	373	422	303	311	296	227	95	6
Arkansas	171	165	150	158	117	128	145	99	34	1
California	1,734	1,689	1,305	1,600	829	1,178	1,199	788	409	29
Colorado	393	387	312	375	231	273	251	207	80	2
Connecticut	210	204	196	197	167	184	125	83	33	4
Delaware	49	45	46	48	41	34	35	28	10	- -
District of Columbia	28	27	22	26	17	21	21	10	11	- -
Florida	712	695	604	678	476	506	446	346	189	4
Georgia	348	341	261	321	193	197	234	141	65	2
Hawaii	161	156	85	154	45	138	92	94	34	1
Idaho	110	109	100	108	91	69	80	61	22	- -
Illinois	713	699	545	675	387	482	452	374	173	5
Indiana	416	402	336	388	244	329	256	174	67	5
Iowa	185	180	152	181	87	162	129	134	34	1
Kansas	170	170	99	165	73	90	111	119	34	- -
Kentucky	477	473	376	458	305	314	330	218	129	1
Louisiana	155	154	111	149	81	115	119	88	44	- -
Maine	196	193	167	193	115	178	90	66	43	- -
Maryland	432	413	316	406	249	350	302	184	103	10
Massachusetts	440	425	321	409	235	411	253	139	73	8
Michigan	455	443	392	436	270	310	281	213	87	1
Minnesota	401	369	299	385	221	286	237	141	70	4
Mississippi	105	104	89	96	74	64	78	57	23	- -
Missouri	278	272	222	256	163	219	164	166	50	4
Montana	129	126	122	122	87	105	105	92	34	- -
Nebraska	123	122	112	115	80	98	75	87	26	1

Continued. See notes at end of table.

Figure 6: Screenshot of the Annual Report of the N-SSATS

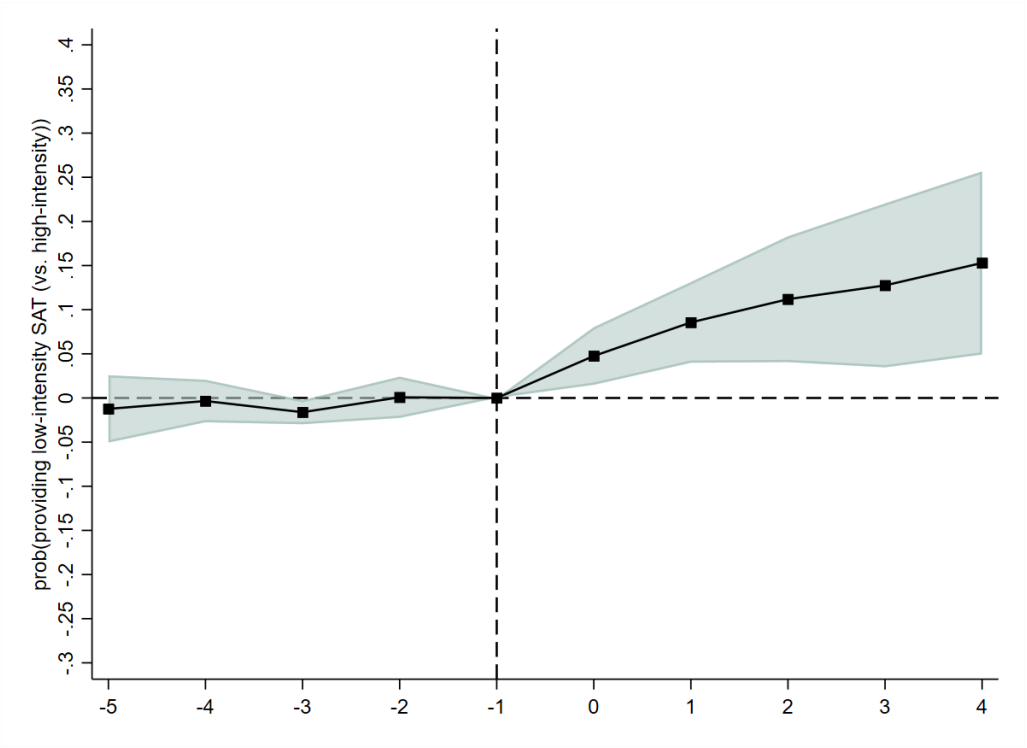


Figure 7: event-study estimates for providing only low-intensity (vs. only high-intensity) SAT

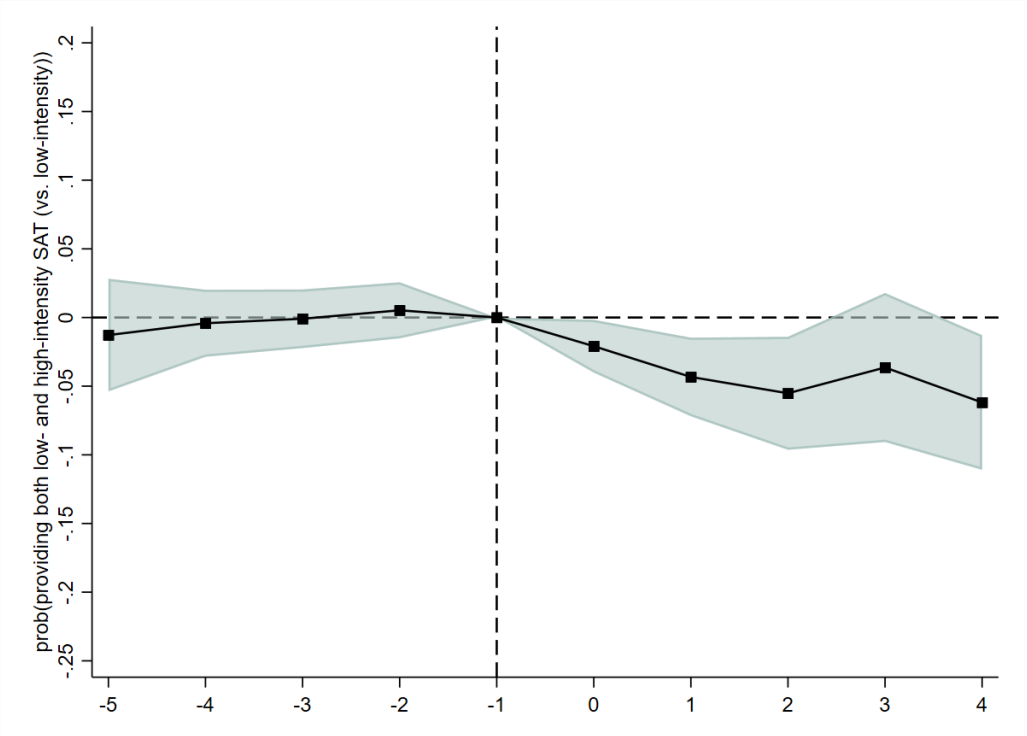


Figure 8: event-study estimates for providing both (vs. only low-intensity) SAT

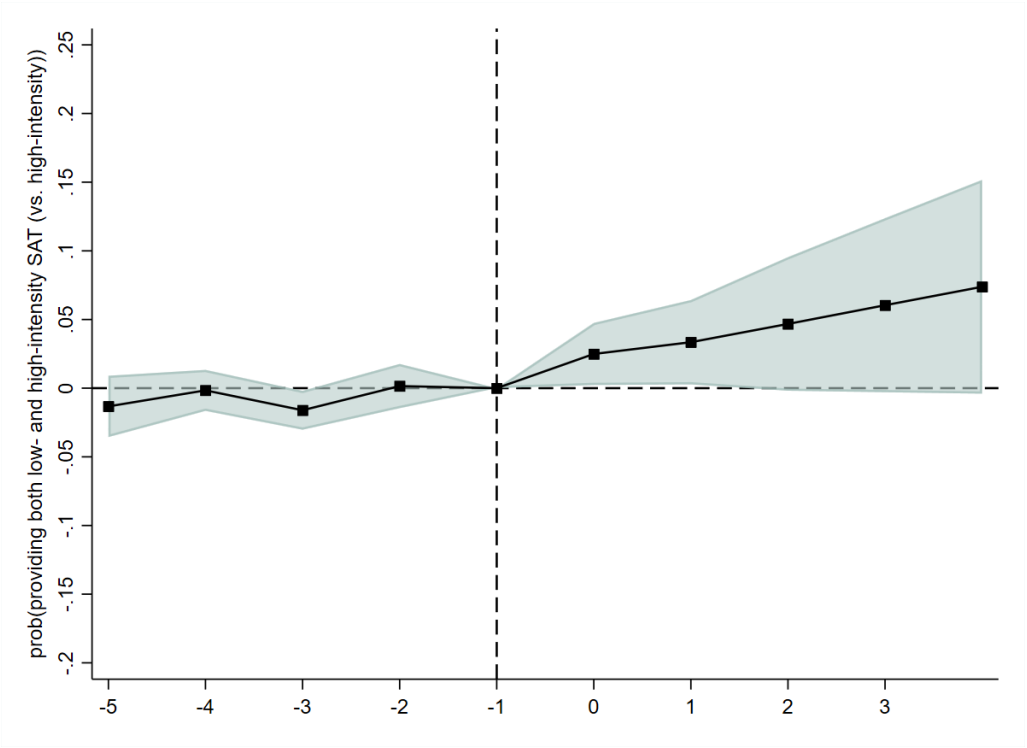


Figure 9: event-study estimates for providing both (vs. only high-intensity) SAT

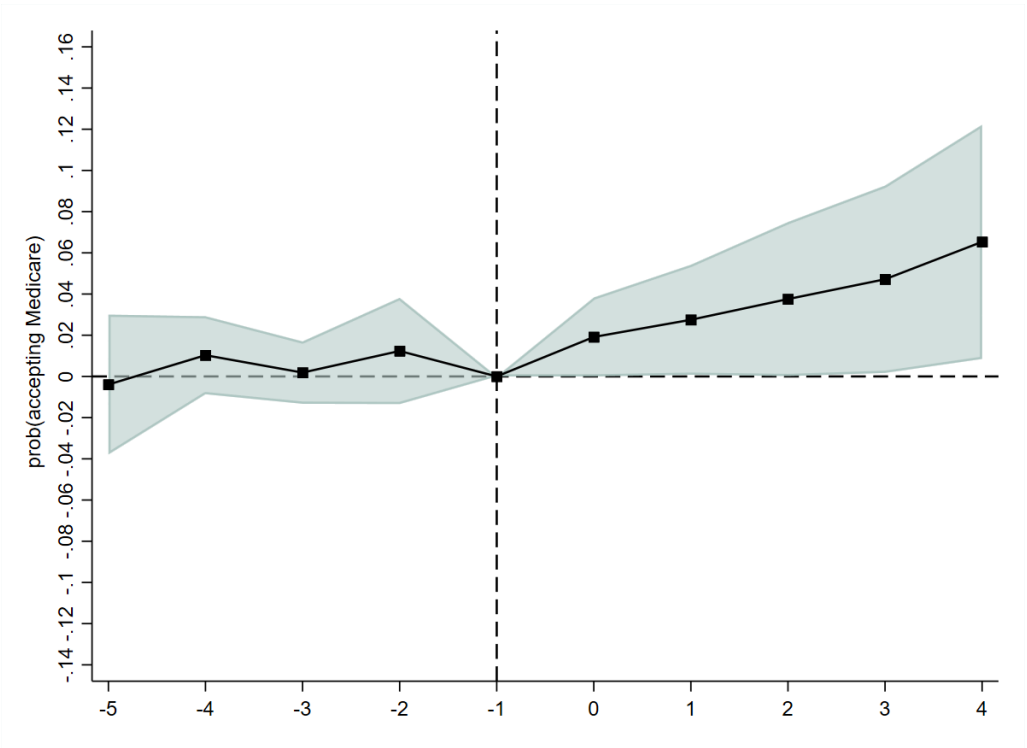


Figure 10: event-study estimates for accepting Medicare

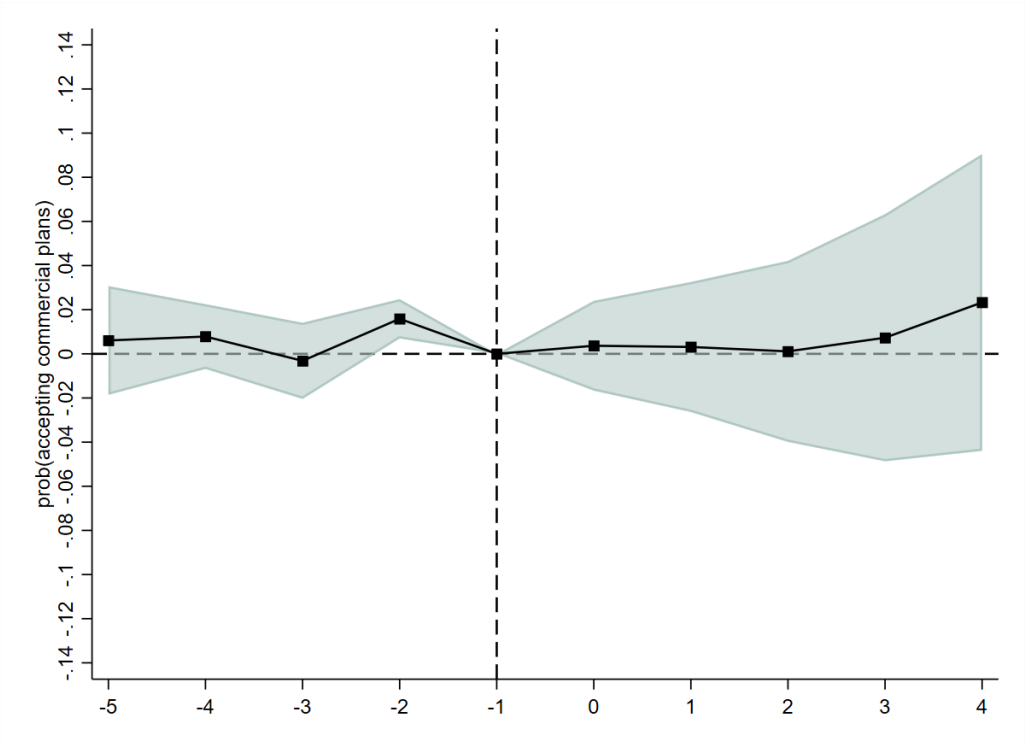


Figure 11: event-study estimates for accepting commercial plans

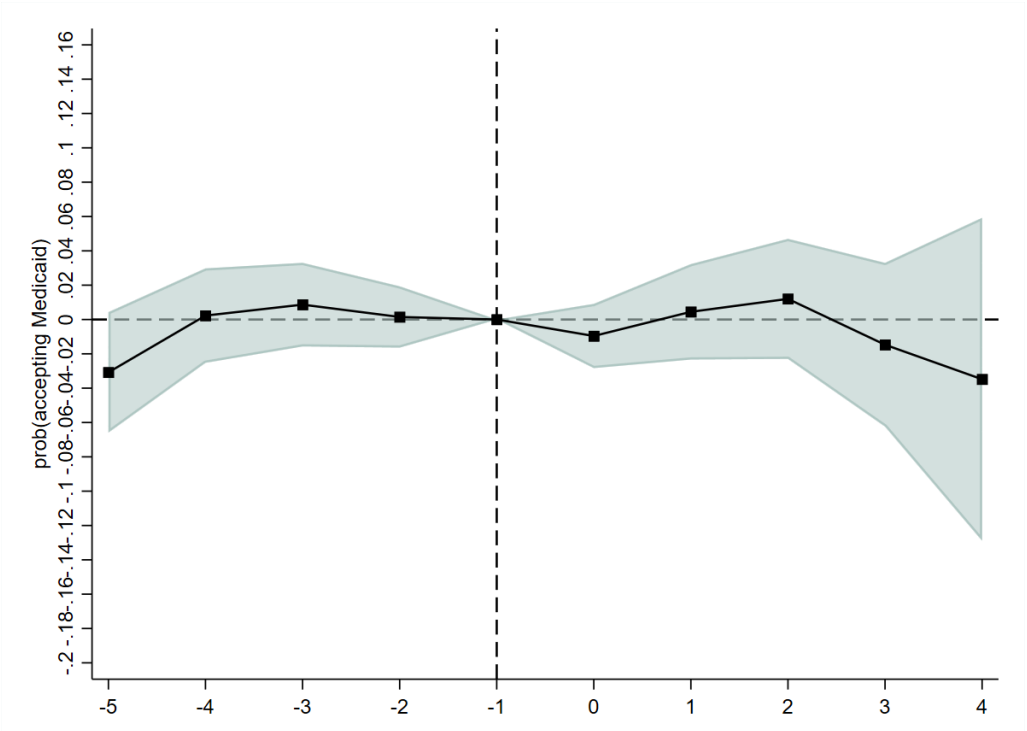


Figure 12: event-study estimates for accepting Medicaid

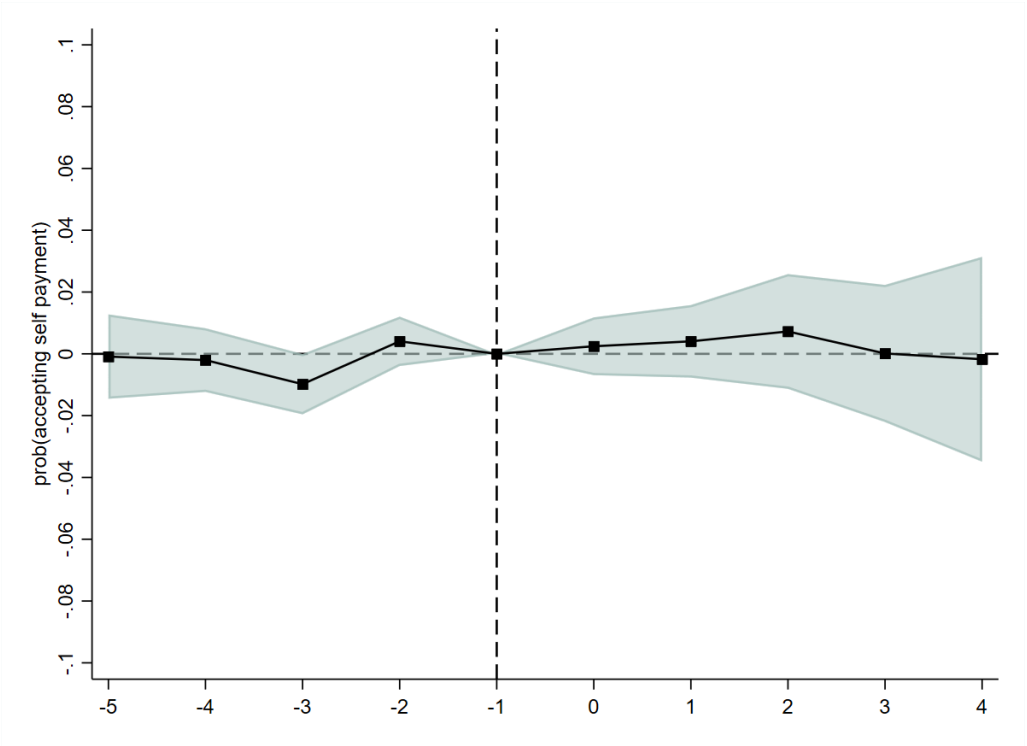


Figure 13: event-study estimates for accepting uninsured

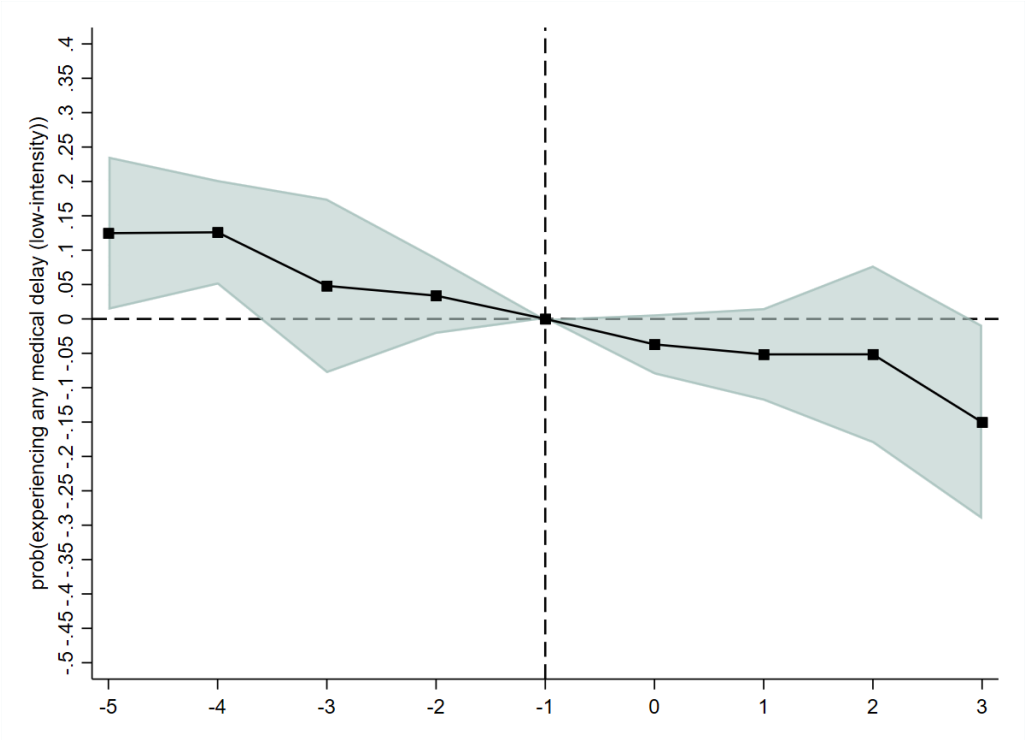


Figure 14: event-study estimates for experiencing any medical delay

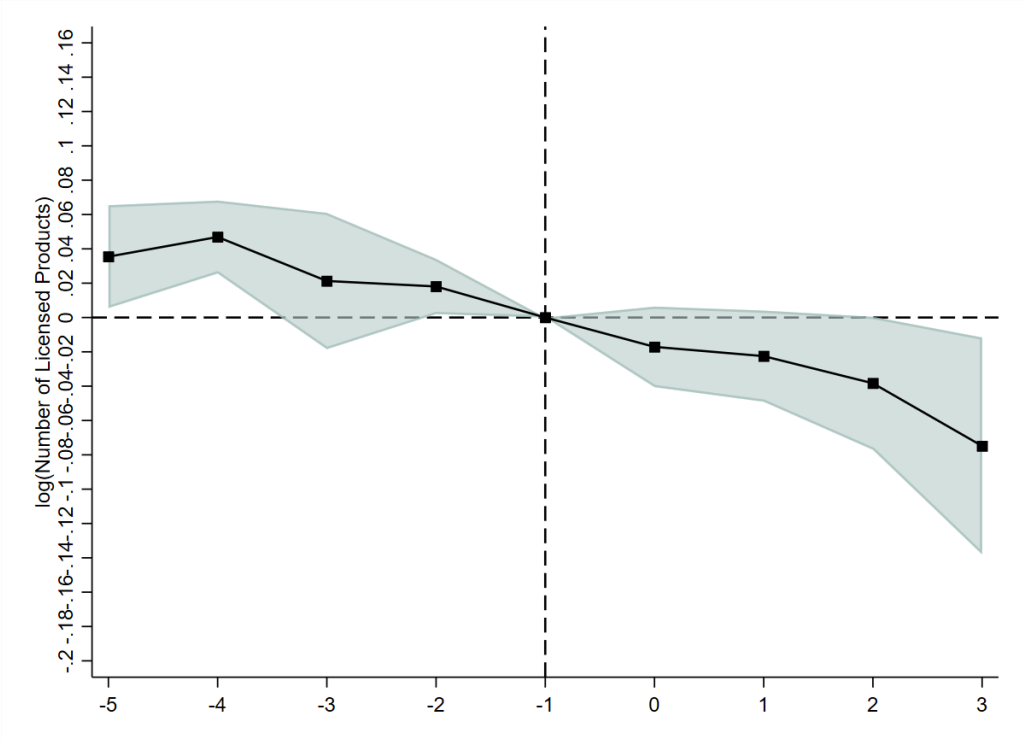


Figure 15: event-study estimates for experiencing normal medical delay

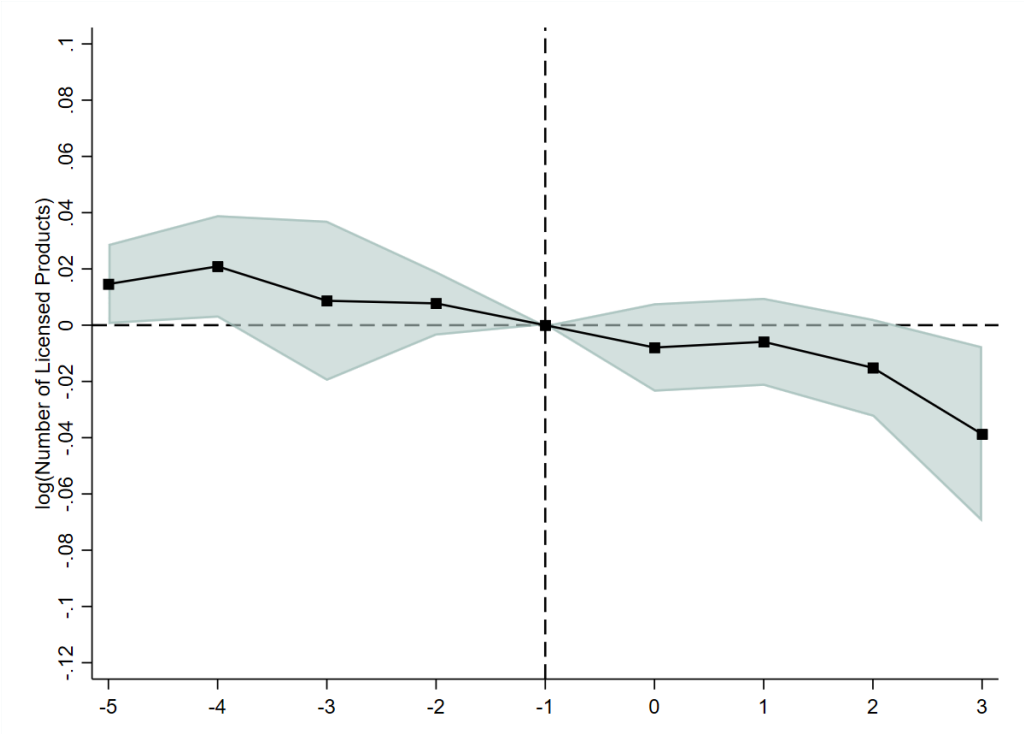


Figure 16: event-study estimates for experiencing severe medical delay

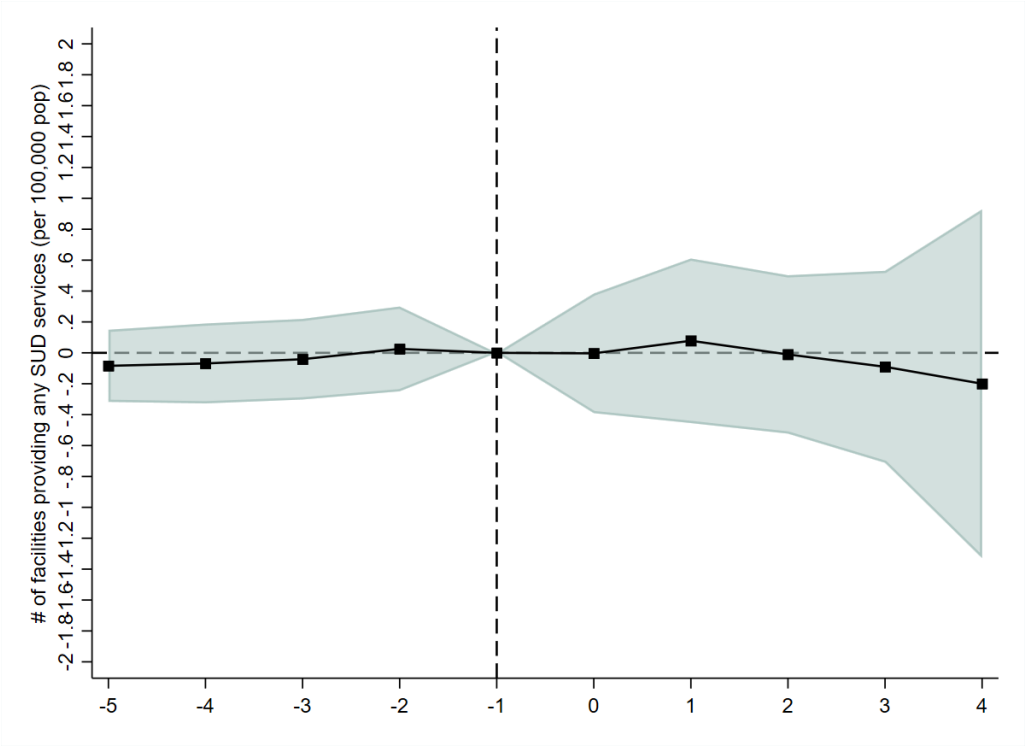


Figure 17: event-study estimates for # of facilities providing any SAT services (per 100,000 pop)

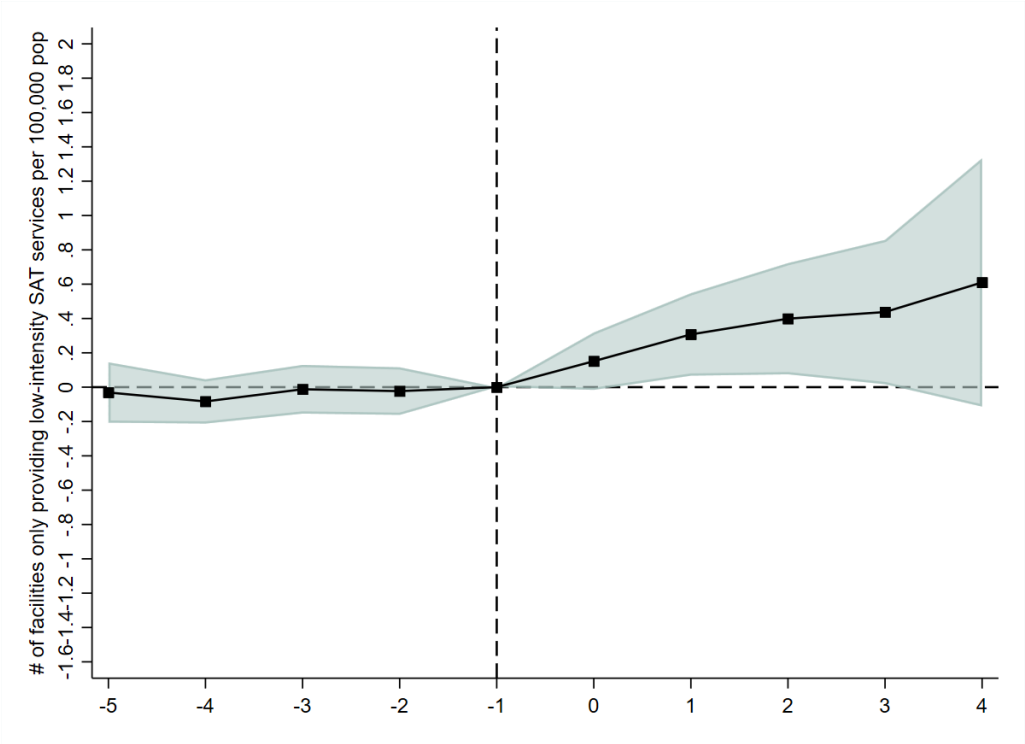


Figure 18: event-study estimates for # of facilities only providing low-intensity SAT services (per 100,000 pop)

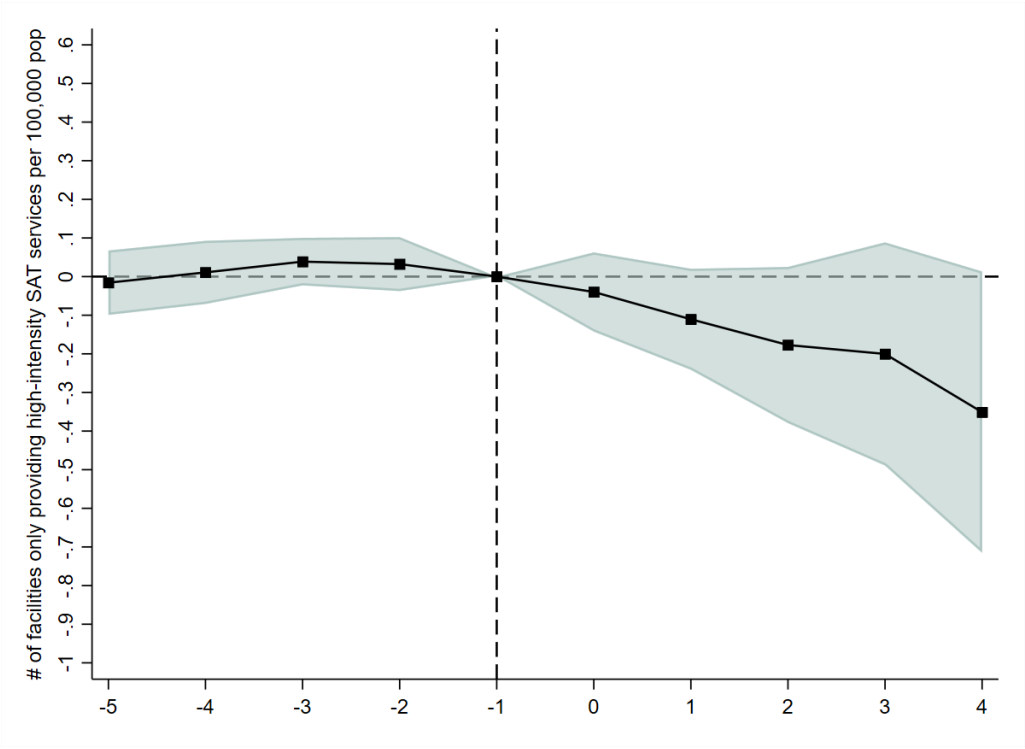


Figure 19: event-study estimates for # of facilities only providing high-intensity SAT services (per 100,000 pop)

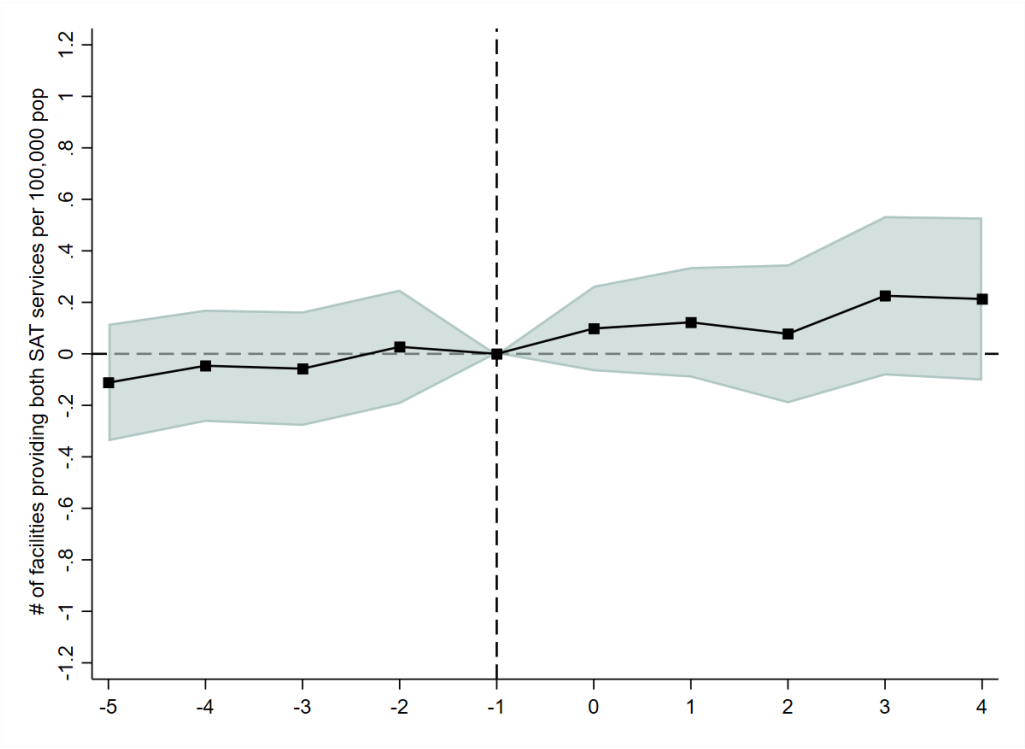


Figure 20: event-study estimates for # of facilities providing both low- and high-intensity SAT services (per 100,000 pop)

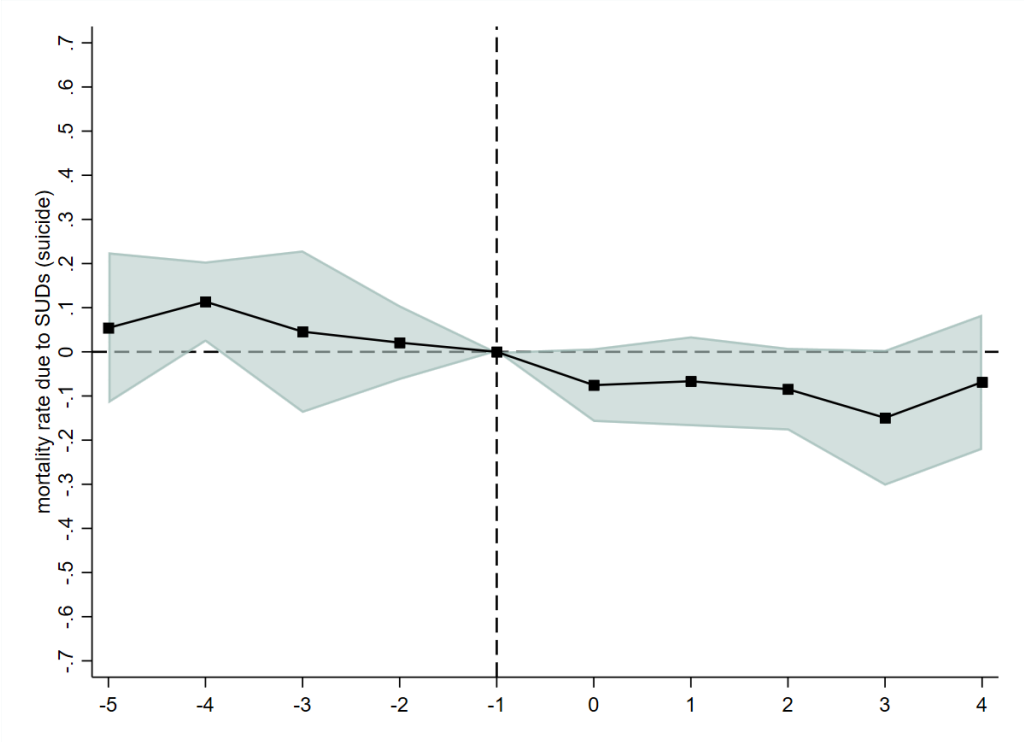


Figure 21: event-study estimates for # of death due to SUD suicide per 100,000 pop

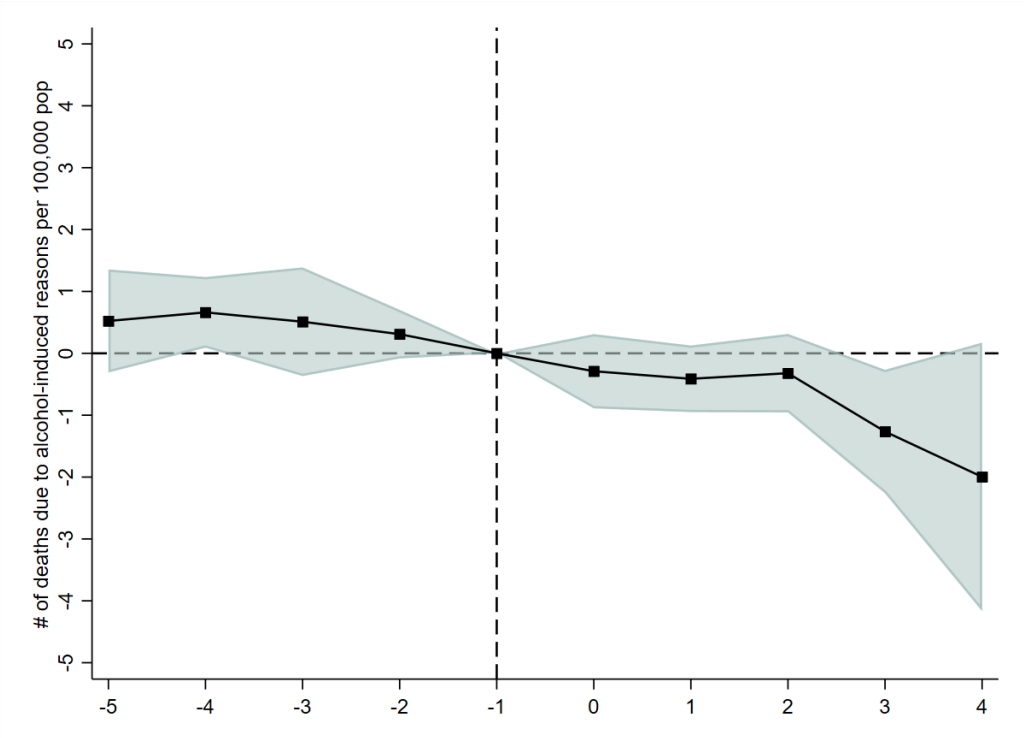


Figure 22: event-study estimates for # of death due to alcohol use reasons per 100,000 pop

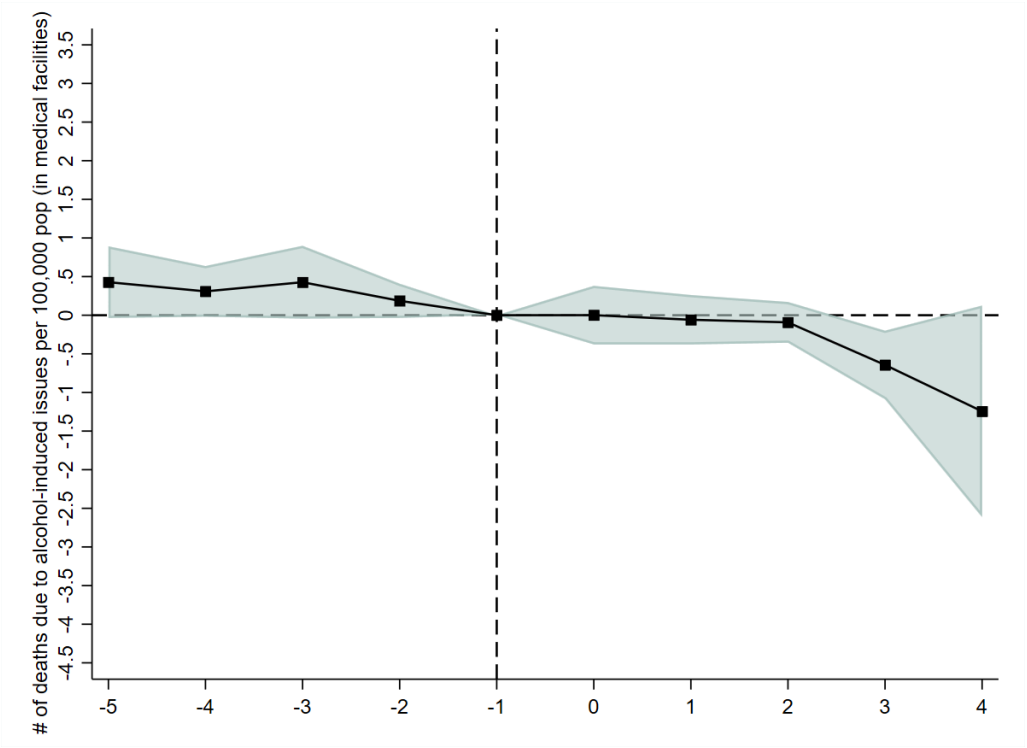


Figure 23: event-study estimates for # of death due to alcohol use reasons per 100,000 pop (within medical facilities)

Appendix

A.1. Prior Authorization

Prior authorization refers to a requirement by health plans for patients to obtain approval of a health-care service or medication before the care is provided (KFF).[39] Typically, PA aims to help plans evaluate whether care or treatment is medically necessary and otherwise covered. Such standards (usually called *medical necessity criteria*) for this pre-treatment review are often developed by the plans themselves, based on medical guidelines, costs, utilization, and other information (KFF).

A standard process to obtain prior authorization can vary across insurers but typically involves the following steps: containing the payer's PA form, completing all required clinical and administrative information, submitting the form to the health plan, and, if necessary, contacting service representatives or other personnel at the plan for follow up (Turner, Miller and Clark, 2019). Common methods for submitting PA requests include electronic medical records (EMR), fax, secure email, phone, and the payer's digital portal. The submitted PA request, along with any supporting materials, will be reviewed by the clinical staff (e.g., pharmacists, registered nurses, etc.). The length of time before requests are processed varies by type of care, payer type, use of automation, and many other factors, ranging from the same day to several days.

In terms of the results of a PA request, it can be approved or denied. In the case that a PA request is denied, providers and patients have the option to appeal. Physicians have reported that, overall, 72% of PA requests are approved on initial request and an additional 7% are approved on appeal. In addition, PAs are typically only valid for a specified length of time, after which additional requests must be submitted for continued prescription refills or therapies (Turner, Miller and Clark, 2019).

[39] See for example, https://www.kff.org/policy-watch/examining-prior-authorization-in-health-insurance/, last accessed July 10, 2024.

A.2. Substance Abuse Treatment Services

In terms of substance abuse treatment (SAT) services, according to the American Society of Addition Medicine (ASAM), there are 5 levels of treatment:[40]

Level 0.5 treatment is usually called *Early Intervention*. Early intervention can consist of assessment and education for people at risk of developing a substance use disorder or programs like DUI classes for people arrested for driving under the influence. The primary goal here is to intervene before a person develops a substance use disorder.

Level 1 treatment includes outpatient treatment consisting of treatment for substance use that is less than 9 hours a week. Level 1 is appropriate for people with less severe disorders as a starting point or as a step-down from more intensive services.

Level 2 treatment includes *intensive outpatient services* and *partial hospitalization*. The former consists of at least 9 and no more than 20 hours per week of treatment. These programs typically offer medical care 24 hours a day by phone or within 72 hours in person. Partial hospitalization is at least 20 hours a week but is less than 24-hour care. This level of care provides structural and daily oversight for people who need daily monitoring but not 24/7 care.

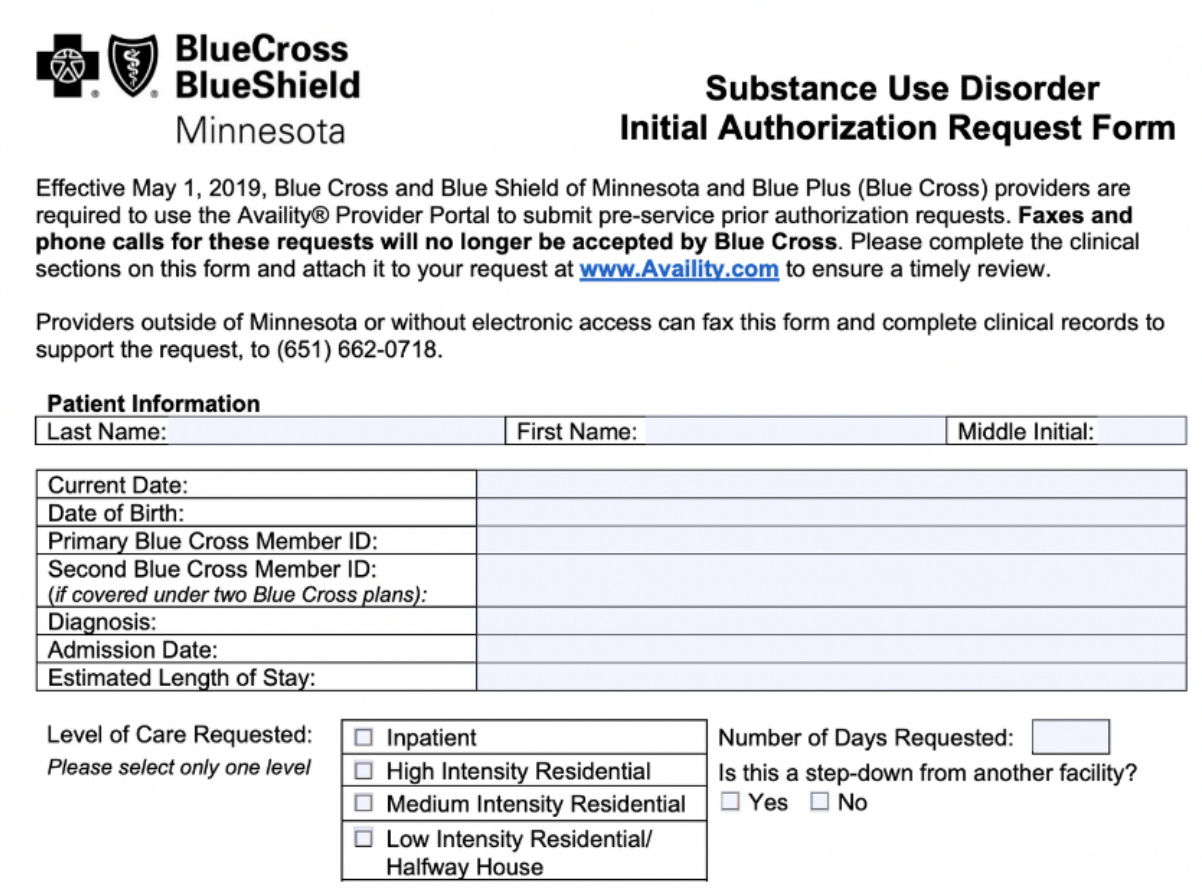
Level 3 treatment is the *inpatient services*, which can include clinically managed low-intensity residential treatment, managed high-intensity and population-specific services, clinically managed residential services, and hospital-based high-intensity inpatient treatment services. Clinically managed low-intensity residential treatment provides a group home and only requires 5 hours per week, which helps people with such topics as relapse management. Clinically managed high-intensity and population-specific services provide treatment designed to move at a slower pace, for people with cognitive functioning issues, including people with traumatic brain injuries, the elderly, or people with developmental disabilities. Clinically managed residential services are designed for people with serious psychological or social issues who need 24-hour oversight and are at risk of imminent harm. Eventually, medically managed high-intensity inpatient treatment is for people who need intensive medical or psychological monitoring in a 24-hour setting but do not need daily physician interaction.

[40] See https://americanaddictioncenters.org/rehab-guide/asam-criteria-levels-of-care, last accessed July 10, 2024.

Level 4 treatment provides 24-hour nursing care and daily physician visits. People in this level of care need daily physician monitoring, along with 24-hour oversight. It is designed for people with severe biomedical, emotional, behavioral and/or cognitive conditions that require primary medical and 24-hour nursing care. Services are provided in hospital settings, such as acute care units, and involve medically directed evaluation and treatment. Primarily designed to provide stabilization, this level then helps people transition to another level of care.[41]

[41] See for example, https://americanaddictioncenters.org/rehab-guide/levels-of-care, last accessed July 10, 2024.

A.3. Tables and Figures



BlueCross BlueShield Minnesota

Substance Use Disorder Initial Authorization Request Form

Effective May 1, 2019, Blue Cross and Blue Shield of Minnesota and Blue Plus (Blue Cross) providers are required to use the Availity® Provider Portal to submit pre-service prior authorization requests. **Faxes and phone calls for these requests will no longer be accepted by Blue Cross**. Please complete the clinical sections on this form and attach it to your request at www.Availity.com to ensure a timely review.

Providers outside of Minnesota or without electronic access can fax this form and complete clinical records to support the request, to (651) 662-0718.

Patient Information

Last Name:	First Name:	Middle Initial:

Current Date:	
Date of Birth:	
Primary Blue Cross Member ID:	
Second Blue Cross Member ID: *(if covered under two Blue Cross plans):*	
Diagnosis:	
Admission Date:	
Estimated Length of Stay:	

Level of Care Requested:
Please select only one level

- ☐ Inpatient
- ☐ High Intensity Residential
- ☐ Medium Intensity Residential
- ☐ Low Intensity Residential/ Halfway House

Number of Days Requested:

Is this a step-down from another facility?
☐ Yes ☐ No

Figure 24: snapshot of prior authorization requests