# Managing Drug Use Through Administrative Burden: Evidence from Medicaid[†]

Abby Alpert

University of Pennsylvania and NBER

Ruochen Sun

University of Southern California

November 2026

**Abstract**

Social safety net programs that allocate benefits to low-income individuals typically rely on administrative hurdles, rather than prices, to ration access. We study the impact of prior authorization, one of the most widely used non-price mechanisms for managing prescription drug use in Medicaid. We introduce a Regression-Discontinuity (RD) design leveraging age-based discontinuities in prior authorization restrictions to isolate its impact on utilization from other features of insurance design. Children below (or above) a certain age must obtain prior authorization for the same drugs that children on the other side of the age cutoff can fill without prior authorization. These age cutoffs vary across plans within a state, providing a unique source of identification. We find significant reductions in prescription drug use and spending for ADHD drugs. Using novel plan-level data on prior authorization approval criteria, which allows us to identify patients eligible for treatment, we show that these effects are primarily driven by the administrative hassles of the prior authorization process rather than by improved targeting of treatment.

[†] We are grateful for helpful comments from Diane Alexander, Zarek Brot, Ben Chartock, Marcus Dillender, Jacob Dorn, Hanming Fang, Tim Layton, Matt Notowidigdo, Alex Olssen, David Powell, Aaron Schwartz, Mark Shepard and seminar and conference participants at Indiana University, Weill Cornell, the ASSA Meetings, ASHEcon, UChicago BFI Health Econ Conference, NYC Health Econ Day, UPenn CHIBE, NBER Health Care Administration and Fraud Conference and Triangle Health Economics Workshop. The authors gratefully acknowledge financial support from the Leonard Davis Institute Pilot Grant, Wharton Dean's Research Fund, and Wharton Mack Institute Research Fellowship. Author Emails: alpertab@wharton.upenn.edu; ruochens@usc.edu

## 1 Introduction

Social safety net programs that allocate benefits to low-income individuals have limited ability to use price-based rationing, as doing so would greatly restrict access for beneficiaries. Instead, these programs primarily rely on non-price instruments—eligibility verification, recertification and waiting costs—that raise the shadow price of access rather than the monetary price. While these mechanisms aim to improve the targeting of benefits, they often impose administrative burdens that can counteract efficient targeting. A large literature examines how these administrative burdens, or "ordeals," impact program take-up (Nichols and Zeckhauser 1982; Currie 2006; Finkelstein and Notowidigdo 2019; Deshpande and Li 2019; Shepard and Wagner 2025). However, far less attention has been paid to the administrative burdens that beneficiaries face after enrollment and their impact on the allocation of program benefits.

In this paper, we study one of the most pervasive post-enrollment administrative burdens in Medicaid: prior authorization for prescription drugs. Prior authorization requires health care providers to obtain pre-approval before a medication can be covered. We study how prior authorization affects access to prescription drugs in Medicaid and ask a critical but unexplored question: how does it impact the targeting of treatment? The effect on targeting is ex ante ambiguous because, on the one hand, prior authorization has the potential to improve treatment targeting by denying coverage for patients who do not meet clinical criteria for approval—what we call the "*screening effect.*" On the other hand, it may also worsen treatment targeting as prior authorization imposes administrative burdens, requiring the submission of detailed and often complex paperwork for approval. These procedural challenges can deter physicians from prescribing medications subject to prior authorization, reducing access among patients who are eligible for treatment—what we call the "*hassle cost effect.*" The extent to which prior authorization improves or worsens treatment targeting depends on the relative importance of these channels. We provide the first evidence disentangling the screening and hassle cost effects underlying the overall change in prescribing.

This question is especially important for Medicaid as it uses prior authorization more heavily than other health insurers. Medicaid serves a low-income population, so there is limited

scope for using copays or traditional cost-sharing incentives to steer patients to lower-cost drugs.[1] In addition, federal law requires that Medicaid cover essentially all drugs, so expensive drugs cannot be excluded from the formulary. However, Medicaid programs must still operate within tight budgets and address moral hazard concerns. As a result, they rely more heavily on non-price mechanisms for managing drug use compared to other types of insurers, with prior authorization being the primary tool for controlling spending (MACPAC 2024).[2,3] Survey evidence from the Kaiser Family Foundation shows that Medicaid beneficiaries are twice as likely to face prior authorization hurdles compared to Medicare enrollees, with one in four beneficiaries experiencing a delay or denial before receiving treatment (Pollitz et al. 2023). Almost 73% of branded drugs without a generic competitor were subject to prior authorization in Medicaid in 2019, compared to 25% in Medicare (Kyle et al. 2026). In addition, pharmacy denial rates for new prescriptions are almost twice as high in Medicaid as in Medicare and commercial insurance (IQVIA 2025).[4]

Despite its widespread use, causal evidence on the effects of prior authorization in Medicaid is scarce. There are two main reasons for this gap. First, the policies themselves are difficult to observe. More than 70% of Medicaid beneficiaries are now enrolled in Medicaid managed care (MMC) plans. Each plan maintains its own prior authorization requirements and clinical approval criteria, which are not publicly disclosed and would be difficult to harmonize across plans. Second, prior authorization is typically implemented alongside other insurance design features, such as cost-sharing, formulary design, and physician reimbursement, making its effects difficult to isolate empirically.

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[1] Because copays are low, there is often little or no difference in copays between preferred and non-preferred drugs, providing limited financial incentive for steering patients to preferred drugs. Federal law caps copays at $4 for preferred drugs and $8 for non-preferred drugs (42 CFR § 447.53(b)) and states often implement their own caps below the federal limits. As a result, drug copays typically range from about $0 to $3 in most states (KFF 2019).

[2] MACPAC (2024) notes the importance of prior authorization: "Medicaid statute requires that any drug excluded from a formulary must be covered to some extent through a prior authorization program (§ 1927(d)(4)(D) of the Act). Because states cannot exclude coverage of most drugs, prior authorization is the primary tool Medicaid has to manage utilization and spending for prescription drugs (§ 1927(d) of the Act, 42 CFR § 438.3(s))."

[3] Other non-price mechanisms commonly used in Medicaid are prescription caps, which limit the total number of prescriptions that can be filled per month; quantity limits, which restrict the days of supply; and step therapy, which requires that patients try a lower cost option before switching to a more expensive drug. However, these mechanisms can also be viewed as forms of prior authorization. Step therapy is typically implemented through a prior authorization process and exemptions from prescription caps and quantity limits can be obtained through prior authorization requests.

[4] The higher denial rates for Medicaid enrollees may reflect more treatments being subject to prior authorization, more restrictive approval criteria, or lower provider effort in managing prior authorization requests.

We address these challenges by introducing the first Regression-Discontinuity (RD) design exploiting age-based discontinuities in prior authorization requirements across Medicaid managed care plans. In Pennsylvania, some managed care plans require prior authorization for children below (or above) a specific age cutoff for certain medications, while children on the other side of the threshold can obtain the same medication without prior authorization. We leverage variation in these age cutoffs *across* Medicaid managed care plans using a differences-in-discontinuities (RD-DID) framework. We compare changes in prescription use at age cutoffs in treated plans with control plans that do not have the same age cutoff. This strategy enables us to isolate the effects of prior authorization from other aspects of insurance design that do not change discontinuously at the age cutoffs. Additionally, comparing treated and control plans accounts for age-related factors that uniformly affect utilization across all plans within the state, such as changes in Medicaid eligibility, treatment guidelines, and school entry age. The presence of different age cutoffs also allows us to examine the utilization effects at various ages, improving the generalizability of our estimates.

We further leverage unique administrative data on plan-level prior authorization policies, including the detailed approval criteria for each Medicaid managed care plan, which we collected from the state through Freedom of Information Act (FOIA) requests. We link this information with Pennsylvania's Medicaid claims data to identify patients who would likely meet the insurer's clinical criteria for treatment eligibility. These detailed prior authorization approval criteria have not been used in prior research. This information allows us to go beyond estimating the overall effect of prior authorization on drug use to examine *who* ultimately receives treatment: specifically, how much of the reduction in prescription use comes from eligible patients deterred by hassle costs versus ineligible patients screened out by the approval criteria.

Our analysis focuses on prior authorization for attention-deficit/hyperactivity disorder (ADHD) drugs. We focus on ADHD because it is one of the most heavily managed therapeutic areas through prior authorization and it is a top spending category for Medicaid. In 2017, ADHD drugs accounted for 6% of Medicaid prescription drug spending (Young 2019). ADHD drug spending has grown substantially in recent years and the majority of this increase has been concentrated in the Medicaid population (Chorniy et al. 2018; Xu et al. 2018). Additionally, concerns over the inappropriate use of ADHD medications have heightened scrutiny of prescribing

practices, underscoring the potential role of prior authorization in curbing inappropriate use or misuse (McCabe et al. 2023).

The paper has three parts. First, we begin by examining the impact of prior authorization on patients' use and spending for ADHD drugs. We find that prior authorization reduces the likelihood of ADHD medication use by 14.7% on average, with effects varying across age groups. Among patients who ultimately receive their medications, prior authorization delays prescription fills by 2.4 days and decreases the probability of same-day prescription fulfillment by 29.5%. These restrictions result in a 14% reduction in overall ADHD medication expenditures.

Second, we take the analysis a step further to estimate how the reduction in prescription use affects the targeting of treatment by disentangling screening and hassle cost effects.[5] To empirically isolate the two channels, we compare the effects of prior authorization across patients based on whether they are likely to meet the insurer's approval criteria for treatment. For patients who meet the approval criteria, any reduction in access is attributable solely to hassle costs, as their requests are expected to be approved once the required documentation is submitted. For patients who do not meet the approval criteria, the reduction in their drug use ultimately reflects screening by the approval criteria: if a request were filed, it would be denied. Comparing the impact of prior authorization across these two groups—patients who would or would not meet approval criteria—allows us to quantify the relative contributions of each channel. Our empirical results show that prior authorization reduces drug use by at least 9% among patients who are likely to meet the approval criteria and by 25% among those who would not. Although prior authorization has a proportionally larger effect among ineligible patients, those ineligible patients account for only a small share of baseline ADHD drug use, so most of the reduction comes from patients the insurer would have approved. As a result, more than 66% of the total reduction in drug use

[5] Our terminology maps onto, but differs from, the ordeals literature, where "screening" (or self-screening) denotes the selection induced by the ordeal itself, which is favorable when the ordeal's cost falls disproportionately on low-value applicants and unfavorable otherwise (Nichols and Zeckhauser 1982; Deshpande and Li 2019; Shepard and Wagner 2025). We instead define the two channels of selection by whose use is reduced: the screening effect is the reduction in use among patients who do not meet the insurer's approval criteria, and the hassle cost effect is the reduction among patients who do. The first corresponds to favorable selection and the second to unfavorable selection. We adopt this terminology for two reasons. First, unlike the settings studied in the ordeals literature, where the burden itself is the screening device, prior authorization combines a burden with an explicit approval rule: the insurer reviews each request against its approval criteria. Screening in our setting therefore need not arise from the burden alone. Second, each channel corresponds to a distinct policy lever: the screening effect operates through the approval criteria, and the hassle cost effect through the burden of the filing process.

attributable to prior authorization occurs among patients who are likely eligible for treatment. Thus, it is the hassle cost effect, instead of the screening effect, that accounts for the majority of the reduction in drug use under prior authorization.

Finally, we also test for spillovers to patients not targeted by prior authorization, which could further distort the targeting of treatment. Although prior authorization is designed to target patients in a specific plan, its influence may extend to patients in other plans by altering physician's prescribing habits through the development of prescribing heuristics or learning. Physicians treating many patients enrolled in managed care plans that require prior authorization may reduce prescriptions even for those in plans not subject to these requirements. Our results, however, rule out this type of spillover effect. We do not find evidence of spillovers on patients of plans without prior authorization. Instead, we find that physicians treating more patients with prior authorization reduce their prescribing for those patients to a greater extent, suggesting a possible cumulative effect of administrative burden.

Our robustness checks show that the observed effects are not driven by compositional changes at Medicaid eligibility thresholds, copay changes, plan switching in response to prior authorization restrictions, or other age-related factors influencing drug use such as school-entry age and clinical guidelines based on age. Estimates are stable across alternative functional forms and a range of alternative bandwidths. Placebo tests at pseudo cutoffs yield no effects.

Overall, our results demonstrate that prior authorization substantially reduces prescription use and spending, with most of the reduction driven by the hassle costs associated with filing requests. These administrative burdens deter providers from prescribing to patients who are eligible for treatment, worsening treatment targeting. Moreover, the administrative workload imposed by prior authorization likely strains physicians' capacity in maintaining optimal prescribing practices. This result has important implications for policies that aim to streamline or automate prior authorization as these changes could reduce hassle costs and reallocate treatment towards patients whom the insurer's own criteria deem appropriate. Refining approval criteria alone, even when aligned with best clinical practices, is less likely eliminate distortions in treatment targeting if hassle costs continue to be significant.

Our analysis contributes to the literature on how Medicaid policies affect healthcare access. Prior research has largely focused on access to Medicaid through eligibility expansions (Miller et

al. 2021; Finkelstein et al. 2012), enrollment obstacles (Aizer 2007; Arbogast et al. 2024), and reimbursement policies that impact provider participation (Alexander and Schnell 2024; Cabral et al. 2025). However, much less attention has been given to the administrative burdens that beneficiaries face after enrollment, despite their widespread use. A beneficiary may be eligible for Medicaid, enroll in the program, and find a provider willing to accept their insurance, but still not receive needed treatment because of the administrative burdens of accessing program benefits. We focus on this understudied aspect of Medicaid access in this paper.

We also contribute to the burgeoning literature on prior authorization. There is surprisingly little causal evidence on its effects in Medicaid, where prior authorization is used most heavily. We are the first to provide quasi-experimental evidence in this context using age-based discontinuities in prior authorization requirements. In Medicare Part D, Brot-Goldberg et al. (2023) leverage the random assignment of low-income subsidy (LIS) beneficiaries to Part D plans and find that drugs subject to prior authorization have lower utilization and spending. Another study of Texas's workers' compensation program found a reduction in the use of abuse-prone drugs after a policy change that required prior authorization (Dillender 2018). Within Medicaid, studies in the medical literature find that state prior authorization policies are associated with reduced use of specific drug classes, however, causal evidence is limited.[6] The study most closely related to ours is Currie and Musen (2025), who show how the staggered adoption of state-level prior authorization programs reduced the use of antipsychotics prescribed to preschool-aged children. Together, these studies show that prior authorization reduces utilization and spending and, in therapeutic areas where inappropriate use is common (such as opioids and antipsychotics), suggest that it may improve treatment targeting. However, none of these studies have directly examined the margin that matters for treatment targeting: whether prior authorization reduces use for ineligible versus eligible patients. Answering this question requires information about the clinical approval criteria for each drug and plan, which is proprietary information maintained by insurance plans that is not typically available to researchers. We hand-collected these data, and find that, while prior authorization generates savings for insurers, it also significantly distorts the targeting

[6] There are a handful of studies in the medical literature examining the association between prior authorization requirements and drug use in Medicaid for nonsteroidal anti-inflammatory drugs, COX-2 inhibitors, antipsychotics, buprenorphine-naloxone and anticancer drugs (Fischer et al. 2004; Siracuse and Vuchetich 2008; Stein et al. 2014; Kyle and Keating 2024).

of treatment due to the hassle costs imposed on physicians. We are unaware of previous studies that have quantified this distortion, which is an important welfare cost of prior authorization.[7]

More broadly, our analysis adds to the growing literature on the effects of administrative burdens in health care. Previous studies have documented how various administrative burdens reduce spending and limit both inappropriate and appropriate use of health services. Examples include billing denials (Dunn et al. 2024), prescription drug monitoring programs (Alpert et al. 2024), Medicare claim audits (Shi 2024), and spending caps on physical therapy (Gandhi and Shi 2025). There is also a long literature documenting how administrative burdens, or "ordeals", can screen individuals and influence the take-up of public programs (Nichols and Zeckhauser 1982; Shepard and Wagner 2025; Ericson et al. 2025). We show that burdens imposed after enrollment can be just as consequential for who ultimately receives program benefits.

The remainder of the paper is organized as follows: Section 2 provides background on the prior authorization process for drugs in Medicaid. Section 3 describes the data sources and sample construction. Section 4 outlines the empirical strategy. Section 5 presents the main results, including the overall impact of prior authorization on drug use and spending and the underlying mechanisms. Section 6 presents the robustness tests and Section 7 examines the heterogeneity in the treatment effect. Finally, Section 8 concludes the paper.

## 2 Background

### 2.1 Prior Authorization Policies

Prior authorization is a utilization management tool widely implemented by health insurers for healthcare services and prescription drugs. It requires healthcare providers to obtain advance approval before specific medications can be covered by insurance. It is extensively employed

[7] Brot-Goldberg et al. (2023) comes closest to examining this in the setting of Medicare Part D. However, because they cannot directly observe which types of patients are screened out by prior authorization, they do a bounding exercise assuming a "perfect" screening scenario where the lowest willingness-to-pay patients are screened out and a "random" screening scenario. They find a social welfare gain only in the perfect case, suggesting that "to improve social welfare, prior authorization need to do a very good job screening out use by those with low value." Our approval criteria data let us estimate the screening effect directly. We find that most of the reduction in use falls on patients who meet the insurer's own criteria, which is far from the perfect screening case under which their welfare analysis produces a positive outcome.

across Medicaid, Medicare, and commercial insurers to control costs and reduce potentially unnecessary or inappropriate care.

The prior authorization process typically involves several sequential steps. When prescribing a medication requiring prior authorization, providers must submit detailed documentation justifying medical necessity, which often includes the patient's diagnosis, previous treatment history, and clinical rationale for the specific medication choice. This documentation is reviewed against predetermined criteria set by the insurer. If denied, providers can appeal through a formal review process, which often requires additional clinical documentation and involves case-by-case review. Once approved, patients can obtain the medication at the covered out-of-pocket price.

### 2.2 Prior Authorization in Pennsylvania's Medicaid Program for ADHD Drugs

#### A. Pennsylvania Medicaid Coverage of Prescription Drugs

Pennsylvania's Medicaid program is the fourth largest in the U.S., covering 2.4 million beneficiaries at a cost of $29 billion in 2017, of which $3.5 billion was spent on outpatient prescription drugs (PA Department of the Auditor General 2019). We focus our analysis on children and young adults ages 4-23, who qualify for Medicaid based on income, disability (Supplemental Security Income), or pregnancy criteria.[8]

Pennsylvania contracted with seven Medicaid Managed Care (MMC) plans, covering around 90% of all Medicaid beneficiaries[9], during our study period from 2017-2018.[10] Federal regulations require Medicaid to cover all drugs but allow states to have considerable flexibility in the

[8] Eligibility for Medicaid is determined under two main categories. The first category is based on the Modified Adjusted Gross Income (MAGI), which includes children aged 18 and under (infant based on income up to 215% FPL, age 1 to age 5 based on income up to 157% FPL, age 6 to age 18 based on income up to 133% FPL), pregnant women until one year postpartum (based on income up to 215% FPL), parent caretakers of children under 21 and adults ages 19-64 with income at or below 133% FPL. The non-MAGI group includes individuals who are blind and/or disabled, Medicaid Assistance for Workers with Disabilities, and individuals receiving long-term care or home and community-based services. More details on eligibility criteria can be found on the PA Medicaid website (https://www.pa.gov/agencies/dhs/resources/medicaid/medicaid-general-eligibility.html) and Medicaid Assistance Eligibility Handbook (http://services.dpw.state.pa.us/oimpolicymanuals/ma/index.htm#t=Title_Page.htm).

[9] Fee-for-service (FFS) covers the remaining 10% of Medicaid enrollees in Pennsylvania, including individuals who are dually eligible for Medicare and Medicaid, as well as those residing in skilled nursing facilities or state-run institutions. This study focuses on managed care plans, which account for the majority of Medicaid enrollment for non-institutionalized kids and young adults.

[10] The Pennsylvania Medicaid program is divided into five service regions, each offering multiple managed care plan options to beneficiaries.

implementation of formulary design (e.g. preferred drug lists), prior authorization, and other utilization management strategies. When pharmacy benefits are provided by MMC plans, each plan independently manages its prescription drug benefits and retains discretion in designing its own drug formularies and establishing prior authorization criteria.[11] This decentralized approach can lead to variation in prior authorization requirements across plans within the same state, potentially creating administrative complexity for providers who must navigate different criteria and submission processes for patients in different plans. The prior authorization processes are subject to approval from Pennsylvania's Medicaid agency to ensure compliance with state minimum coverage requirements. Additionally, MMC plans have some discretion in setting cost-sharing amounts, but copays must not exceed federal and state limits.[12] In Pennsylvania, copays are capped at $3 for brand drugs and $1 for generics for all plans. Beneficiaries under age 18 are exempt from copays.[13]

### B. Prior Authorization of ADHD Drugs

We study prior authorization for prescription drugs to treat attention-deficit/hyperactivity disorder (ADHD). In the U.S., approximately 1 in 9 children have ever received an ADHD diagnosis (Danielson et al. 2024). ADHD medications—stimulants and non-stimulants— together with behavioral therapies are recommended to be the first-line therapy for children aged six years and older (American Academy of Pediatrics 2011).[14] Behavioral therapies are typically more

[11] In Pennsylvania, the prior authorization process needs to be initiated by phone or fax. After providers submit a prior authorization form along with supporting documents to the MMC, pharmacists in MMCs review each request and decide whether to approve or deny treatment. MMCs are required by the state Medicaid program to provide a response within 24 hours. However, if additional supporting documents are requested, the process may extend beyond this timeframe.

[12] Pennsylvania does not impose a statewide prescription cap on the total number of prescriptions or refills (Lieberman et al. 2016) in our study period. However, individual drugs may be subject to quantity limits, which are managed separately by each Medicaid managed care plan (MMC) and typically do not vary by patient age.

[13] While the minimum age at which prescription drug copayments can be charged is 18 (see https://www.pa.gov/agencies/dhs/resources/medicaid/copay-help.html#accordion-ea5833630f-item-9b20b25be1), Medicaid managed care plans (MMCs) may choose to begin imposing copays at a later age. Since we leverage age variation in prior authorization restrictions, we will account for any copay differences across plans which change discontinuously at the age cutoffs. Specifically, for age 18 and 21 prior authorization changes, we will test for the effect of copay changes by restricting our analysis to plans that have the same copay schedule around the age cutoff. We find that these copay changes do not influence our estimates. Prior authorization changes under age 18 are unaffected by copay changes because copays are always zero for all plans.

[14] The FDA approves ADHD medications for specific age groups based on clinical trial evidence and safety profiles. Stimulants are the primary category of ADHD medications and are generally approved as first-line treatments for children aged six years and older, while behavioral therapy is often recommended as the primary intervention for children under six years of age.

costly than ADHD medications, as many ADHD drugs are available in generic form. Timely access to ADHD medications is crucial for mitigating the adverse effects of the condition, such as long-term academic and behavioral challenges (Harstad et al. 2014; Arnold et al. 2020). However, stimulants, the primary drug class used in ADHD treatment, carry their own risks including the potential for misuse, substance use and other adverse effects (Cooper et al. 2011). To balance these benefits and risks, prior authorization is heavily implemented for ADHD medications.

In Pennsylvania, MMC plans implement age cutoffs for prior authorization such that children below (or above) a certain age must obtain prior authorization for ADHD medications, while children on the other side of the cutoff can obtain the same medication without prior authorization. These age-based prior authorization requirements reflect differences in clinical appropriateness and benefits across the age spectrum. We show in Figure 1 that the probability of receiving an ADHD drug increases with age—peaking at age 12 when about 10% of Medicaid beneficiaries receive an ADHD drug—and then declines in later adolescence.[15] Plans will typically require prior authorization for patients at the extremes of the age distribution (i.e., under age 6 and over age 18 or 21), when ADHD treatment is less common and patients may be more marginal for treatment.

These age-based prior authorization restrictions are commonly implemented in Medicaid programs for ADHD, but there is considerable variation in age cutoffs across states and MMC plans (Hulkower et al. 2017; MACPAC 2024). In Pennsylvania, three MMC plans require prior authorization based on age while the other four plans do not impose any age cutoffs. This makes Pennsylvania an advantageous setting for our analysis because we can estimate changes in prescription use at age cutoffs in treated plans compared to control plans that do not have the same age cutoff, using a difference-in-discontinuities (RD-DID) design. As shown in Figure 2, UnitedHealth requires prior authorization only for children under age 6. UPMC and AmeriHealth/Keystone First require prior authorization only above age 18 and 21, respectively.[16]

[15] We find a similar distribution of ADHD drug use by age using the MEPS for Medicaid and privately insured patients.

[16] AmeriHealth and Keystone First are listed as two separate plans for consumers, but Keystone First is part of the AmeriHealth umbrella. These two plans share the same formulary and prior authorization guidelines for ADHD drugs, so we combine these two plans together in the analysis. We impose two sample restrictions involving UnitedHealthcare (UHC). First, during the first six months of our sample period, UHC required prior authorization for a subset of ADHD drugs above age 18 and revised this policy a few times. Because UHC was neither a clean treated plan nor a clean control plan at this age-cutoff during that period, we exclude UHC from the analysis of the

At each age cutoff, the plan whose prior authorization requirement changes at that age is the treated plan and all other plans are in the control group. The remaining four plans (Gateway, Health Partner, Aetna, and Geisinger) are always in the control group because they either require prior authorization for ADHD drugs across all ages or do not impose prior authorization requirements at any age.[17]

These age cutoffs apply to nearly all ADHD medications. At the age 18 and 21 cutoffs, the prior authorization restriction applies to virtually all drugs.[18] The one main exception is at the age 6 cutoff, where the immediate release version of Adderall was available without prior authorization before age 6. Consequently, for patients under age 6, physicians could prescribe the less-expensive Adderall without incurring the administrative burden. In our main analysis, we apply the age cutoffs to the entire drug class and focus on estimating the extensive margin outcome of whether a patient receives an ADHD drug or not. We do this because the prior authorization requirements cover nearly all ADHD drugs, making substitution less important in our context. Additionally, drugs not directly subject to prior authorization may still be affected via substitution effects in prescribing, so a class-level measure better captures overall effects of prior authorization on prescription drug access.[19]

For patients subject to prior authorization based on age, their provider must submit documentation demonstrating that they meet the plan's approval criteria for medical necessity. These criteria define the set of patients who the insurer intends to screen out from treatment. The specific approval criteria vary across plans but typically include proof of ADHD diagnosis that meets DSM-V criteria, failure of alternative therapies and medications (i.e., step therapy), or a comprehensive evaluation from a specialist such as a pediatric neurologist (see example criteria in Appendix Figure A.1).

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age 18 cutoff. Second, UHC temporarily suspended its prior authorization requirement at age 6 from September 2017 through January 2018. We exclude these months from the analysis of the age 6 cutoff.

[17] In robustness tests, we test the sensitivity of our results to alternative control groups (e.g., plans that have prior authorization at all ages or never have prior authorization). The results are not sensitive to how the control group is constructed because there are no discontinuities in utilization at these age cutoffs for the other plans.

[18] At the age-21 threshold, non-preferred drugs require prior authorization both below and above the cutoff. The change in prior authorization requirement applies only to preferred drugs. However, non-preferred products represent <1% of market share.

[19] In Section 5.1.C, we conduct additional analysis that estimates substitution effects for the drugs not subject to prior authorization, although these drugs account for a very small share of prescribing.

## 3 Data and Sample Construction

### 3.1 Prior Authorization Guidelines and Approval Criteria

We obtained each MMC plan's prior authorization guidelines and drug formulary in Pennsylvania's Medicaid program through a Freedom of Information Act (FOIA) request. The drug formulary indicates whether each drug is preferred or non-preferred and whether there is prior authorization, step therapy requirement, and quantity limits for that drug. Importantly for our study, the guidelines specify the age groups for which prior authorization is required. The prior authorization guidelines also show the specific criteria used by each MMC plan to determine whether to approve or deny treatments for ADHD drugs. These criteria consider some or all of the following factors: the patient's diagnosis, prescribing doctor's specialty, and patient's drug usage history (e.g., whether certain drugs were previously used and failed). We use this information to identify which patients in our sample are likely to meet these criteria and quantify the share of the utilization effect that is due to ineligible patients being screened out by these approval rules versus eligible patients being deterred by hassle costs.

### 3.2 Medicaid Claims

We use the Transformed Medicaid Statistical Information System (T-MSIS) administrative data for the Pennsylvania Medicaid program for 2017-2018, obtained from the Centers for Medicare & Medicaid Services (CMS). These data provide comprehensive information on beneficiary demographics, monthly enrollment status, managed care plan, prescription drug utilization, and outpatient service use within the Medicaid program.[20] Through unique beneficiary identifiers, we constructed a dataset that tracks individual enrollment status and prescription drug utilization at each age measured in months. We identify all ADHD medications in the Medicaid prescription claims by NDC and link these data with the formulary and prior authorization criteria based on the enrollee's managed care plan. Reports from CMS and Mathematica confirm the high quality and reliability of the prescription utilization variables in the T-MSIS data (CMS 2024).

### 3.3 Medicaid State Drug Utilization Data (SDUD)

[20] Pharmacy-PBM discount programs (e.g., GoodRx) only account for 3.82% of U.S. prescription transactions in 2017-2019 (Curran et al. 2024), so this is unlikely to account for a significant share of fills by Medicaid enrollees.

To study how prior authorization affects drug spending, which is not fully captured in the claims, we use Medicaid State Drug Utilization Data (SDUD) in 2017 to 2018 to obtain ADHD drug prices for Pennsylvania's Medicaid program. SDUD records the total number of prescriptions and total amount of reimbursement for each NDC that is used in the Medicaid program for each state separately for Fee-For-Service and MMC plans. SDUD derives more accurate spending information from the Medicaid Drug Rebate Program.[21] We construct the ADHD drug prices at the NDC level by dividing the total amount of Medicaid reimbursement by the total number of prescriptions among MMCs in Pennsylvania. We further compute ADHD drug spending for beneficiaries by multiplying the price of each drug (constructed using the SDUD) by the number of prescriptions in the Medicaid claims.

### 3.4 Sample Construction and Summary Statistics

We restricted our analysis to Medicaid beneficiaries aged 4 to 23 as this age range encompasses the primary age group for ADHD medication utilization. In our RD analysis, we further restrict to one-year bands around each prior authorization age cutoff. We defined monthly enrollment status based on a minimum threshold of 15 enrolled days per month and included only beneficiaries with at least one month of Medicaid enrollment between January 2017 and December 2018.[22] The final analytical sample comprises 1,445,123 beneficiaries in 2017 and 1,466,168 beneficiaries in 2018. We construct the dataset at the beneficiary-age level, with age measured in months. For each beneficiary, we include only the ages during which they maintained Medicaid enrollment. We measure both prescription drug utilization and outpatient service use during these corresponding ages.

Table 1 presents summary statistics for our sample around the three prior authorization age cutoffs. The demographic characteristics are mostly comparable between treated and control plans at each of these cutoffs, suggesting minimal selection bias in plan enrollment patterns.[23] We will test for the causal effects of prior authorization in the next section.

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[21] We follow Dranove et al. (2021) and Starc and Wollmann (2022) to construct drug spending and price.

[22] We also exclude beneficiaries simultaneously enrolled in the CHIP program (determined by the presence of duplicate demographic information in the data).

[23] The one exception is the share of white beneficiaries, which differs between treated and control plans around age 18. This difference reflects geography rather than selection: UPMC, the treated plan, enrolls beneficiaries mainly in western and central Pennsylvania, where the population is predominantly white.

## 4 Empirical Strategy

To understand the causal effect of prior authorization on ADHD drug prescribing, we leverage age-based discontinuities in prior authorization requirements which vary across Medicaid managed care plans. We begin by estimating a separate regression-discontinuity (RD) equation at each age cutoff, comparing ADHD use for patients who are just above versus just below the age cutoff for prior authorization. This RD strategy allows us to disentangle the effects of prior authorization from other insurance design features (e.g. copays, physician reimbursement, etc.) that are often implemented simultaneously but do not vary by age. For each age cutoff—ages 6, 18, 21— we estimate the following specification for the plan subject to the change in prior authorization requirements:[24]

$$Y_{ipa} = \alpha_0 + \alpha_1 D_{pa} + \alpha_2 f(Age_i) + \alpha_3 f(Age_i) \cdot D_{pa} + \Sigma_k X_{it}^k \gamma^k + \epsilon_{ipa} \quad (1)$$

where $Y_{ipa}$ is the outcome of interest for beneficiary $i$ enrolled in managed care plan $p$ with age in months $a$. $D_{pa}$ is a binary indicator for whether the beneficiary needs prior authorization to obtain ADHD drugs at age $a$ in plan $p$. Specifically, $D_{pa}$ equals 1 for beneficiaries under age 6 in UnitedHealth, over age 18 in UPMC, and over age 21 in AmeriHealth/Keystone First, and equals 0 on the other side of each cutoff. $f(Age_i)$ denotes a smooth function of beneficiaries' age in months, the running variable, and we allow separate trends on either side of the age cutoff via the interaction between $f(Age_i)$ and $D_{pa}$. $\alpha_1$ is the coefficient of interest and represents the treatment effect of prior authorization. Guided by the visual inspection of raw data, we use a global second-order polynomial as the main functional form for the smooth function of the running variable, with a 12-month bandwidth. We test different functional forms and different bandwidths, including the optimal bandwidth proposed in Calonico et al. (2020), in the robustness checks. $X_{it}^k$ is a set of controls including female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

[24] We separately estimate this equation for all other plans which do not have the same prior authorization age cut-off as a placebo test.

Next, we estimate a pooled RD regression aggregating the effect of prior authorization across all three age cutoffs. We normalize the running variable, pool the three age cutoffs together and estimate the following equation:

$$Y_{ipa'} = \alpha_0 + \alpha_1 D_{pa'} + \alpha_2 f(Age_i) + \alpha_3 f(Age_i) \cdot D_{pa'} + \sum_k X_{it}^k \gamma^k + \epsilon_{ipa'} \quad (2)$$

where $a'$ is the standardized age around each age cutoff, running from -12 to 12 months, and $f(\text{Age}_i)$ is the smooth function of the standardized age in months. This allows us to estimate the overall effect of prior authorization using variation from three quasi-experiments simultaneously. This pooled RD estimate—the so called "double average" (Cattaneo et al. 2016)— captures the combined treatment effect across all cutoffs weighted by the density around each cutoff and the likelihood of each individual being near a cutoff. We use the pooled RD estimate as our main estimate and also report estimates from the separate age-cutoffs to examine heterogeneity across ages.

Finally, to formalize the comparison between treated and control plans, we estimate a difference-in-discontinuities (RD-DID) regression interacting each term in the RD equation with an indicator for whether the beneficiary is enrolled in a treated plan.[25] This approach enables us to directly control for unobserved shocks at the age cutoffs, such as state and national level policies that vary by age but not across plans within Pennsylvania (e.g., Medicaid eligibility thresholds, FDA approval criteria and clinical guidelines for ADHD drugs, school entry age, etc.). We estimate the following equation:

$$\text{Y}_{\text{ipa}} = \delta_0 + \delta_1 f(\text{Age}_\text{i}) + \text{D}_{\text{pa}}(\gamma_0 + \gamma_1 f(\text{Age}_\text{i})) +$$

$$\text{T}_{\text{ip}}\left[\alpha_0 + \alpha_1 f(\text{Age}_\text{i}) + \text{D}_{\text{pa}}(\beta_0 + \beta_1 f(\text{Age}_\text{i}))\right] + \sum_k X_{it}^k \gamma^k + v_{iap} \quad (3)$$

[25] Around age 6, United Health is the treated plan and all other plans (AmeriHealth/Keystone First, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 18, UPMC is the treated plan and all other plans (United Health, AmeriHealth/Keystone First, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 21, AmeriHealth/Keystone First is the treated plan and all other plans (United Health, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans.

where $T_{ip}$ equals 1 when patient $i$ is enrolled in a treated plan. $\beta_0$ is the coefficient of interest, representing the difference in the discontinuity of outcomes at the age cutoffs between treated and control plans.[26]

The identifying assumption of our RD design is that ADHD drug use would trend smoothly across the age distribution near the age discontinuities absent changes in prior authorization requirements. To test this assumption, we examine the balance of covariates around the age cutoffs. The results in Appendix Table A.1 indicate that RD estimates of the beneficiary's gender, race, eligibility category and ZIP code-level median income are either statistically insignificant or have small point estimates in treated plans, suggesting no meaningful differences in pre-determined demographic characteristics around the age thresholds. The covariates are also balanced using the RD-DID specification, demonstrating that the demographic characteristics are not trending differently in treated and control plans near the age cutoffs. Most importantly, as we show in Section 5, ADHD drug use trends smoothly around these age thresholds in control plans, where there is no change in prior authorization requirements, providing the most direct test of our identifying assumption.

We further use these specifications to examine heterogeneity in the effects of prior authorization for patients who are likely eligible versus ineligible for ADHD treatment based on the insurer's approval criteria to disentangle hassle and screening effects. We also estimate spillover effects on patients not subject to prior authorization. We describe these analyses in more detail in Sections 5.3 and 5.4.

# 5 Results

## 5.1 Impact on ADHD drug use and spending

*A. Drug Utilization*

We begin by examining the impact of prior authorization on ADHD drug use and spending. We focus on the extensive margin effect and measure drug use as the probability of having any ADHD prescription. Figure 3 presents the proportion of beneficiaries using any ADHD drug in

[26] We include the same control variables as in Eq. (1) and (2) except that managed care plan fixed effects are subsumed by the treatment indicator. We do not interact the controls with the treatment indicator, thus constraining the coefficients to be the same for treated and control plans.

treated and control plans around the age cutoffs of 6, 18, and 21. In all three panels, ADHD drug use exhibits a clear discontinuity in treated plans at each age threshold where prior authorization begins but trends smoothly among control plans.

The figures show two additional patterns. First, the gap between treated and control plans persists in the months after the cutoff, suggesting that prior authorization leads to a more sustained reduction in the likelihood of treatment rather than simply delaying treatment. Second, we do not observe bunching in use near the age cutoffs. This suggests that patients and providers are not systematically postponing treatment until the prior authorization requirement lifts at age 6 or shifting prescriptions earlier at ages 18 and 21. Taken together, these patterns suggest limited anticipatory behavior around the cutoffs.

Column (1) in Table 2 quantifies the magnitudes of these effects on drug use for treated plans. Column (1) shows that prior authorization decreases the probability of filling any ADHD prescription by 10.6% at age 18 and 29.4% at age 21. At age 6, the point estimate indicates a 7.7% reduction, although this effect is not statistically significant. Overall, across the three age cutoffs, using Eq. (2), prior authorization reduces ADHD drug use by 14.7% on average.[27] In column (2), we show placebo tests on control plans where there are no age-based discontinuities in prior authorization requirements. In the control group, we find no evidence of discontinuities in prescription use in the absence of prior authorization changes as the coefficients are all close to zero and not statistically significant.

The RD-DID estimates closely mirror those from our main specification.[28] Prior authorization reduces the probability of using ADHD drugs by 14.5% (compared to 14.7% in the main RD specification). This similarity is expected given that the RD estimates for the control plans are close to zero.

### *B. Drug Spending*

[27] We also examine whether there is a discontinuity in ADHD diagnosis. Appendix Table A.3 shows no discontinuity in enrollees' ADHD diagnoses, indicating that the effects we observe are not driven by shifts in the diagnostic composition of the patient population.

[28] Because we do not interact control variables with the treatment indicator, the RD-DID estimates differ slightly from simply taking the difference between columns (1) and (2).

We also examine the effects of prior authorization on drug spending, as reducing costs is a key rationale for state Medicaid programs to implement prior authorization. Figure 4 illustrates average ADHD drug spending among all beneficiaries in treated and control plans around the three age cutoffs. As expected, ADHD drug spending decreases sharply at all three age thresholds among treated plans, while spending trends remain smooth for control plans. In Column (4) of Table 2, the estimated magnitude of the discontinuities is 16.2% around age 6, 10% around age 18, and 29.8% around age 21, which are all statistically significant at the 1% level. Across all three age cutoffs, prior authorization reduces ADHD drug spending by 13.7% relative to a baseline mean of $7.43 per beneficiary per month. The RD-DID estimates show a similar decrease in ADHD drug spending by 12.8%.

### *C. Drug Prices*

Because prior authorization applies to nearly all ADHD medications at the age cutoffs, reductions in spending primarily reflect reductions in utilization rather than substitution to cheaper drugs. The one exception is at the age 6 cutoff where the treated plan allows the immediate release version of Adderall to be prescribed without prior authorization before age 6, while making Vyvanse—one of the most frequently prescribed branded medications—along with all other ADHD medications subject to prior authorization, effectively encouraging substitution toward the cheaper alternative.[29] Consistent with this, Appendix Figure A.2 and Appendix Table A.2 show a discontinuous reduction in drug prices around age 6 of 22.8% for treated plans, but no significant discontinuity is observed around ages 18 and 21. We further show that at age 6, use of drugs subject to prior authorization falls by 18.5%, while use of exempt drugs rises by an imprecisely estimated 17.5% (as shown in Appendix Table A.4 and Figure A.3). This helps to explain the smaller and less precise utilization effect at the age 6 cutoff, because utilization for the two groups of drugs partially offset each other. We find no substitution effects at the later age cutoffs, where prior authorization applies to nearly all ADHD medications.[30] Taken together, we find that prior

[29] As discussed previously, our main specification considers all ADHD drugs as treated when prior authorization turns on in a plan. In Appendix Figure A.3 and Table A.4, we separately consider the drugs that require prior authorization (treated drugs) versus those that do not (control drugs). Most ADHD drugs require prior authorization, so there is minimal opportunity for substitution to avoid the prior authorization requirement. At baseline, 0.6% of beneficiaries who are age 6 use any control drugs that do not require prior authorization (compared to 2.3% who use treated drugs). There are no control drugs at age 18 and almost no beneficiaries use control drugs at age 21.

[30] It is worth mentioning that the price effect at the age 6 cutoff could relate to treatment initiation timing. Age 6 often coincides with the initiation of ADHD treatment, where the choice of medication is particularly significant. It

authorization significantly reduces ADHD medication use and spending. For the remainder of our analysis, we estimate the pooled effect across the three age cutoffs to study other effects of prior authorization and its implications for treatment targeting.

### 5.2 Delays in filling ADHD prescriptions

Next, we investigate whether prior authorization delays access to ADHD medications. Even when a prescription is ultimately filled, the hassle costs associated with the prior authorization process, which involves submission and manual reviews of medical documents, can introduce delays. We measure these delays using three metrics: (1) the number of days between the drug prescription date and fill date, (2) the probability of filling the prescription on the same day as it was written, and (3) the probability of filling the prescription within seven days of the prescription date.

Table 3 summarizes the estimated effects of prior authorization on these outcomes. Column (1) shows that prior authorization significantly increases the average time to fill a prescription by 2.4 days, representing a 17.3% increase relative to the pre-policy mean of 14 days. Additionally, prior authorization reduces the likelihood of same-day fills by 10 percentage points, corresponding to a 29.5% decline from the baseline mean. Prior authorization also reduces the probability of filling the prescription within seven days by 8.1 percentage points, reflecting a 13% drop. In contrast, the results for control plans are close to zero, as shown in Panel B. These findings highlight the substantial delays introduced by the prior authorization process, which may hinder timely access to ADHD medications. While these delays could result from both submission and review procedures inherent to prior authorization and patients' delayed actions in filling prescriptions, the findings particularly underscore the significant hassle costs associated with obtaining prior authorization approval.

### 5.3 Hassle vs. Screening Effects of Prior Authorization

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is common for patients to try different medications for mental health conditions when starting treatment to identify the most effective option. Prior authorization policies could significantly influence which medications are available to try, while having a more minimal impact on overall initiation rates. In contrast, older patients are more likely to have established medication regimens and may choose to forgo treatment if they cannot access their preferred drug. These differential responses could motivate insurers to strategically steer patients toward preferred medications at younger ages when treatment patterns remain malleable, rather than at older ages. Our results highlight the importance of jointly considering patient-side clinical factors and insurer-specific prior authorization policy designs when evaluating the overall effectiveness of prior authorization as a policy tool.

Prior authorization affects not only the overall level of drug use and delays in treatment, but also *who* receives treatment. Prior authorization can affect treatment targeting through two channels. First, it can reduce ADHD drug use among patients who do not meet the approval criteria. We refer to this channel as the "*screening effect.*" Such screening can occur on both the insurer side and the provider side: insurers deny requests for patients who fail to meet the criteria, and the criteria themselves may prompt providers to self-screen a patient's clinical eligibility more carefully before prescribing, leading them to choose not to prescribe if the patient does not meet the criteria. By restricting treatment to medically eligible patients, screening can potentially improve the targeting of prescribing. Second, prior authorization imposes administrative burdens on providers, who must compile and submit supporting documentation to obtain approval. These burdens may deter prescribing for patients who meet the approval criteria. We refer to this channel as the "*hassle cost effect*." Because insurers rely on physicians to supply the information needed to verify clinical eligibility, hassle costs can potentially worsen the targeting of treatment when they lead providers to forgo the authorization process for eligible patients.

In Appendix B, we present a model of prescribing under prior authorization that formalizes these two channels and shows why separating them matters for welfare. In the model, physicians rank patients by clinical benefit but do not internalize the full cost of the drug, so in the absence of prior authorization, some patients will receive treatment whose health benefit from the drug is lower than the drug's cost. In other words, utilization exceeds the socially efficient level, which is what creates a role for utilization management. Prior authorization then reduces use through the two channels, and they have opposite welfare consequences. The screening effect is welfare-improving: it reduces drug use among ineligible patients, for whom the drug costs are greater than the health benefit (green area in Appendix Figure B.2). The hassle cost effect is welfare-reducing: it reduces drug use among eligible patients, whose treatment would generate more benefits than costs and would meet the insurer's own approval criteria (orange area in Appendix Figure B.2). The welfare effect of prior authorization therefore depends not only on how much it reduces drug use, but on the composition of the reduction: how much comes from eligible and ineligible patients. There is no existing empirical evidence on the relative size of these two groups, which we shed light on in this paper.

This decomposition also matters for the design of prior authorization policies. If the hassle cost effect dominates, such that most of the reduction in prescribing falls on eligible patients, the binding margin is the filing process itself. Therefore, streamlining or automating prior authorization would increase treatment for patients whom the insurer's own criteria deem eligible. If instead the screening effect dominates, prior authorization operates mainly through the insurer's approval criteria, and its welfare gains hinge on those criteria correctly identifying low-value use. The relevant margin for regulation is then the quality of the criteria themselves, such as whether they reflect the most recent clinical guidelines.

We disentangle the screening and hassle cost effects by comparing the effects of prior authorization across patients based on their likelihood of meeting insurers' approval criteria. Because insurers do not observe everything a physician knows about a patient and must review prior authorization requests efficiently at scale, the criteria largely rely on a limited set of objective and verifiable information. For example, in the documents we reviewed, the approval criteria for ADHD drugs included, depending on the plan, having an ADHD diagnosis meeting the DSM-V criteria, prior experience with treatment when step therapy was required, or evaluation by a specialist such as a pediatric neurologist or psychologist. Like insurers, we observe the objective information on which these criteria are based, much of which is recorded in claims, including diagnoses, prior prescription fills, and prescriber specialty. Our data therefore approximate the information set the insurer uses to screen. We then use these criteria as the benchmark for evaluating how well prior authorization targets treatment according to its own standards for approval.[31]

We begin by defining treatment eligibility based on the presence of an ADHD diagnosis. This is a conservative starting point, which we further refine using additional criteria described below. An ADHD diagnosis is the primary approval criteria observed in all prior authorization guidelines in Pennsylvania MMC plans. For example, AmeriHealth's guideline requires that

[31] We do not take a stance on whether these criteria identify the patients who would benefit most from treatment. The treatment for ADHD, and mental health conditions in general, involves great clinical uncertainty. ADHD can be overdiagnosed or underdiagnosed, and not every patient with a diagnosis benefits from medication. Our goal is instead to evaluate how well prior authorization targets treatment according to the insurer's own criteria. This benchmark is informative regardless of whether the criteria are socially optimal: if prior authorization reduces use substantially among patients who meet the approval criteria, that suggests that it is not an effective tool for targeting treatment even if the criteria were set in a socially optimal way.

physicians must provide documentation showing that patients meet the DSM-V criteria for an ADHD diagnosis that includes at least 5 specified symptoms. While we observe ADHD diagnoses in the outpatient claims, identifying the full set of eligible patients poses some challenges. These include the limited observation period of the dataset, the under-coding of ADHD diagnoses in administrative claims, and the fact that many mental health providers do not accept insurance and may not be included in the claims data (although this may not be as much of an issue in Medicaid where most patients will likely seek providers covered by insurance). To address these challenges, we apply the LightGBM (Light Gradient-Boosting Machine) algorithm to predict whether a beneficiary had an ADHD diagnosis before the index age. The model uses a range of predictors, including demographic variables (gender, age, ZIP code), managed care plan, and all prior non-ADHD diagnoses recorded before the index age from outpatient claims.[32] We then use both observed and predicted diagnoses to classify patients. Patients with an observed ADHD diagnosis are considered eligible patients. Among patients without an observed ADHD diagnosis, those who also have a predicted probability of an ADHD diagnosis below a specified threshold[33] are considered ineligible patients.[34]

Table 4 shows the effect of prior authorization among eligible and ineligible patients based on ADHD diagnosis using the pooled RD from Eq. (2). Comparing column (1) which presents the effect among ineligible patients, and column (2) which shows the effect among eligible patients, we find that prior authorization reduces ADHD drug use by 25.4% for ineligible patients and by 17.5% for eligible patients. The larger effect for ineligible patients is consistent with prior authorization screening out some patients who do not meet coverage criteria. However, the sizable reduction for eligible patients also suggests substantial hassle costs.

[32] Diagnosis is observed in outpatient files but not in prescription drug files.
[33] Patients who do not have an observed ADHD diagnosis but have a predicted probability of diagnosis exceeding 0.5 are excluded from the ineligible group. Appendix Table A.5 shows robustness tests using alternative thresholds.
[34] This asymmetric classification rule reflects the nature of measurement error in claims data. The primary concern is missed diagnoses rather than spurious ones, so an observed diagnosis is reliable evidence of eligibility, whereas the absence of a diagnosis may reflect either true ineligibility or a diagnosis the data do not capture. The prediction step addresses the latter case. Misclassifying such patients as ineligible would matter for our decomposition: a patient with an undocumented diagnosis who stops treatment under prior authorization is responding to hassle costs, not to the screening mechanism, so including these patients in the ineligible group would attribute part of the hassle cost effect to screening leading us to bias downwards our estimates of hassle costs.

Because an ADHD diagnosis alone[35] may not be sufficient to meet all of the eligibility requirements imposed by insurers, we further refine our measure of eligibility using additional criteria specified in some plans' prior authorization requirements. These refinements ensure that we are narrowing in on the patients who are most likely to be eligible for treatment. In column (3), in addition to restricting the sample to patients with an ADHD diagnosis, we further condition on prior use of ADHD drugs, as some prior authorization guidelines approve patients based on continuation of use or separately require documented failures of previous ADHD medications which would also necessitate prior use. In column (4), we further restrict to patients whose primary provider during the study period is a pediatrician, psychologist, or neurologist, as these specialists are typically able to satisfy the requirement for an evaluation by a specialist.[36] Tightening these criteria reduces the estimated prior authorization effect to about a 10% reduction in prescription use, as stricter eligibility criteria identify patients least likely to face coverage denial. Nevertheless, the effects remain large among patients who are most likely to be approved, providing strong evidence that there are substantial hassle costs.

While the estimates in Table 4 show larger effects on utilization for ineligible patients, the relative contribution of ineligible and eligible patients to the overall decline in ADHD drug use depends on the size of these groups and their baseline rate of drug use in the absence of prior authorization. Because eligible patients have a much higher baseline rate of ADHD drug use than ineligible patients (30% vs. 0.6%), we calculate that approximately 81% of the total reduction in utilization stems from eligible patients who would likely meet approval criteria, while the remaining 19% comes from ineligible patients, based on estimates from columns (1) and (2). The decomposition is described in Appendix C and shown in Panel (a) of Figure 5. The estimates remain broadly similar across all specifications: eligible patients account for 77% of the utilization reduction using the criteria in column (3) and 66% under the strictest eligibility criteria in column (4). Because these eligible patients would likely be approved if they submitted the required paperwork, we attribute their reduction in use to the hassle costs of completing the prior

[35] Only about 30 percent of patients with an ADHD diagnosis use ADHD medication, so many diagnosed patients may not seek or be candidates for drug treatment. This does not affect our interpretation because our identification comes from the change in use at the age cutoff rather than the level of use. Diagnosed patients who would not use medication in either regime contribute no change at the cutoff.

[36] The primary provider is defined as the provider who most frequently prescribed medications to each beneficiary across all prescription drug claims between 2017 and 2018.

authorization process, while the reduction for ineligible patients is due to the screening effect. These results suggest that hassle costs, rather than improved targeting through screening, account for the vast majority of the decline in ADHD drug use.

Reassuringly, we do not observe any discontinuity for either eligible or ineligible patients among control plans, as shown in Panel B of Table 4. We also test the robustness of our ineligibility definition to different classification thresholds used in the machine learning algorithm. Table A.5 shows that the estimated effect is similar across alternative thresholds. Regardless of our approach, hassle costs explain the majority of the prior authorization effect. Prior authorization therefore deters a substantial share of treatment from patients whom its own criteria are designed to approve.

Panel (b) of Figure 5 illustrates why hassle costs dominate screening effects in our setting and the conditions under which this conclusion would be reversed. The share of the reduction attributable to eligible and ineligible patients equals that group's proportional response weighted by its share of baseline use. We use simulations with illustrative parameter values to show three scenarios where the decomposition could instead produce a dominating screening effect. The first scenario is when few patients meet the insurer's eligibility criteria. For example, this might occur for a drug that treats a condition with a narrowly defined patient population or rare disease.[37] Holding all other parameters fixed, reducing the eligible share from 11% (as in the case of ADHD) to 1% moves the point down along the same red curve, lowering the hassle cost share to 26% (lower red dot). Intuitively, when relatively few patients are eligible, there are many more opportunities for prior authorization to reduce use among patients who do not meet the criteria, leading the screening effect to dominate. The second scenario is when drug use is relatively high among patients who do not meet the insurer's criteria. This may occur for drugs that have substantial off-label or low-value use, or when a drug has the potential for misuse.[38] Raising baseline use among ineligible patients from 0.6% (as in the case of ADHD) to 5% shifts the curve down (blue curve) and lowers the hassle cost share to 35%. When there is substantial drug use among ineligible patients, there is greater scope for prior authorization to screen out patients, making the screening effect more important. Finally, estimating substantially different treatment

[37] For example, PCSK9 Inhibitors can lower cholesterol in a broad population of patients with hyperlipidemia, but an insurer could restrict coverage to a narrower group of high-risk patients with a genetic subtype of familial hypercholesterolemia (Doshi et al. 2018).

[38] Examples might include antipsychotics prescribed to young children or drugs with potential for misuse such as opioids or benzodiazepines.

effects for the ineligible and eligible groups could also reverse our conclusion. For example, if we estimate treatment effects of 60% for ineligible patients and 3% for eligible patients (compared to 25% and 18% as in the case of ADHD), the curve shifts down further (purple curve) and the hassle cost share falls to 24%. This could occur, for example, if eligibility could be automatically determined based on easily observed criteria at the pharmacy counter, making hassle costs negligible for eligible patients.

In each of these scenarios, the point moves into the green region, where the screening effect dominates. ADHD medications have none of these features. ADHD is common among children and young adults, so a large share of patients meet the eligibility criteria; most drug use occurs among eligible patients (i.e., providers rarely prescribe these medications to patients without a diagnosis even in the absence of prior authorization); and the process requires substantial documentation which creates administrative burdens even for patients who are likely to be approved. Thus, when prior authorization is applied to drugs for common conditions where a substantial proportion of use is already consistent with approval criteria, hassle costs are more likely to dominate screening effects. This case is likely to generalize to many other commonly used drug classes that are currently restricted through prior authorization in Medicaid.

### 5.4 Spillover effects of prior authorization across patients

In this section, we examine potential spillover effects of prior authorization policies—another unintended impact of these policies which might also affect the targeting of prescription drug access. While prior authorization is designed to target specific patients or managed care plans, its impact may extend beyond the directly affected groups through changes in physician's prescribing behavior. Physicians handling prior authorization requests operate under resource constraints and limited attention. The administrative burden imposed by prior authorization can shape their prescribing practices by influencing how they allocate time and effort across patients. Physicians may also develop simplified prescribing heuristics in response to frequently encountered restrictions, applying similar prescribing patterns to all patients regardless of their specific insurance requirements. There may also be learning from the insurer approval criteria which might raise the threshold for prescribing. Such prescribing heuristics or learning can cause prior authorization policies to influence those patients not directly subject to the restrictions.

To conduct this analysis, we exploit variation across physicians in the composition of their patients' insurance plans. Physicians see patients with coverage from multiple Medicaid managed care plans and there is significant variation across physicians in which plan is dominant for their patient panel. We examine whether prior authorization rules for a physician's dominant plan influence prescribing for their patients in other plans not directly subject to those rules. We define a provider's dominant "modal" plan as the insurance plan covering the largest share of their patients. For some providers, their modal plan is a treated plan that experiences a change in prior authorization for ADHD drugs, while for other providers, the modal plan is a control plan. We compare how prior authorization impacts patients' ADHD drug use based on the treatment status of each patient's own plan and the treatment status of their provider's modal plan.[39] Appendix Figure A.4 illustrates the resulting four groups.

Table 5 presents the pooled RD estimates of the impact of prior authorization on the probability of using any ADHD drugs, stratified by the treatment status of the patient's plan and their provider's plan. Panel A presents the estimates for patients enrolled in control plans, who should not experience any change in utilization at the prior authorization age cutoff. As expected, we do not observe a discontinuity in prescription use when patients see a provider whose modal plan is also a control plan. However, we also do not find any evidence of spillovers for patients who see a provider whose modal plan is treated. In both cases, the estimated discontinuities are statistically insignificant, with a magnitude close to zero. This suggests that providers are unlikely to adjust their prescribing behavior for patients in control plans based on their experience with treated plans. This pattern is consistent with the raw data in Figure 3, which shows no visible decline in ADHD drug use among control-plan enrollees overall.

Panel B focuses on patients whose own plans are treated and experience a change in prior authorization at the age cutoff. Comparing estimates in columns (1) and (2), we observe that the age discontinuity is twice as large when the provider's modal plan is also treated (17.2%), compared to when the provider's modal plan is a control plan (8.1%). These results suggest that the cumulative administrative burden spills over across patients, which further reduces prescription rates. Moreover, the findings suggest an absence of a learning effect related to the prior

[39] To assign patients to a provider, we use the patient's modal provider, which we define as the provider from whom the patient receives the majority of their prescriptions during the study period.

authorization process. If treated providers became more proficient in navigating the prior authorization process and achieved higher approval rates, we would expect smaller reductions in ADHD drug use among patients seeing these treated providers. Instead, the larger discontinuity among treated-plan patients whose providers' modal plans are also treated further suggests that the reduction is driven by the ongoing hassle and administrative burden of the prior authorization process, rather than by providers' lack of familiarity with how to navigate it. Overall, the only spillovers we observe are for patients whose own plan requires prior authorization at the age cutoff. Seeing a provider whose dominant plan also requires prior authorization at the age cutoff makes it less likely that the provider will prescribe and seek approval for ADHD medications.

Although our spillover analysis is confined to Medicaid data and ADHD medications, this scope is still highly policy relevant as Medicaid insures roughly 40 percent of U.S. children and ADHD medications are among the most frequently prescribed pediatric drugs. Furthermore, while physicians in our sample treat both Medicaid and commercially insured patients, the absence of prescribing discontinuities in control plans is reassuring that contemporaneous changes in commercial prior authorization are unlikely to explain our findings. Assessing whether Medicaid prior authorization rules spill over to patients in commercial insurance remains a question for future research.

### 5.5 Substitution toward Psychotherapy

When patients lose access to ADHD medication, do they substitute toward other forms of care? We examine whether patients subject to prior authorization are more likely to use psychotherapy, the main non-drug treatment for ADHD. More specifically, we examine whether a patient has any psychotherapy claim in the three-month window beginning in the patient's current age month. Psychotherapy is the recommended first-line treatment for children under age 6, but it is more costly to insurers than most ADHD drugs, which are often generic. Appendix Table A.6 shows suggestive evidence of substitution only at the age 6 cutoff. Using the RD estimates, the probability of any psychotherapy use rises by 8% at the cutoff where prior authorization takes effect, although this is imprecise. At older age cutoffs, we find effects that are close to zero, suggesting no substitution toward psychotherapy. This is consistent with guidelines that recommend behavioral therapy for young children as first line therapy but medication as the standard of care for older children and young adults, leaving physicians with limited substitutes

at older age-cutoffs. For these patients, the reduction in ADHD medication could represent a total loss of treatment rather than a shift in the type of treatment.[40]

## 6 Robustness

We conducted a series of robustness checks to validate our results. We began with several standard checks for our RD design. Additionally, we conducted several robustness tests of our empirical specification and potential alternative explanations.

### 6.1 RD Specification

First, we performed RD analyses at different placebo cutoffs among treated plans to ensure the observed discontinuities are not spurious. We estimate this for the pooled specification in Eq. (2). Figure 6(a) demonstrates that no discontinuity is observed at any of the placebo cutoffs. Second, we estimated the effects using alternative bandwidths, including the optimal bandwidth in Calonico et al. (2020). Estimates using different bandwidths in Figure 6(b) are similar to our main estimates. Third, we use different functional forms, including global linear and local linear regressions. Figure 6(c) shows that estimates using different functional forms yield similar estimates as our main specification.

### 6.2 Impact of Copays

Prescription drug copay schedules may change after age 18 for different plans in the Pennsylvania Medicaid program. Around the age 6 cutoff, copays are required to be zero across all plans. To rule out the possibility that our observed effect is driven by any copay changes, we restricted the control plans to those with the same copay schedule as the treated plan around each age cutoff to isolate the impact of prior authorization from potential copay effects. As shown in Appendix Table A.8, no discontinuities were observed among control plans that have the same

[40] We also examine outpatient claims for office visits, behavioral and mental health services, and diagnostic encounters at each age month. Behavioral therapy is the primary non-drug treatment for ADHD, while additional office visits and diagnostic testing could indicate that patients are seeking reassessment, alternative diagnoses, or the documentation needed to satisfy the approval criteria. Appendix Table A.7 shows no significant increase in office visits or behavioral health visits following the introduction of prior authorization. If anything, prior authorization is associated with a 9% decline in diagnostic encounters in treated plans relative to control plans. These results suggest that patients who lose drug access forgo treatment rather than switch to alternatives, and the reduction in ADHD medication is not offset by greater use of non-pharmacological care.

copay schedule as treated plans and the coefficients were also stable for treated plans, suggesting that copay changes cannot explain the observed changes in prescribing.

### 6.3 Plan Switching

As beneficiaries face more than one managed care plan option in every service region in the Pennsylvania Medicaid program and they are allowed to change plan enrollment at any time[41], a potential concern is that beneficiaries would switch to a control plan without prior authorization after their access to ADHD drugs is restricted by prior authorization in a treated plan. To address this concern, we examine whether there is a discontinuity in plan switching behavior around the age cutoff for prior authorization. As shown in Appendix Table A.9, we find no evidence of any discontinuities in plan switching. This finding also aligns with our previous observation that ADHD drug use does not increase among control plans near the age cutoff. Although this exercise only rules out immediate switching in response to the prior authorization changes and beneficiaries may still switch plans over the longer term, any long-term plan switching would not bias our RD estimates, which are identified near the age cutoffs.

### 6.4 Impact of Eligibility Changes

Pennsylvania's Medicaid eligibility rules change at age 6, 18 and 19.[42] The largest change occurs at age 19 when many young adults age out of Medicaid. However, the age 19 eligibility discontinuity falls outside the 12-month bandwidth used to study the prior authorization cutoffs at age 18 and 21 and thus does not directly affect our RD estimates. The other two changes coincide with the prior authorization age cutoffs. However, we find that they do not confound our estimates for several reasons. First, although eligibility changes occur around the age cutoffs, the drop in plan enrollment is similar across both treated and control plans. To test this, we estimate the difference in discontinuities (RD-DID) in plan enrollments by age in months around the three age cutoffs using Eq. (3). As reported in Appendix Table A.10, there is no meaningful or statistically significant differential change in plan enrollment between treated and control plans. Second, we

[41] See the website of Pennsylvania Enrollment Services https://www.enrollnow.net/en/faq#:~:text=Can%20I%20change%20my%20health,plan's%20provider%20network%20(group)

[42] The income threshold for eligibility increases slightly at each of these age-cutoffs. See Pennsylvania Medicaid/Medical Assistance General Eligibility Requirements: https://www.pa.gov/agencies/dhs/resources/medicaid/medicaid-general-eligibility.html

showed previously that there was no change in ADHD drug use around the age cutoffs for control plans, suggesting that the decline in enrollment did not alter the composition of beneficiaries who would use ADHD medications. Third, we re-estimate our main specification using a sample of individuals who remain continuously enrolled in their plan across the age cutoff.[43] The estimates in Appendix Table A.11 show a similar reduction in ADHD drug use and spending as the main results among continuously enrolled beneficiaries in treated plans, despite reduced statistical power due to a much smaller sample. We do not observe any discontinuity in outcomes among continuously enrolled beneficiaries in the control plans. Finally, to address potential eligibility-code changes at age thresholds, we re-estimate the main specification with individual fixed effects to control for time-invariant individual factors. Appendix Table A.12 shows the estimates are similar to our main results.

### 6.5 Alternative Construction of Control Group

In our main specification, the control group includes both plans that impose prior authorization at all ages ("always treated") and plans that never impose prior authorization at any age ("never treated"). To address the concern that these two types of plans may differ, we separately estimate the RD-DID discontinuities in drug use and spending including each group of plans separately. Appendix Table A.13 shows that the RD-DID estimates are not sensitive to how we construct the control group because ADHD drug use trends smoothly in control plans.[44]

### 6.6 Impact of ADHD Drug Approval and School Age

A potential concern for our estimates around age 6 is that the FDA approval age for many ADHD drugs and the start of compulsory schooling coincide with the age cutoff in prior authorization. Age 6 is the first year of compulsory schooling in Pennsylvania. This may confound our results due to increased ADHD medication use linked to school enrollment (Layton et al. 2018). Additionally, most ADHD drugs are approved for use at age 6 and above.[45] However, two features of our RD-DID research design mitigate these concerns. First, our running variable is measured as

[43] Continuous enrollment is defined as being enrolled in the treated/control plans at centered age -1, 0 and 1.
[44] While the approval criteria may change at age cutoffs for "always treated" plans, that does not affect our estimates. Both control groups produce similar results.
[45] Adderall (Immediate Release), ProCentra, and Zenzedi are approved for age 3 and above. Mydayis are approved for age 13 and above. Among these exceptions, only Adderall IR is widely used; the combined market share of the other drugs is below 3%.

age in *months* so identification comes from the exact month a child turns 6, whereas school entry typically begins in September. Moreover, treatment initiation does not necessarily coincide with the child's exact birthday month but is spread across the year in which the child turns 6. Second, our control plans act as a falsification test. Since we did not find any evidence of discontinuities in ADHD drug use at the age 6 threshold, this rules out the possibility that the observed effects are driven by the FDA drug approval age or compulsory school entry.

### 6.7 Impact of Prior Authorization for Other Mental Health Drugs

Another potential concern is that the estimated discontinuities could be driven by prior authorization requirements for other psychotropic agents, given the high comorbidity between ADHD and conditions such as depression or schizophrenia. We therefore reviewed prior authorization policies for antidepressants and antipsychotics over the study window and found that a subset of plans applied an age-18 prior authorization threshold for these drug classes, where prior authorization was required for enrollees younger than 18. To test for spillovers, we re-estimate Eq. (1) within the control sample, stratifying plans into those with and without an age-18 cutoff for antidepressants or antipsychotics, using any ADHD prescription as the outcome. Appendix Table A.14 shows that the estimated discontinuity for ADHD use among these control plans at age 18 is economically small and statistically indistinguishable from zero. These null results rule out spillover effects from non-ADHD drug policies, confirming that the observed reduction in ADHD prescribing is attributable to the ADHD-specific prior authorization requirement rather than to concurrent restrictions from other psychotropic agents.

## 7 Heterogeneity in Prior Authorization Effects on Drug Use and Spending

The impact of prior authorization differs across age thresholds as shown in Table 2. This variation may stem from three potential sources: age-specific effects (heterogeneous treatment effects at each age threshold), plan-specific implementation (insurers managing prior authorization requirements differently), and patient composition differences (varying patient populations due to Medicaid eligibility rules). Differences in patient population composition are not likely to explain

these differences because we control for these changes using control plans within the state.[46] However, we cannot rule out heterogeneous treatment effects by age or plan-specific prior authorization requirements. Regarding plan implementation, we analyzed the detailed prior authorization requirements we collected from all plans. All insurers require providers to provide documentation of an ADHD diagnosis, but AmeriHealth imposes additional constraints at age 21, including documented trials and failures of preferred medications or contraindications for preferred medications based on the patient's diagnosis, medical conditions, and ongoing therapies. In contrast, UPMC has less stringent requirements at age 18, allowing continuation of stimulant medication for patients who began treatment before age 18. Understanding this type of heterogeneity in prior authorization effects is important and has not been a focus of prior research that has primarily studied aggregated effects across plans.

These multiple age cutoffs also reveal how treatment effects vary with patient age, a dimension that studies of a single policy change cannot recover but that matters for policy design, since clinical needs, treatment alternatives, and the risk of misuse could change as patients age. For young children, drug use more often reflects treatment initiation, which typically follows a recent diagnostic evaluation. Physicians are therefore more likely to have the documentation required for approval on hand, and families seeking a first prescription may be more motivated to complete the process, making it less sensitive to prior authorization requirements. At older ages, ADHD medication use is more often marginal and concerns about stimulant misuse and diversion may increase a provider's threshold for prescribing, making it more sensitive to administrative frictions.

We further explore heterogeneous treatment effects across demographic and provider characteristics. Appendix Table A.15 Panel A examines differences by gender, while Panel B analyzes variation by self-reported race and ethnicity. Despite higher baseline ADHD medication use among boys and white Medicaid beneficiaries, prior authorization reduces utilization by similar magnitudes across gender and racial/ethnic groups. Panel C shows heterogeneity by

[46] Regarding eligibility differences, most enrollees around age 18 qualify for Medicaid based on age criteria (under 19 years), while those around age 21 primarily qualify due to poverty-related factors. Individuals around the age 21 cutoff (i.e. age 20-21) qualify for Medicaid for the following Poverty related eligibility codes in our data: 46 (Poverty Level Aged or Disabled), 72 (Adult Group-Individuals at or below 133% FPL, 19-64, newly eligible for all states), and 02 (Transitional Medicaid Assistance). This demographic distinction results in a generally healthier patient population at age 18, who may navigate the prior authorization process more effectively than at 21.

provider type, comparing patients whose modal prescriber is a physician versus a non-physician provider such as a nurse practitioner.[47] The results suggest that prior authorization effects are concentrated among patients treated by physicians, with a smaller impact on those treated by non-physician providers.[48]

## 8 Conclusion

Medicaid relies heavily on prior authorization, an administrative ordeal rather than prices, to manage prescription drug use. This type of non-price rationing can reallocate care by raising shadow prices in ways that are hard to observe but first-order for access. Despite the importance of these policies for Medicaid, there is limited evidence of their impact and underlying mechanisms. Leveraging the age discontinuities in prior authorization restrictions in Pennsylvania's Medicaid program, this study demonstrates that the prior authorization of ADHD drugs reduces spending but restricts patient access to medications. More importantly, we found that the reduction in access is primarily driven by patients who would likely meet the insurer's own approval criteria. Depending on how strictly we define eligibility criteria, these patients account for roughly 66 to 81% of the decline in use. Our results suggest that prior authorization works mainly through deterring eligible patients via hassle costs instead of screening out ineligible patients and improving treatment targeting.

The magnitudes of these effects are economically meaningful. Pennsylvania spent $1.5 billion (net-of-rebate spending) on Medicaid prescription drugs in 2017, the first year of our study period, with ADHD medications accounting for approximately $90 million (6% of total prescription drug spending).[49] The implementation of prior authorization reduced ADHD medication expenditures by 13.7%, generating nearly $12.33 million in annual savings. We estimate that around 19% to 34% of savings ($2.3 to $4.2 million) come from reductions in use among patients likely to be ineligible for treatment, which could improve welfare by preventing unnecessary use of ADHD drugs. However, as much as 66% to 81% of savings ($8.1 to $10 million) come from reductions in use among eligible patients who would likely meet insurer approval

[47] Defined as the provider from whom the patient receives the majority of their prescriptions during the study period.
[48] Scope of practice law in Pennsylvania allows nurse practitioners to prescribe ADHD drugs.
[49] See the audit report from Pennsylvania Department of the Auditor General in 2019.

criteria, reflecting the administrative burden that deters providers from submitting prior authorization requests.[50] This suggests that hassle costs account for the majority of the reduction in utilization and spending from prior authorization. This misalignment between clinical need and treatment access represents a welfare cost that must be weighed against the savings from reduced prescription drug spending.

Taken together, our findings indicate that prior authorization does more than screen out the patients it is designed to screen by insurer's own approval criteria. It also screens out patients who would meet these criteria because of the hassle costs of prior authorization process. We do not take a stand on whether the insurer's criteria are socially optimal. ADHD diagnosis and treatment involve considerable clinical uncertainty, so the criteria may approve some patients whose benefit from medication is low and exclude others whose benefit is high, and the fact that plans within the same state apply different criteria suggests that no single rule is likely to be optimal. Our conclusion does not depend on resolving this question. Even if the criteria perfectly reflected social value, most of the savings from prior authorization would not be efficiency gains from better targeting but instead reductions in treatment for patients the plan itself would have approved. Because we find no offsetting increase in psychotherapy or other outpatient care for older children and young adults, forgone medication for these patients most likely means forgone treatment rather than a shift to alternatives. We also acknowledge that because we do not account for the time spent by physicians and administrative staff preparing and reviewing requests, nor the cost of delayed treatment for patients who eventually fill their prescriptions, our estimates understate the full welfare cost of prior authorization. A full welfare assessment would also multiply the treatment forgone under prior authorization in our analysis by its value to the patients who lose it, which requires linking prior authorization to other downstream outcomes such as school performance, behavioral problems, criminal justice involvement, substance use, and later earnings. We leave the valuation of that forgone treatment from prior authorization to future work.

This trade-off underscores the need for policymakers to carefully balance cost containment goals with ensuring access to necessary medications. The observed hassle costs for physicians, which play a significant role in driving reductions in access, point to inefficiencies in the current prior authorization system that may diminish patients' access to needed medications. We show that

[50] Figure 5 (a) presents the sensitivity analyses of the welfare calculations.

the binding margin is the upstream hassle costs in the filing process, not the downstream approval decision. Reforms that reduce the upstream burden on prescribers are therefore more likely to reallocate treatment toward eligible patients than reforms that only speed up adjudication. Examples may include simpler documentation, electronic prior authorization built into prescribing systems, and "gold-card" exemptions for prescribers with high approval rates. Refining approval criteria, even to match best clinical practice, will do little to improve targeting when hassle costs are substantial.

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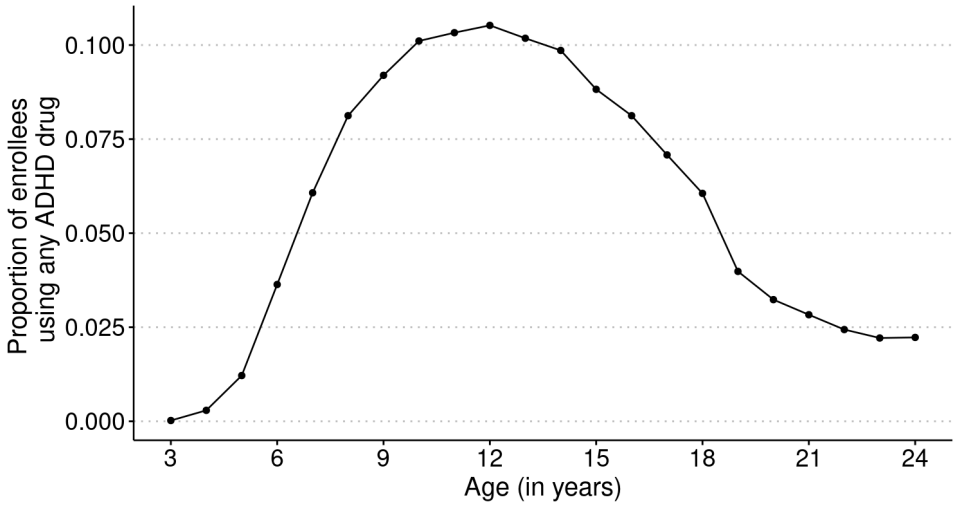
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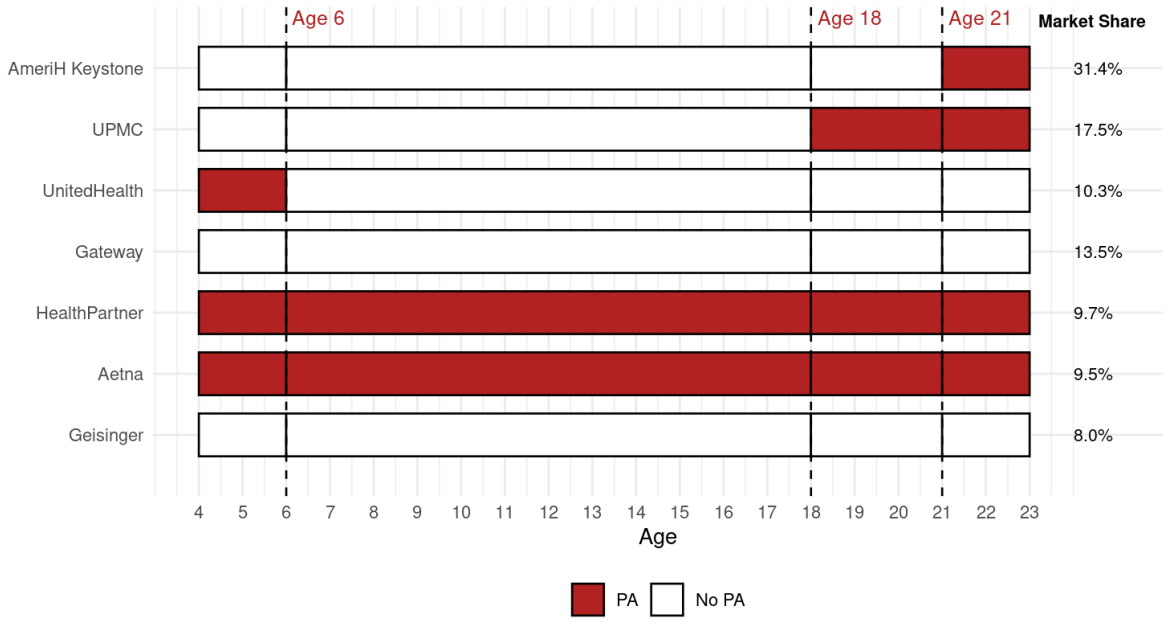
# Figures and Tables

Figure 1: ADHD Prescription Drug Use by Age



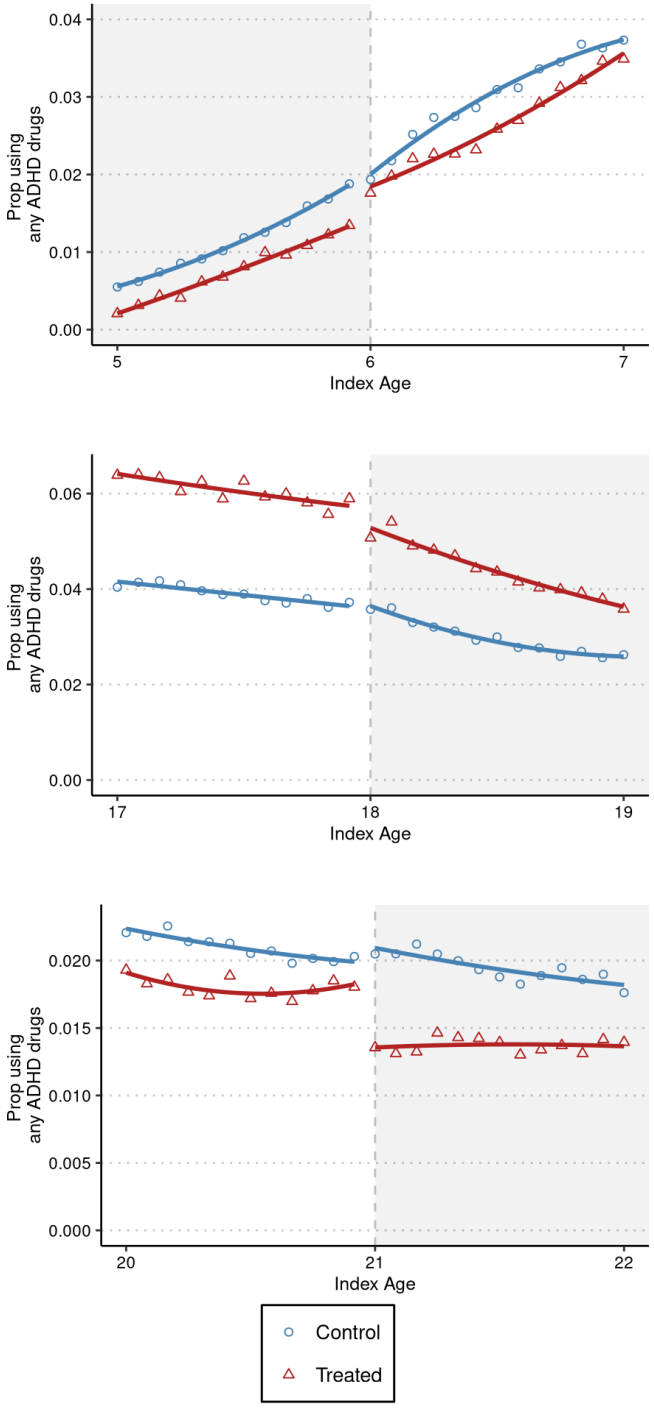

Note: The graph shows the probability of using any ADHD medication at each age in our sample. Age is measured in years

Figure 2: Prior Authorization Requirement by Age across Plans



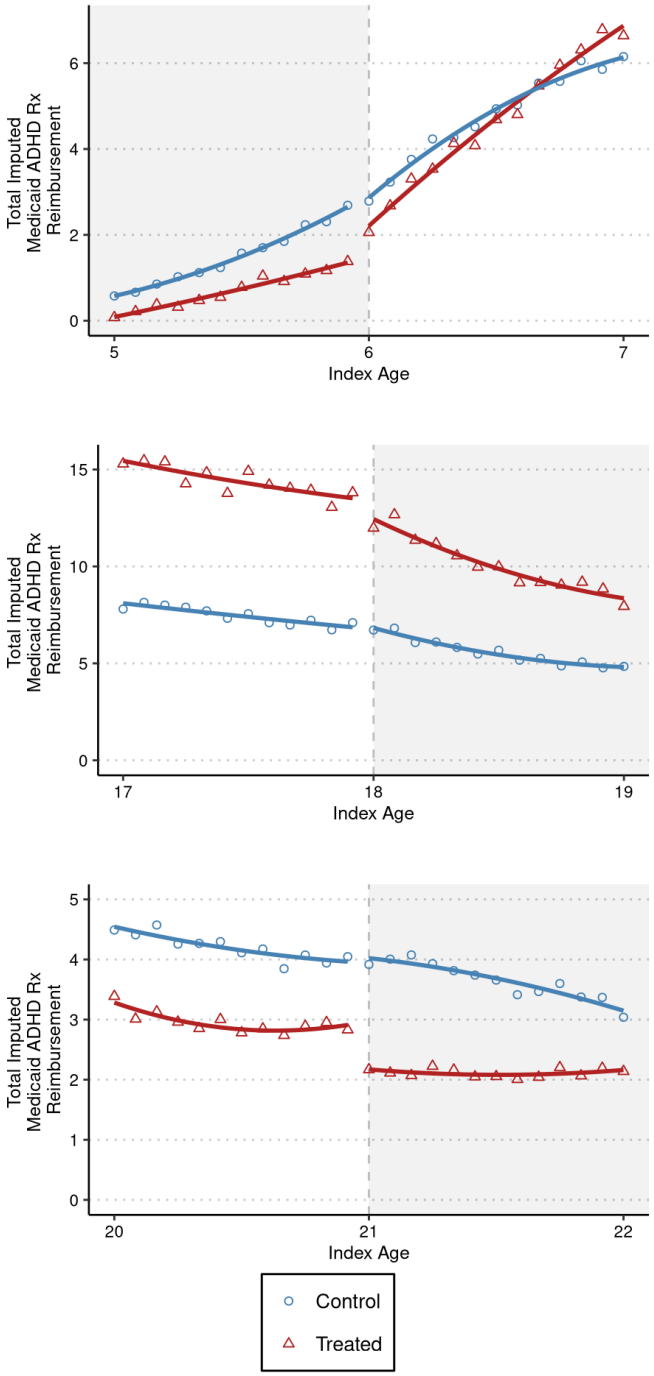

Note: Prior authorization requirement for ADHD drugs by age in all MMC plans in Pennsylvania Medicaid. Two age cutoffs are excluded: UPMC has prior authorizations for before age 4 and AmeriHealth Keystone has prior authorization before age 3. These age cutoffs are excluded in this study as there are few patients using ADHD drugs before age 4, as shown in Figure 1. Market share is the share of MMC enrollees in each plan.

Figure 3: ADHD Prescription Drug Utilization in Treated and Control Plans by Age



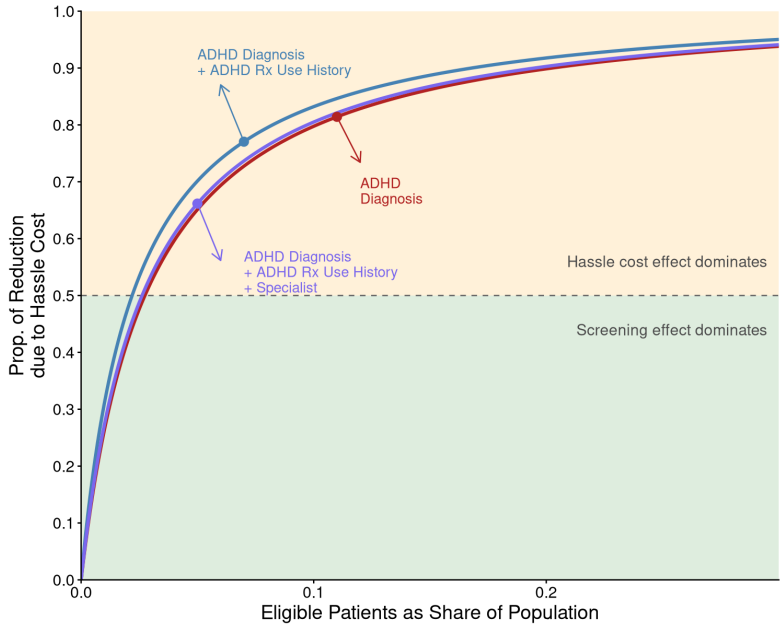

Note: Each graph displays the proportion of beneficiaries who filled any ADHD prescription drugs at different ages (measured in months). Shaded areas indicate that prior authorizations are required. Line fitted using a second-order polynomial regression to illustrate the relationship without adjusting for controls. The vertical dashed lines represent age cutoffs around which prior authorization requirements change in treated plans. Around age 6, United Health is the treated plan and beneficiaries under age 6 in this plan are subject to prior authorization, while all other plans (AmeriHealth/Keystone, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 18, UPMC is the treated plan and beneficiaries above age 18 in this plan are subject to prior authorization, while all other plans (United Health, AmeriHealth/Keystone, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 21, AmeriHealth/Keystone is the treated plan and beneficiaries above age 21 in this plan are subject to prior authorization, while all other plans (United Health, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans.

Figure 4: ADHD Prescription Drug Spending in Treated and Control Plans by Age

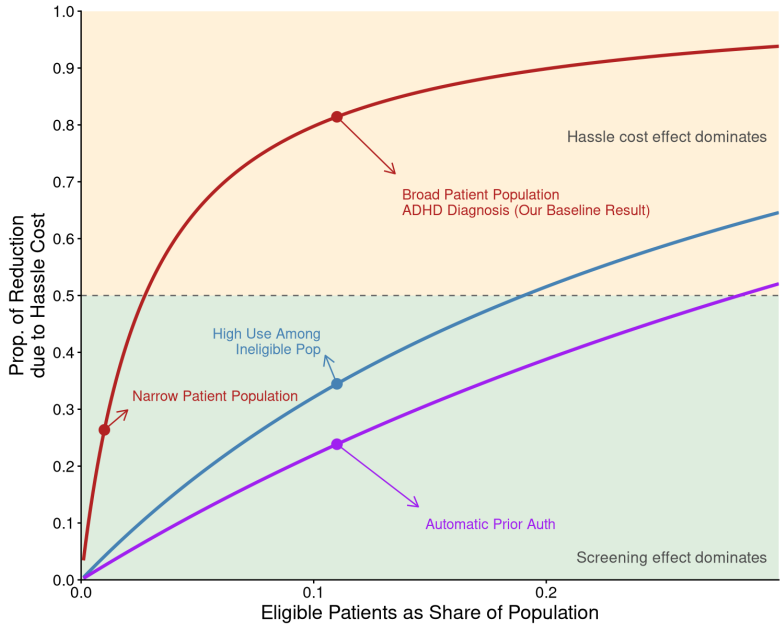



Note: Each graph displays the average of total Medicaid spending on ADHD prescription drugs per beneficiary at different ages (measured in months). Medicaid spending is zero when a patient doesn't use any ADHD prescription drug. Shaded areas indicate that prior authorizations are required. Line fitted using a second-order polynomial regression to illustrate the relationship without adjusting for controls. The vertical dashed lines represent age cutoffs around which prior authorization requirements change in treated plans. Around age 6, United Health is the treated plan and beneficiaries under age 6 in this plan are subject to prior authorization, while all other plans (AmeriHealth/Keystone, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 18, UPMC is the treated plan and beneficiaries above age 18 in this plan are subject to prior authorization, while all other plans (United Health, AmeriHealth/Keystone, Aetna, Geisinger, Health Partner, Gateway) are control plans. At age 21, AmeriHealth/Keystone is the treated plan and beneficiaries above age 21 in this plan are subject to prior authorization, while all other plans (United Health, UPMC, Aetna, Geisinger, Health Partner, Gateway) are control plans.

Figure 5: Decomposition of Hassle Cost and Screening Effect



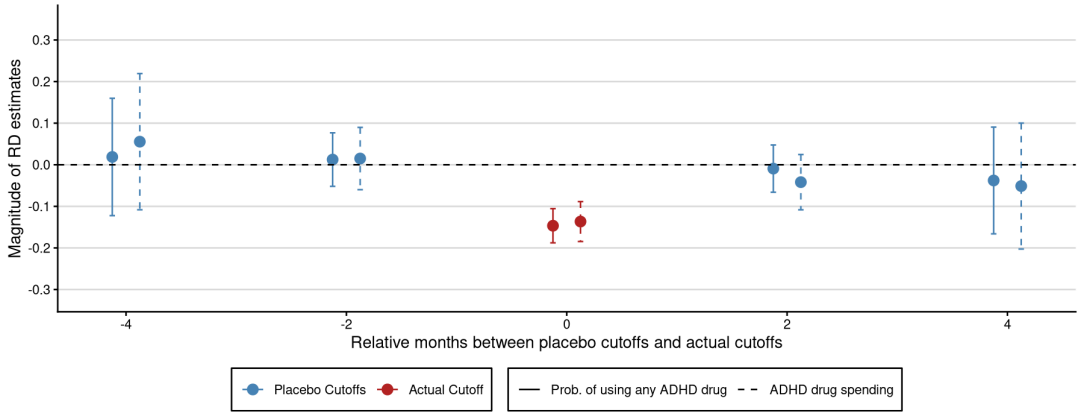

(a) Decomposition - ADHD drugs



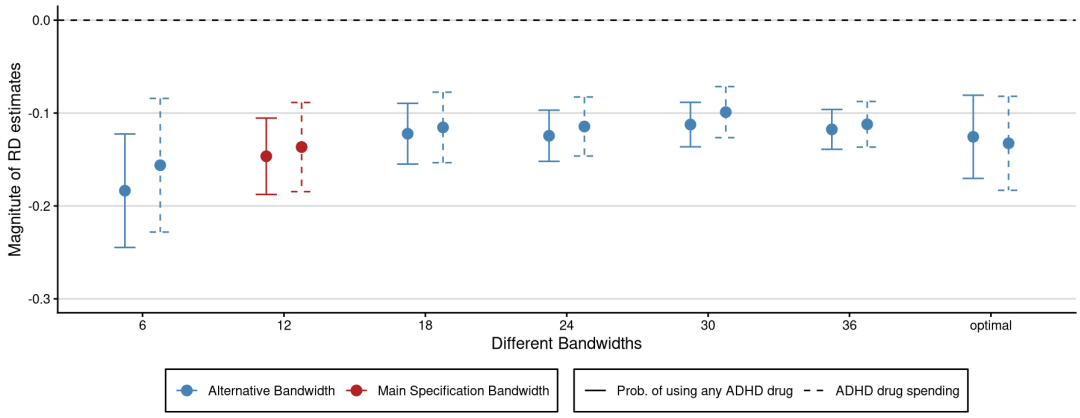

(b) Decomposition: Counterfactual Scenarios

Note: This figure plots the share of the reduction in ADHD drug use attributable to eligible patients (defined by ADHD diagnosis), which we interpret as the hassle cost effect, against the share of the population that is eligible. Panel A shows our estimates under three eligibility definitions: an ADHD diagnosis (red); an ADHD diagnosis and prior ADHD medication use (blue); and an ADHD diagnosis, prior use, and a specialist as primary prescriber (purple). Dots mark the eligible share observed in our sample under each definition and the share of decline in utilization that is due to hassle costs. Panel B shows the hassle cost share under illustrative counterfactual parameters, starting from our baseline results. Red line: our baseline estimates with eligibility defined as an ADHD diagnosis evaluated at the actual eligible share of 11% (upper dot) and counterfactual eligible share of 1% (lower dot). Blue dot: mean baseline ADHD drug use among ineligible patients raised from the actual rate of 0.6 to 5%. Purple dot: counterfactual treatment effects from automatic prior authorization (low hassle cost, stringent screening) of 3% for eligible patients and 60% for ineligible patients. In both panels, the dashed line marks 50%: above it (orange), the hassle cost effect dominates; below it (green), the screening effect dominates. Appendix C describes the calculations and parameters.

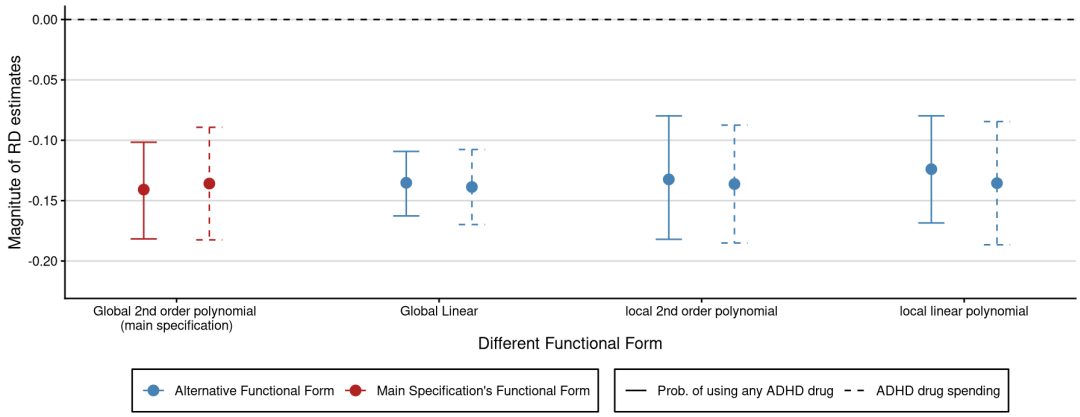
Figure 6: Robustness checks




(a) Placebo Cutoffs




(b) Alternative Bandwidths




(c) Alternative Functional Form

Note: Panel (a) presents the estimates of Eq.(2) using placebo age cutoffs. For example, "-2" indicates the discontinuity is estimated two months before the actual age cutoff, while "2" indicates it is estimated two months after the cutoff. Panel (b) displays the estimates of Eq.(2) using different bandwidths, measured in months. “Optimal bandwidth” denotes the local-linear estimate obtained using the optimal bandwidth of Calonico et al. (2020). Panel (c) shows the estimates of Eq.(2) using alternative functional forms, including global linear regression, local linear and local second-order polynomial regression.

Table 1: Summary Statistics

| | Age 5-7 | | Age 17-19 | | Age 20-22 | |
|---|---|---|---|---|---|---|
| | Treated | Control | Treated | Control | Treated | Control |
| ***Demographic variables*** | | | | | | |
| Female | 0.4763 | 0.4778 | 0.4824 | 0.4884 | 0.5740 | 0.5718 |
| | (0.4994) | (0.4995) | (0.4997) | (0.4999) | (0.4945) | (0.4948) |
| White | 0.4312 | 0.4776 | 0.764 | 0.4639 | 0.4117 | 0.5704 |
| | (0.4952) | (0.4995) | (0.4246) | (0.4987) | (0.4921) | (0.495) |
| Zipcode AGI | 54238.9792 | 50818.4061 | 52236.6704 | 52480.6661 | 53616.3984 | 50662.5579 |
| | (20488.4852) | (19163.9568) | (15585.0967) | (20927.8905) | (23063.5251) | (18071.2562) |
| Eligibility | | | | | | |
| Under Age 19 | 0.8061 | 0.7963 | 0.6979 | 0.7133 | 0.0025 | 0.0023 |
| Poverty | 0.0830 | 0.0818 | 0.1269 | 0.1080 | 0.4415 | 0.4241 |
| SSI | 0.0465 | 0.0519 | 0.0957 | 0.1047 | 0.0759 | 0.0746 |
| Pregnancy | 0.000 | 0.000 | 0.0005 | 0.0005 | 0.0817 | 0.0904 |
| Other | 0.0644 | 0.0701 | 0.0791 | 0.0734 | 0.3985 | 0.4086 |
| ***Outcome variables (in age-months)*** | | | | | | |
| Prob of using any ADHD drugs | 0.0170 | 0.0206 | 0.0527 | 0.0346 | 0.016 | 0.0202 |
| | (0.1292) | (0.1419) | (0.2235) | (0.1828) | (0.1256) | (0.1408) |
| Average ADHD drug claims in the population | 0.0205 | 0.0256 | 0.0661 | 0.0430 | 0.0192 | 0.0245 |
| | (0.1672) | (0.1912) | (0.3046) | (0.2471) | (0.1611) | (0.1828) |
| Average ADHD drug claims conditional on using any ADHD drug | 1.2080 | 1.2442 | 1.2534 | 1.2436 | 1.1958 | 1.2101 |
| | (0.4612) | (0.5111) | (0.5208) | (0.5205) | (0.462) | (0.4661) |
| ADHD diagnosis | 0.0606 | 0.0705 | 0.1174 | 0.0900 | 0.0358 | 0.0449 |
| | (0.2386) | (0.256) | (0.3219) | (0.2861) | (0.1859) | (0.2071) |
| ADHD drug spending | 2.6953 | 3.1004 | 12.361 | 6.5730 | 2.5612 | 3.9355 |
| | (25.6922) | (26.803) | (58.3899) | (41.1310) | (24.5734) | (32.0937) |
| Number of unique patients | 24,157 | 223,774 | 35,889 | 146,768 | 55,631 | 128,485 |
| Number of age-month observations | 196,573 | 2,241,111 | 341,271 | 1,457,859 | 490,248 | 1,121,062 |

Note: Summary statistics are calculated at the beneficiary-age level separately for treated and control plans. Age is measured in months. Standard deviations are shown in parentheses. The treated plan is United Healthcare around age 6, UPMC around age 18, and AmeriHealth/Keystone First around age 21. Control plans are those without changes in prior authorization requirements around each cutoff age. These plans consistently have prior authorization on both sides of the age threshold or lack prior authorization on both sides. ADHD drug spending represents total Medicaid reimbursement for prescriptions at each age.

Table 2: Impact of Prior Authorization on ADHD Drug Use and Spending by Age Cutoff

| | Prob of using any ADHD drug | | | ADHD drug spending | | |
|---|---|---|---|---|---|---|
| | Treated (1) | Control (2) | RD-DID (3) | Treated (4) | Control (5) | RD-DID (6) |
| ***Panel A: All ages*** | | | | | | |
| Prior Authorization | -0.0052*** | 0.0006 | -0.0051*** | -1.0148*** | 0.1377 | -0.9493*** |
| | (0.0007) | (0.0004) | (0.0009) | (0.182) | (0.0765) | (0.1965) |
| Pre-Treatment Mean | 0.0353 | 0.0303 | 0.0353 | 7.4301 | 5.5335 | 7.4301 |
| Magnitude | -14.73% | 1.98% | -14.45% | -13.66% | 2.49% | -12.78% |
| Obvs. | 1,028,092 | 4,820,032 | 5,848,124 | 1,028,092 | 4,820,032 | 5,848,124 |
| ***Panel B: Age 6*** | | | | | | |
| Prior Authorization | -0.0021 | -0.0001 | -0.0018 | -0.7963** | -0.0131 | -0.6732* |
| | (0.0014) | (0.0005) | (0.0018) | (0.3026) | (0.0948) | (0.3384) |
| Pre-Treatment Mean | 0.0274 | 0.0309 | 0.0274 | 4.9292 | 4.9285 | 4.9292 |
| Magnitude | -7.66% | -0.32% | -6.57% | -16.15% | -0.27% | -13.66% |
| Obvs. | 196,573 | 2,241,111 | 2,437,684 | 196,573 | 2,241,111 | 2,437,684 |
| ***Panel C: Age 18*** | | | | | | |
| Prior Authorization | -0.0064*** | 0.0002 | -0.0066*** | -1.4458** | 0.0592 | -1.4954*** |
| | (0.0016) | (0.0007) | (0.0017) | (0.4463) | (0.1585) | (0.4005) |
| Pre-Treatment Mean | 0.0606 | 0.039 | 0.0606 | 14.4129 | 7.4645 | 14.4129 |
| Magnitude | -10.56% | 0.51% | -10.89% | -10.03% | 0.79% | -10.38% |
| Obvs. | 341,271 | 1,457,859 | 1,799,130 | 341,271 | 1,457,859 | 1,799,130 |
| ***Panel D: Age 21*** | | | | | | |
| Prior Authorization | -0.0053*** | -0.0002 | -0.005*** | -0.8792*** | -0.2291 | -0.6521** |
| | (0.0008) | (0.0006) | (0.0011) | (0.1673) | (0.1371) | (0.2376) |
| Pre-Treatment Mean | 0.018 | 0.021 | 0.018 | 2.9483 | 4.2076 | 2.9483 |
| Magnitude | -29.44% | -0.95% | -27.78% | -29.82% | -5.44% | -22.12% |
| Obvs. | 490,248 | 1,121,062 | 1,611,310 | 490,248 | 1,121,062 | 1,611,310 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Panel A presents the pooled regression estimates of Eq.(2) in columns 1-2 and 4-5 and Eq.(3) in columns 3 and 6, comparing treated and control plans separately. Panels B through D present estimates for Eq.(1) in columns 1-2 and 4-5 and Eq.(3) in columns 3 and 6 for patients around age cutoffs at 6, 18, and 21, respectively, with treated and control plans reported separately in each case. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects. The pre-treatment mean is calculated at ages when prior authorization is not in effect.

Table 3: Impact of Prior Authorization on Drug Fill Time

| | Number of days (1) | Same day (2) | Within 7 days (3) |
|---|---|---|---|
| ***Panel A: Treated Plans*** | | | |
| Prior Authorization | 2.4306** | -0.0998*** | -0.0806*** |
| | (0.7494) | (0.0165) | (0.017) |
| Pre-Treatment Mean | 14.0135 | 0.3382 | 0.621 |
| Magnitude | 17.34% | -29.51% | -12.98% |
| Obvs. | 27,828 | 27,828 | 27,828 |
| ***Panel B: Control Plans*** | | | |
| Prior Authorization | 0.3418 | -0.0066 | -0.0162* |
| | (0.3366) | (0.0084) | (0.0082) |
| Pre-Treatment Mean | 13.5065 | 0.3532 | 0.6269 |
| Magnitude | 2.53% | -1.87% | -2.58% |
| Obvs. | 115,155 | 115,155 | 115,155 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Panel A presents the estimates of Eq.(2) among treated plans and Panel B presents these estimates among control plans. The outcome is the number of days between the prescription date and drug fill date in column (1), whether Rx is filled on the same day as the prescription date in column (2) and whether Rx is filled within 7 days of the prescription date in column (3). The sample includes beneficiary–age–month observations with at least one ADHD prescription. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table 4: Impact of Prior Authorization on ADHD Drug Utilization by Patient's Eligibility Status

| | Ineligible Patients | Eligible Patients | | |
|---|---|---|---|---|
| | No Diagnosis | Diagnosis | Diagnosis + Use History | Diagnosis + Use History + Specialist |
| | (1) | (2) | (3) | (4) |
| ***Panel A: Treated Plans*** | | | | |
| Prior Authorization | -0.0016*** | -0.0532*** | -0.0669*** | -0.0557** |
| | (0.0004) | (0.0077) | (0.0136) | (0.0171) |
| Pre-Treatment Mean | 0.0063 | 0.3041 | 0.5817 | 0.5979 |
| Magnitude | -25.40% | -17.49% | -11.50% | -9.32% |
| Obvs. | 743,806 | 69,546 | 32,441 | 20,628 |
| ***Panel B: Control Plans*** | | | | |
| Prior Authorization | 0.0002 | -0.0025 | 0.0027 | 0.0157 |
| | (0.0002) | (0.0035) | (0.0068) | (0.0085) |
| Pre-Treatment Mean | 0.0045 | 0.2886 | 0.5689 | 0.5801 |
| Magnitude | 4.44% | -0.87% | 0.47% | 2.71% |
| Obvs. | 3,571,732 | 339,464 | 138,492 | 89,880 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Eligible patients are defined as: those with an observed ADHD diagnosis in their outpatient claims at or before their age in column (2); those with ADHD diagnosis and with ADHD drug filled before their age in column (3); those with an ADHD diagnosis, with ADHD drug filled before their age and their main prescriber is a pediatrician, psychologist, or neurologist in column (4). Ineligible patients in column (1) are defined as those who do not have an ADHD diagnosis in their claims at or before their age and are also predicted by our ML algorithm not to have an ADHD diagnosis. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table 5: Spillover Effect of Prior Authorization on ADHD Drug Utilization

| | Prescriber's Modal Plan | |
|---|---|---|
| | Treated (1) | Control (2) |
| ***Panel A: Patient's plan is control*** | | |
| Prior Authorization | -0.0006 | 0.0008 |
| | (0.0015) | (0.0005) |
| Pre-Treatment Mean | 0.0509 | 0.0457 |
| Magnitude | -1.23% | 1.73% |
| Obvs. | 348,836 | 2,929,476 |
| ***Panel B: Patient's plan is treated*** | | |
| Prior Authorization | -0.0094*** | -0.0041* |
| | (0.0013) | (0.0016) |
| Pre-Treatment Mean | 0.0548 | 0.0503 |
| Magnitude | -17.18% | -8.12% |
| Obvs. | 470,228 | 226,272 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We split our sample into 4 subgroups based on whether the patient's plan is a control (Panel A) or treated (Panel B) plan and whether their physician's modal plan is a treated (column 1) or control (column 2) plan. In each quadrant, we present RD estimates from Eq.(2) for the given subgroup. A prescriber's modal plan refers to the Medicaid MMC plan with the highest number of patients for that prescriber. Prescribers with a tie in patient frequency across plans are excluded. A patient's prescriber is defined as the most frequent prescriber for a patient across all prescription claims during the study period. Patients with fewer than five prescription claims are excluded due to insufficient data. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

# Online Appendix

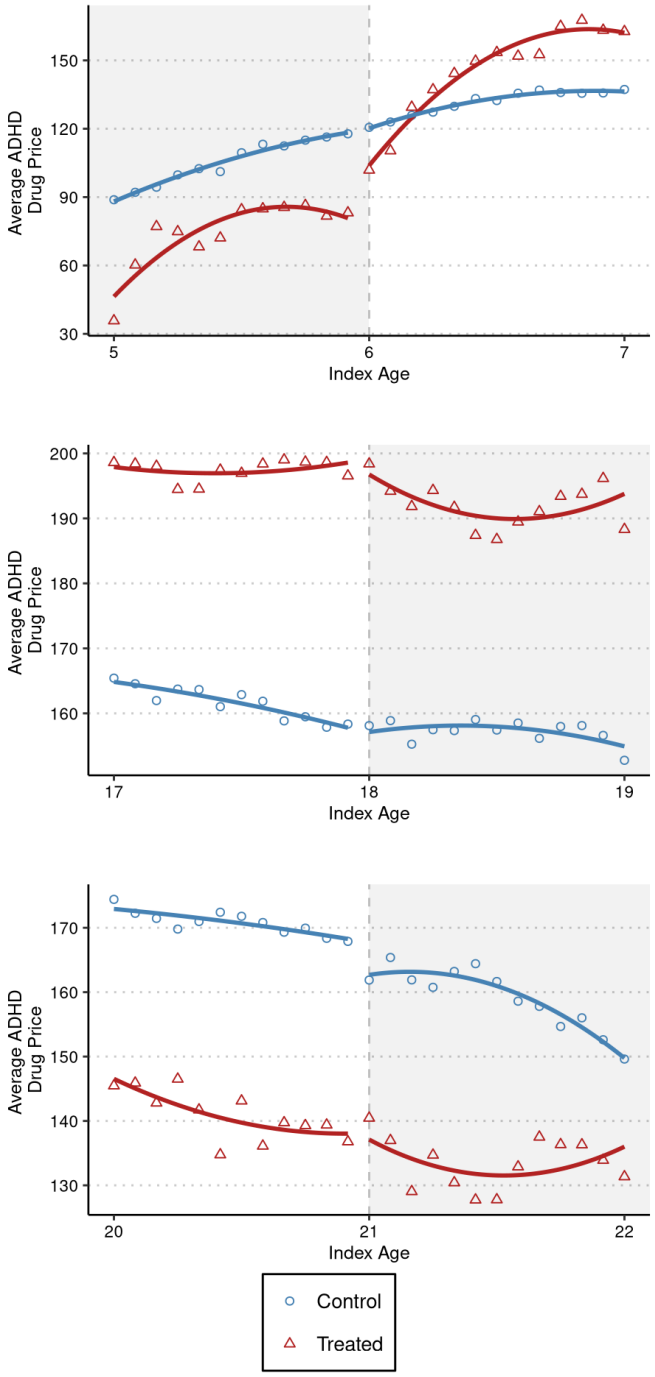
# A Additional Tables and Figures

Figure A.1: Example of Prior Authorization Guideline

| Field Name | Field Description |
|---|---|
| Prior Authorization Group Description | **ADHD Medications** |
| Drugs | |
| Covered Uses | Medically accepted indications are defined using the following sources: the Food and Drug Administration (FDA), Micromedex, American Hospital Formulary Service (AHFS), United States Pharmacopeia Drug Information for the Healthcare Professional (USP DI), the Drug Package Insert (PPI), or disease state specific standard of care guidelines. |
| Exclusion Criteria | N/A |
| Required Medical Information | See "other criteria" |
| Age Restrictions | Members ≥ 21 years old (See other Criteria) |
| Prescriber Restrictions | N/A |
| Coverage Duration | If the criteria are met, the request will be approved with up to a 6 month duration; if the criteria are not met, the request will be referred to a clinical reviewer for medical necessity review. |
| Other Criteria | **Initial Authorization:**<br><br>**For members 21 and older:**<br>o Appropriate diagnosis/indication for requested ADHD medication<br>o For use in adults for Attention Deficit Hyperactivity Disorder, the DSM-V criteria must be met: 5 symptoms are required (see attachment 1). |

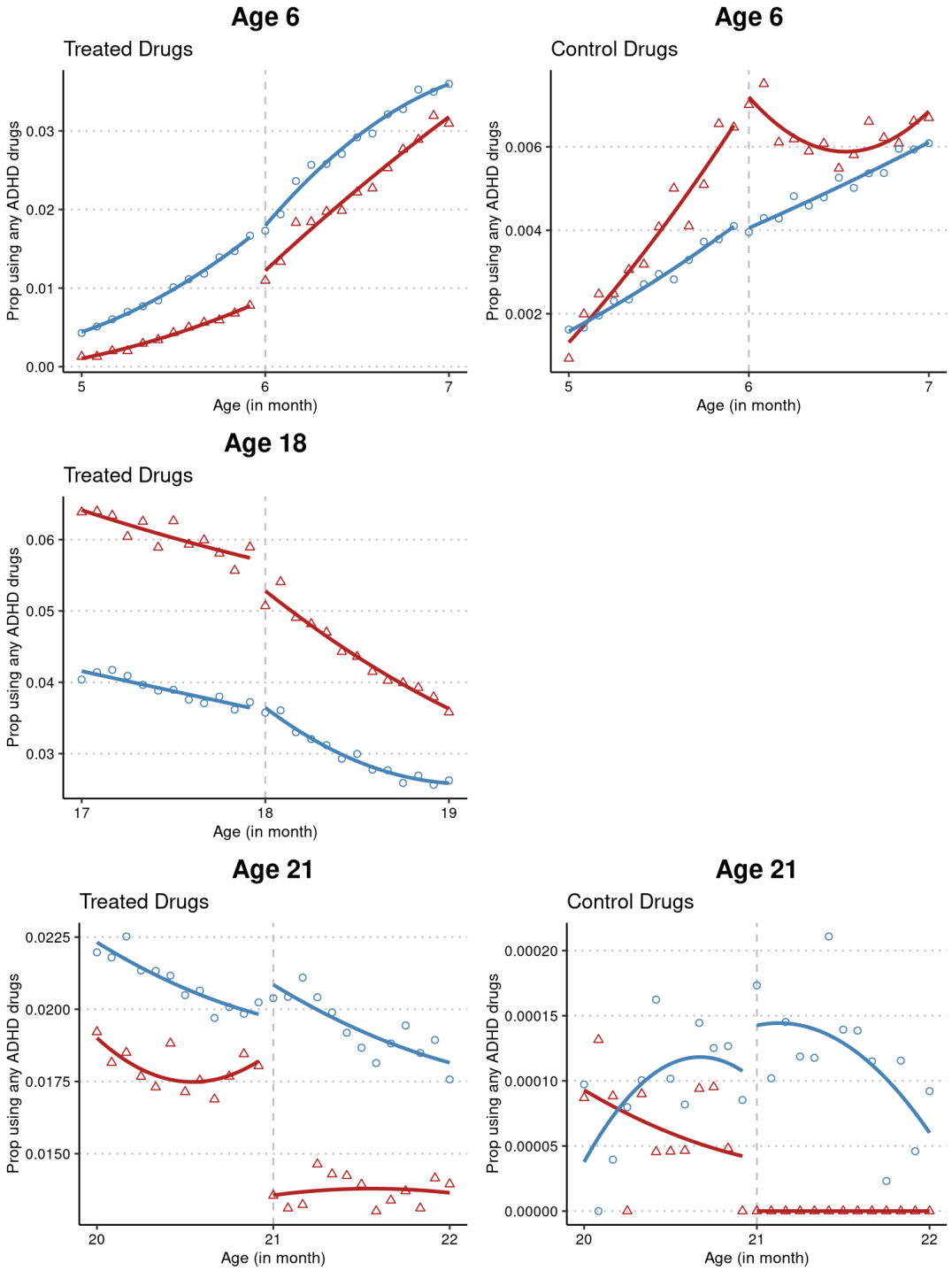
Note: Amerihealth/Keystone First's prior authorization guideline for ADHD Medications.

Figure A.2: ADHD Prescription Drug Prices in Treated and Control Plans by Age



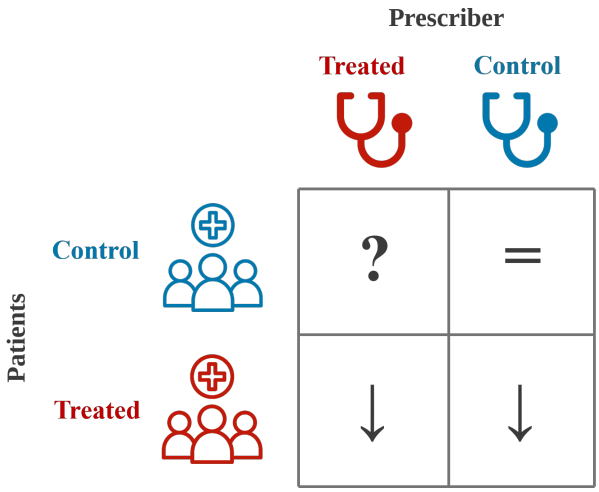

Note: Each graph displays the average price of ADHD prescription drugs at different indexed ages. Price is imputed using the total amount of Medicaid reimbursement divided by the total number of prescriptions among MMCs in the Pennsylvania Medicaid program using the State Drug Utilization Dataset. Shaded areas indicate that prior authorizations are required. Line fitted using a second-order polynomial regression to illustrate the relationship without adjusting for controls. The vertical dashed lines represent age cutoffs around which prior authorization requirements change in treated plans.

Figure A.3: Robustness Check: Treated vs. Control Drugs




Note: Each graph displays the proportion of beneficiaries who filled any treated or control ADHD prescription drugs at different ages. Treated drugs are those directly subject to prior authorization changes at the age cutoff, while control drugs are not subject to prior authorization changes. As discussed in the paper, only a small share of ADHD drugs are control drugs. For UPMC, all drugs become subject to prior authorization at age 18. Line fitted using a second-order polynomial regression to illustrate the relationship without adjusting for controls. The vertical dashed lines represent age cutoffs around which prior authorization requirements change in treated plans.

Figure A.4: Illustration of Predicted Direct and Spillover Effects of Prior Authorization by Patient and Prescriber Treatment Status




Note: This figure illustrates how prior authorization is predicted to affect patients in plans not directly subject to prior authorization. We split patients into four subgroups. Rows classify patients by the treatment status of their own plan, and columns classify patients by the treatment status of their prescriber's modal plan. A patient is treated if enrolled in a treated plan. A patient's prescriber is treated if the modal plan among the prescriber's patients is a treated plan. Each cell shows the predicted change in ADHD drug use. Treated patients face prior authorization regardless of their prescriber's status, so their use is predicted to decline. Control patients of control prescribers are not exposed to the policy, so their use is predicted to be unchanged. Control patients of treated prescribers do not face prior authorization themselves, but their use may change if their prescribers adjust their overall prescribing in response to the prior authorization policies of other patients, for example by switching drugs or changing prescribing thresholds. It is an empirical question whether or not there are spillovers to these patients. Table 5 reports estimates for each cell.

Table A.1: Covariates Tests

| | Female | Zipcode Median Household Income | White | SSI |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Panel A: Treated Plans*** | | | | |
| Prior Authorization | -0.0049** | -8.3879 | -0.0008 | -0.0000 |
| | 0.0017 | 7.2982 | 0.0010 | 0.0009 |
| Pre-mean | 0.5033 | 53511.0132 | 0.5363 | 0.0698 |
| Magnitude | -0.97% | -0.02% | -0.16% | -0.05% |
| Obvs. | 1028092 | 1022425 | 1028092 | 1028092 |
| ***Panel B: Control Plans*** | | | | |
| Prior Authorization | -0.0021 | -4.2777 | -0.0005 | -0.0018** |
| | 0.0011 | 3.4575 | 0.0007 | 0.0006 |
| Pre-mean | 0.5067 | 51435.2558 | 0.5068 | 0.076 |
| Magnitude | -0.42% | -0.01% | -0.1% | -2.41% |
| Obvs. | 4820032 | 4800903 | 4820032 | 4820032 |
| ***Panel C: RD-DID*** | | | | |
| Prior Authorization | -0.0051 | -7.8005 | -0.0016 | -0.0044** |
| | 0.0026 | 8.1794 | 0.0016 | 0.0014 |
| Pre-mean | 0.5033 | 53511.0132 | 0.5363 | 0.0698 |
| Magnitude | -1.01% | -0.01% | -0.3% | -6.26% |
| Obvs. | 5848124 | 5823328 | 5848124 | 5848124 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Columns (1), (3), and (4) use individual-level gender, race, and eligibility information from Medicaid enrollment files as outcomes. The outcome in column (2) is ZIP code-level median household income for 2017-2018 from the American Community Survey. Controls include managed care plan fixed effects, quarter-year fixed effects, and ZIP code fixed effects for column (1), and gender, managed care plan fixed effects, quarter-year fixed effects, and ZIP code fixed effects for columns (2)-(4). Results are RD estimates from Eq.(2) in Panel A and B and RD-DID estimates from Eq.(3) for each outcome.

Table A.2: Impact of Prior Authorization on the Price of Used ADHD Drugs

| | ADHD Drug Price | | |
|---|---|---|---|
| | Treated | Control | RD-DID |
| ***Panel A: Age 6*** | | | |
| Prior Authorization | -34.0484*** | -2.3849 | -27.2803*** |
| | (6.7555) | (1.6535) | (6.8034) |
| Pre-Treatment Mean | 149.2609 | 132.3814 | 149.2609 |
| Magnitude | -22.81% | -1.8% | -18.28% |
| Obvs. | 3,336 | 46,046 | 49,382 |
| ***Panel B: Age 18*** | | | |
| Prior Authorization | -0.5057 | -0.4174 | 0.2062 |
| | (1.9169) | (1.1559) | (2.2846) |
| Pre-Treatment Mean | 197.4721 | 161.6391 | 197.4721 |
| Magnitude | -0.26% | -0.26% | 0.1% |
| Obvs. | 17,999 | 50,459 | 68,458 |
| ***Panel C: Age 21*** | | | |
| Prior Authorization | -1.3193 | 1.2097 | -1.1573 |
| | (2.6182) | (1.6802) | (3.3239) |
| Pre-Treatment Mean | 140.9636 | 170.7824 | 140.9636 |
| Magnitude | -0.94% | 0.71% | -0.82% |
| Obvs. | 7,856 | 22,682 | 30,538 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The outcome variable is the average price of ADHD prescription drugs at different indexed ages. Price is imputed using the total amount of Medicaid reimbursement divided by the total number of prescriptions among MMCs in the Pennsylvania Medicaid program using the State Drug Utilization Dataset. The sample includes beneficiary–age–month observations with at least one ADHD prescription. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.3: Robustness Check: ADHD Diagnosis Changes Around Age Cutoffs.

| | Treated (1) | Control (2) | RD-DID (3) |
|---|---|---|---|
| ***Panel A: All ages*** | | | |
| Prior Authorization | -0.0004 | 0.0012* | -0.0008 |
| | (0.0009) | (0.0005) | (0.0013) |
| Pre-Treatment Mean | 0.0828 | 0.0804 | 0.0830 |
| Magnitude | -0.48% | 1.49% | -0.96% |
| Obvs. | 1,028,092 | 4,820,032 | 5,848,124 |
| ***Panel B: Age 6*** | | | |
| Prior Authorization | -0.003 | -0.0001 | -0.0017 |
| | (0.0021) | (0.0008) | (0.0028) |
| Pre-Treatment Mean | 0.0831 | 0.094 | 0.0831 |
| Magnitude | -3.61% | -0.11% | -2.05% |
| Obvs. | 196,573 | 2,241,111 | 2,437,684 |
| ***Panel C: Age 18*** | | | |
| Prior Authorization | 0.0005 | 0.0014 | -0.0005 |
| | (0.0017) | (0.0009) | (0.0021) |
| Pre-Treatment Mean | 0.1277 | 0.0985 | 0.1277 |
| Magnitude | 0.39% | 1.42% | -0.39% |
| Obvs. | 341,271 | 1,457,859 | 1,799,130 |
| ***Panel D: Age 21*** | | | |
| Prior Authorization | 0.0001 | 0.0004 | 0.0003 |
| | (0.0009) | (0.0007) | (0.0013) |
| Pre-Treatment Mean | 0.0381 | 0.0486 | 0.0381 |
| Magnitude | 0.26% | 0.82% | 0.79% |
| Obvs. | 490,248 | 1,121,062 | 1,611,310 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The outcome variable is whether an ADHD diagnosis is recorded in outpatient claims at or before the given age for each beneficiary. Panel A presents the estimates of Eq.(2) (the first two columns under each outcome) and Eq.(3) (the last column under each outcome) for all ages, comparing treated and control plans separately. Panels B through D present the estimates of Eq.(1) (the first two columns under each outcome) and Eq.(3) (the last column under each outcome) for patients around age cutoffs at 6, 18, and 21, respectively, with treated and control plans reported separately in each case. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.4: Robustness Check: Treated vs. Control Drugs

| | Treated Plan | | Control Plan | |
|---|---|---|---|---|
| | Treated drugs (1) | Control drugs (2) | Treated drugs (3) | Control drugs (4) |
| ***Panel A: Age 6*** | | | | |
| Prior Authorization | -0.0043*** | 0.0011 | -0.0005 | 0.0003 |
| | (0.0013) | (0.0008) | (0.0005) | (0.0002) |
| Pre-Treatment Mean | 0.0233 | 0.0063 | 0.0282 | 0.0052 |
| Magnitude | -18.45% | 17.46% | -1.77% | 5.77% |
| Obvs. | 196,573 | 196,573 | 2,241,111 | 2,241,111 |
| ***Panel B: Age 18*** | | | | |
| Prior Authorization | -0.0064*** | - | -0.0001 | - |
| | (0.0016) | - | (0.0007) | - |
| Pre-Treatment Mean | 0.0606 | - | 0.0396 | - |
| Magnitude | -10.56% | - | -0.25% | - |
| Obvs. | 341,271 | - | 1,661,878 | - |
| ***Panel C: Age 21*** | | | | |
| Prior Authorization | -0.0053*** | 0.0000 | 0.0001 | 0.0000 |
| | (0.0008) | (0.0000) | (0.0007) | (0.0001) |
| Pre-Treatment Mean | 0.0179 | 0.0001 | 0.0209 | 0.0001 |
| Magnitude | -29.61% | 0.00% | -0.96% | 0.00% |
| Obvs. | 490,248 | 490,248 | 1,121,062 | 1,121,062 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Treated drugs are those directly subject to prior authorization changes at the age cutoff, while control drugs are not subject to prior authorization changes. For UPMC, all drugs become subject to prior authorization at age 18. The outcome variable indicates whether a beneficiary fills a treated or control drug at a given age. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.5: Robustness to Alternative Cutoffs for Ineligible Patients

| | Threshold | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 |
| **Panel A: Treated Plans** | | | | | | | | | |
| Prior Authorization | -0.0013** | -0.0013*** | -0.0015*** | -0.0016*** | -0.0016*** | -0.0014*** | -0.0014*** | -0.0014*** | -0.0015*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Pre-Treatment Mean | 0.0059 | 0.0058 | 0.0059 | 0.0061 | 0.0063 | 0.0064 | 0.0065 | 0.0066 | 0.0068 |
| Magnitude | -22.10% | -22.07% | -25.49% | -25.57% | -24.93% | -22.08% | -21.83% | -20.93% | -22.00% |
| Obvs. | 589,135 | 631,277 | 678,326 | 719,665 | 743,806 | 787,329 | 811,438 | 824,943 | 837,178 |
| **Panel B: Control Plans** | | | | | | | | | |
| Prior Authorization | 0.0001 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Pre-Treatment Mean | 0.0041 | 0.0041 | 0.0043 | 0.0045 | 0.0045 | 0.0047 | 0.0049 | 0.0050 | 0.0053 |
| Magnitude | 3.18% | 4.02% | 4.10% | 4.95% | 3.86% | 4.10% | 3.91% | 3.40% | 3.19% |
| Obvs. | 2,637,153 | 2,834,772 | 3,134,552 | 3,377,368 | 3,571,732 | 3,714,415 | 3,793,411 | 3,846,702 | 3,910,935 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. RD estimates of Equation (2) among treated plans (Panel A) and control plans (Panel B) under alternative thresholds for defining ineligible patients. Each column corresponds to a different threshold applied to a beneficiary's predicted probability of having an ADHD diagnosis recorded outside the claims data. Smaller thresholds impose a stricter standard for classifying a patient as ineligible. The outcome variable indicates whether a beneficiary fills any ADHD drug at a given age. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.6: Impact of Prior Authorization on Psychotherapy

| | Prob of Having Any Psychotherapy | | |
|---|---|---|---|
| | Treated | Control | RD-DID |
| | (1) | (2) | (3) |
| ***Panel A: All ages*** | | | |
| Prior Authorization | -0.0005 | 0.0007 | -0.0013 |
| | (0.0014) | (0.0008) | (0.0019) |
| Pre-Treatment Mean | 0.097 | 0.0953 | 0.097 |
| Magnitude | -0.52% | 0.73% | -1.39% |
| Obvs. | 799,088 | 3,813,849 | 4,612,937 |
| ***Panel B: Age 6*** | | | |
| Prior Authorization | 0.007* | 0.0023* | 0.0066 |
| | (0.0031) | (0.0011) | (0.0039) |
| Pre-Treatment Mean | 0.0865 | 0.0984 | 0.0865 |
| Magnitude | 8.09% | 2.34% | 7.58% |
| Obvs. | 154,651 | 1,801,464 | 1,956,115 |
| ***Panel C: Age 18*** | | | |
| Prior Authorization | -0.0041 | -0.0033* | -0.0013 |
| | (0.0028) | (0.0013) | (0.0031) |
| Pre-Treatment Mean | 0.1405 | 0.1168 | 0.1405 |
| Magnitude | -2.92% | -2.83% | -0.89% |
| Obvs. | 267,816 | 1,150,802 | 1,418,618 |
| ***Panel D: Age 21*** | | | |
| Prior Authorization | 0.0001 | -0.0004 | -0.0002 |
| | (0.0018) | (0.0013) | (0.0024) |
| Pre-Treatment Mean | 0.0642 | 0.0707 | 0.0642 |
| Magnitude | 0.16% | -0.57% | -0.35% |
| Obvs. | 376,621 | 861,583 | 1,238,204 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Columns (1) and (2) report RD estimates, and Column (3) reports RD-DID estimates. The outcome is whether the beneficiary has any observed psychotherapy visit in each age-month and the next three months.

Table A.7: Impact of Prior Authorization on Outpatient Visits

| | Clinic Visits | Diagnostic Encounters | Behavioral Health |
|---|---|---|---|
| | (1) | (2) | (3) |
| ***Panel A: Treated*** | | | |
| Prior Authorization | 0.0012 | -0.0013 | -0.0038 |
| | (0.0029) | (0.0015) | (0.0068) |
| Pre-Treatment Mean | 0.1223 | 0.0364 | 0.2543 |
| Magnitude | 0.96% | -3.48% | -1.51% |
| Obvs. | 1,028,092 | 1,028,092 | 1,028,092 |
| ***Panel B: Control*** | | | |
| Prior Authorization | 0.0012 | 0.0023*** | -0.0087* |
| | (0.0014) | (0.0000) | (0.0041) |
| Pre-Treatment Mean | 0.1192 | 0.0363 | 0.273 |
| Magnitude | 0.98% | 6.34% | -3.2% |
| Obvs. | 4,820,032 | 4,820,032 | 4,820,032 |
| ***Panel C: RD-DID*** | | | |
| Prior Authorization | 0.0023 | -0.0032* | 0.0023 |
| | (0.0035) | (0.0015) | (0.0097) |
| Pre-Treatment Mean | 0.1223 | 0.0364 | 0.2543 |
| Magnitude | 1.88% | -8.79% | 0.90% |
| Obvs. | 5,848,124 | 5,848,124 | 5,848,124 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Categories are groupings of Type-of-Service (TOS) codes from the T-MSIS Analytic File (TAF) other-services claims. Behavioral health, including mental health and substance use disorder services, comprises TOS codes 014, 043, 044, 045, 048, 049, 050, 069, 145, 146, and 147. Clinic visits comprise TOS codes 003, 004, 028, and 057. Diagnostic encounters include TOS codes 005, 006, 007, 008, 039, and 040. The outcome is the counts of each qualifying service (measured by visit-days) per beneficiary-age-month.

Table A.8: Robustness Check: Copay Changes.

| | Prob of using any ADHD drug | | ADHD drug spending | |
|---|---|---|---|---|
| | Treated (1) | Control (2) | Treated (3) | Control (4) |
| ***Panel A: Age 18*** | | | | |
| Prior Authorization | -0.0064*** | -0.0002 | -1.4458** | -0.0637 |
| | (0.0016) | (0.0007) | (0.4463) | (0.1746) |
| Pre-Treatment Mean | 0.0606 | 0.0394 | 14.4129 | 5.9853 |
| Magnitude | -10.56% | -0.51% | -10.03% | -1.06% |
| Obvs. | 341,271 | 1,300,593 | 341,271 | 999,944 |
| ***Panel B: Age 21*** | | | | |
| Prior Authorization | -0.0053*** | -0.0002 | -0.8792*** | -0.0714 |
| | (0.0008) | (0.0007) | (0.1673) | (0.1569) |
| Pre-Treatment Mean | 0.018 | 0.0219 | 2.9483 | 3.8863 |
| Magnitude | -29.44% | -0.76% | -29.82% | -1.84% |
| Obvs. | 490,248 | 967,061 | 490,248 | 754,231 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription and the total Medicaid spending on ADHD drugs at a given age. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects. Copay changes occur at age 18 in AmeriHealth/Keystone, Geisinger, UPMC, and UnitedHealth, and at age 21 in Aetna, Health Partners, and Gateway. Since UPMC is the treated group at age 18 with a copay change, control plans are restricted to AmeriHealth/Keystone, Geisinger, and UnitedHealth, which also experience copay changes at age 18. For age 21, AmeriHealth/Keystone is the treated group without a copay change, so control plans are restricted to Geisinger, UPMC, and UnitedHealth, which similarly do not have copay changes at age 21. Results in columns (2) and (4) show no discontinuity in these newly constructed control groups, indicating that our findings are not driven by underlying copay changes.

Table A.9: Robustness check: Impact of Prior Authorization on Plan Switching

| | Prob of Switching Plan | | Prob of Switching Plan (ever) | |
|---|---|---|---|---|
| | Treated (1) | Control (2) | Treated (3) | Control (4) |
| Prior Authorization | 0.0000 | 0.0003 | 0.0008 | 0.0007 |
| | (0.0004) | (0.0002) | (0.0006) | (0.0004) |
| Pre-Treatment Mean | 0.0039 | 0.0035 | 0.0328 | 0.0297 |
| Magnitude | 0% | 8.57% | 2.44% | 2.36% |
| Obvs. | 1028092 | 4820032 | 1028092 | 4820032 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Plan switching is defined as enrollment in a different plan compared to the previous age month (columns 1-2), and ever switching plans at a given age or before (columns 3-4). 2.7% of beneficiaries ever switched plans in our sample. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.10: RD-DID Estimates on the Number of Plan Enrollees

| | Age 6 (1) | Age 18 (2) | Age 21 (3) |
|---|---|---|---|
| Prior Authorization | -54.4995 | -5.4081 | -0.7326 |
| | (74.1102) | (84.9554) | (21.5692) |
| Pre-Treatment Mean | 7414.8333 | 15011.4167 | 21831 |
| Magnitude | -0.74% | -0.04% | 0% |
| Obvs. | 175 | 150 | 175 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Estimation using Eq.(3). The outcome is the total number of enrollees at plan-age level. No additional demographic controls are included.

Table A.11: Robustness check: Impact of Prior Authorization among Continuously Enrolled Beneficiaries

| | Prob of using any ADHD drug | | ADHD drug spending | |
|---|---|---|---|---|
| | Treated (1) | Control (2) | Treated (3) | Control (4) |
| Prior Authorization | -0.0024 | 0.0007 | -1.0131** | 0.1714 |
| | (0.0018) | (0.0004) | (0.3501) | (0.0898) |
| Pre-Treatment Mean | 0.0294 | 0.0322 | 5.3716 | 5.867 |
| Magnitude | -8.16% | 2.17% | -18.86% | 2.92% |
| Obvs. | 83908 | 1996064 | 94199 | 2090185 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects. The sample is restricted to those who are enrolled in Medicaid one month before and the age cutoff and one month after the age cutoff. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age in column (1) and (2), and the total ADHD drug spending at a given age in column (3) and (4).

Table A.12: Impact of Prior Authorization on ADHD Drug Use - with Individual Fixed Effects

| | Prob of using any ADHD drug | | | ADHD drug spending | | |
|---|---|---|---|---|---|---|
| | Treated | Control | RD-DID | Treated | Control | RD-DID |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Prior Authorization | -0.0049*** | 0.0002 | -0.0050*** | -0.9547*** | 0.0228 | -0.9752*** |
| | (0.0007) | (0.0003) | (0.0007) | (0.1675) | (0.0645) | (0.1608) |
| Pre-Treatment Mean | 0.0353 | 0.0303 | 0.0353 | 7.4301 | 5.5335 | 7.4301 |
| Magnitude | -13.88% | 0.66% | -14.16% | -12.85% | 0.41% | -13.12% |
| Obvs. | 1,028,092 | 4,820,032 | 5,848,124 | 1,028,092 | 4,820,032 | 5,848,124 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Controls include female, managed care plan fixed effects, quarter-year fixed effects, zipcode and beneficiary fixed effects. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age in column (1) to (3), and the total ADHD drug spending at a given age in column (4) to (6).

Table A.13: Robustness check: RD-DID Estimates Using Alternative Construction of Control Group Based on Prior Authorization Requirement.

| | Probability of using any ADHD drug | | ADHD drug spending | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Panel A: All Ages*** | | | | |
| Prior Authorization | -0.0044*** | -0.0061*** | -0.8980*** | -1.1394*** |
| | (0.0009) | (0.0010) | (0.1927) | (0.2198) |
| Pre-Treatment Mean | 0.0353 | 0.0353 | 7.4301 | 7.4301 |
| Magnitude | -12.46% | -17.28% | -12.09% | -15.33% |
| Observations | 3,116,763 | 3,759,453 | 3,116,763 | 3,759,453 |
| ***Panel B: Age 6*** | | | | |
| Prior Authorization | -0.0006 | -0.0030 | -0.6020* | -0.8494* |
| | (0.0018) | (0.0018) | (0.2957) | (0.3670) |
| Pre-Treatment Mean | 0.0274 | 0.0274 | 4.9292 | 4.9292 |
| Magnitude | -2.19% | -10.95% | -12.21% | -17.23% |
| Observations | 858,358 | 1,775,899 | 858,358 | 1,775,899 |
| ***Panel C: Age 18*** | | | | |
| Prior Authorization | -0.0071*** | -0.0061*** | -1.6393*** | -1.3846** |
| | (0.0019) | (0.0018) | (0.4567) | (0.4493) |
| Pre-Treatment Mean | 0.0606 | 0.0606 | 14.4129 | 14.4129 |
| Magnitude | -11.72% | -10.07% | -11.37% | -9.61% |
| Observations | 859,925 | 1,280,476 | 859,925 | 1,280,476 |
| ***Panel D: Age 21*** | | | | |
| Prior Authorization | -0.0049*** | -0.0057*** | -0.7384** | -0.3165 |
| | (0.0010) | (0.0016) | (0.2268) | (0.3616) |
| Pre-Treatment Mean | 0.0180 | 0.0180 | 2.9483 | 2.9483 |
| Magnitude | -27.22% | -31.67% | -25.04% | -10.73% |
| Observations | 1,398,480 | 703,078 | 1,398,480 | 703,078 |
| **Control plans** | Always treated | Never treated | Always treated | Never treated |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. RD-DID estimates of Equation (3). Treated plans are United Healthcare at age 6, UPMC at age 18, and Amerihealth/Keystone at age 21. The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age in column (1) and (2), and total ADHD drug spending in column (3) and (4). Control groups vary by columns: columns (1) and (3) use plans with prior authorization both one year before and after the age cutoff (Always Treated), while columns (2) and (4) use plans without prior authorization in either period (Never Treated). Control variables include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.14: Robustness check: Impact of Prior Authorization Age Restrictions for Antidepressants and Antipsychotics.

| | Prob of using any ADHD drug |
|---|---|
| ***Panel A: Plans with Prior Auth for Antipsychotics and Antidepressants*** | |
| Prior Authorization | 0.0008 |
| | (0.0008) |
| Pre-Treatment Mean | 0.0323 |
| Magnitude | 2.48% |
| Obvs. | 988,953 |
| ***Panel B: Plans with no Prior Auth for Antipsychotics and Antidepressants*** | |
| Prior Authorization | -0.001 |
| | (0.0013) |
| Pre-Treatment Mean | 0.0528 |
| Magnitude | -1.89% |
| Obvs. | 468,906 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. RD estimates of Eq. (1). The outcome variable indicates whether the beneficiary filled any ADHD medication prescription at a given age. The table reports estimates for beneficiaries in control plans without age-based prior-authorization cutoffs for ADHD medications. In Panel A, the control group consists of plans that impose an age-18 cutoff for prior authorization of antidepressants or antipsychotics (Aetna, AmeriHealth/Keystone, UnitedHealthcare, and Health Partners). In Panel B, the control group consists of plans with no age-based prior-authorization cutoffs for either antidepressants or antipsychotics (Geisinger and Gateway). Control variables include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

Table A.15: Impact of Prior Authorization on ADHD Drug Use: Heterogeneity

| | | |
|---|---|---|
| ***Panel A: By Gender*** | | |
| | **Female** | **Male** |
| Prior Authorization | -0.0032*** | -0.0075*** |
| | (0.0009) | (0.0014) |
| Pre-Treatment Mean | 0.0236 | 0.0466 |
| Magnitude | -13.56% | -16.09% |
| Obvs. | 2,963,560 | 2,884,564 |
| ***Panel B: By Race/Ethnicity*** | | |
| | **White** | **Non-White** |
| Prior Authorization | -0.0070*** | -0.0027** |
| | (0.0014) | (0.001) |
| Pre-Treatment Mean | 0.0479 | 0.0207 |
| Magnitude | -14.61% | -13.04% |
| Obvs. | 2,914,642 | 2,933,482 |
| ***Panel C: By Modal Provider's Type*** | | |
| | **Physicians** | **Non-physicians** |
| Prior Authorization | -0.0107*** | -0.0020 |
| | (0.0017) | (0.0016) |
| Pre-Treatment Mean | 0.0639 | 0.0305 |
| Magnitude | -16.74% | -6.56% |
| Obvs. | 2,411,855 | 1,189,484 |

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. RD-DID estimates of Eq. (3). The outcome variable is whether a beneficiary uses any ADHD drug at a given age. Modal providers in Panel C are defined as the prescriber who gives the highest number of prescriptions for each patient during the study period. Patients with fewer than five prescription claims are excluded due to insufficient data. Beneficiaries without any prescription records in our data are also excluded. Controls include female, managed care plan fixed effects, quarter-year fixed effects and zipcode fixed effects.

# B A Model of Prior Authorization

This appendix develops a model of how prior authorization reduces drug use, and what this reduction implies for the targeting of treatment and for welfare.

## B.1 Setup

Patients are indexed by their clinical benefit for the drug, $v_i \sim F$, where $F$ is atomless with density $f > 0$ on its support. The prescribing physician's private payoff from writing the prescription is $b(v)$, and the social value of treating a patient of benefit $v$ is $s(v)$; both are continuous and strictly increasing. The physician's cost of prescribing absent prior authorization is $c$, including time, counseling, and, for controlled substances, monitoring. The plan's net cost of covering a course of treatment is $p$. The administrative resource cost of a single authorization request is $C$: a filing burden $a$ borne by the prescribing practice, together with the plan's review cost.

Monotonicity of $b$ implies that every prescribing decision takes the form of a cutoff rule in $v$, which is what makes the model's geometry transparent. The economically important feature is that the physician's decision does not involve $p$: she bears her own time cost but not the cost of the drug. That wedge, which is not a result of clinical misjudgment, creates a role for utilization management.

Absent prior authorization, the physician prescribes and the patient receives the drug whenever $b(v_i) \geq c$, that is, whenever

$$v_i \;\geq\; v^N \;\equiv\; b^{-1}(c), \tag{B.1}$$

so baseline utilization is $U^N = 1 - F(v^N)$.

Prior authorization changes the problem in two ways. It adds an administrative burden $a > 0$ that the physician must incur before the prescription can be filled, and it imposes the plan's clinical approval criteria. The physician files a request whenever $b(v_i) \geq c + a$, that is, whenever

$$v_i \;\geq\; v^H \;\equiv\; b^{-1}(c+a) \;>\; v^N. \tag{B.2}$$

The plan approves a request if and only if $v_i \geq v^S$. A patient therefore receives the drug under prior authorization only if the physician files *and* the plan approves:

$$\underbrace{\mathbf{1}\{v_i \geq v^H\}}_{\text{hassle}} \times \underbrace{\mathbf{1}\{v_i \geq v^S\}}_{\text{screening}} \;=\; \mathbf{1}\{v_i \geq \bar{v}\}, \qquad \bar{v} \;\equiv\; \max\{v^H,\, v^S\}, \tag{B.3}$$

and utilization falls by $\Delta \equiv F(\bar{v}) - F(v^N)$.

## B.2 Three regimes

Since $v^N < v^H$ always, the model's predictions depend only on the position of the plan's approval threshold $v^S$ relative to the two prescribing thresholds $v^N$ and $v^H$. We decompose the reduction in utilization by whether the patient would meet the approval criteria. Patients below ($v < v^S$) fail to meet the criteria, while those above it ($v > v^S$) will meet it. These are precisely the two subgroups we identify in our empirical design.

Exactly one of three orderings holds and generates distinct patterns of utilization reductions across the two subgroups:

| | | Reduction among patients who… | |
|---|---|---|---|
| | Ordering | fail the criteria | meet the criteria |
| R1: lenient criteria | $v^S \leq v^N$ | $0$ | $F(v^H) - F(v^N)$ |
| R2: intermediate criteria | $v^N < v^S < v^H$ | $F(v^S) - F(v^N) > 0$ | $F(v^H) - F(v^S) > 0$ |
| R3: stringent criteria | $v^S \geq v^H$ | $F(v^S) - F(v^N)$ | $0$ |

R1 represents lenient criteria, under which all patients who would have been prescribed the drug absent prior authorization meet the plan's approval criteria. Thus, screening does not contribute to any of the reduction in utilization. Instead, the entire reduction comes from administrative burden which deters prescribing among patients who meet the approval criteria. R3 represents stringent criteria, under which the plan's approval threshold exceeds the physician's prescribing threshold under prior authorization. In this case, the patients who lose access are those who fail to meet the approval criteria, so screening accounts for the entire reduction in utilization. R2 is the intermediate case, in which the approval threshold lies between the physician's prescribing threshold with and without prior authorization. In this case, both channels operate. Some patients lose access because they fail to meet the approval criteria, while others meet the criteria but are deterred by the administrative burden.

Figure B.1 displays the three regimes. Because we observe reductions among patients who do not meet the approval criteria, R1 is rejected; because we also observe reductions among patients who *do* meet them, R3 is rejected. The remainder of this model therefore works in R2.

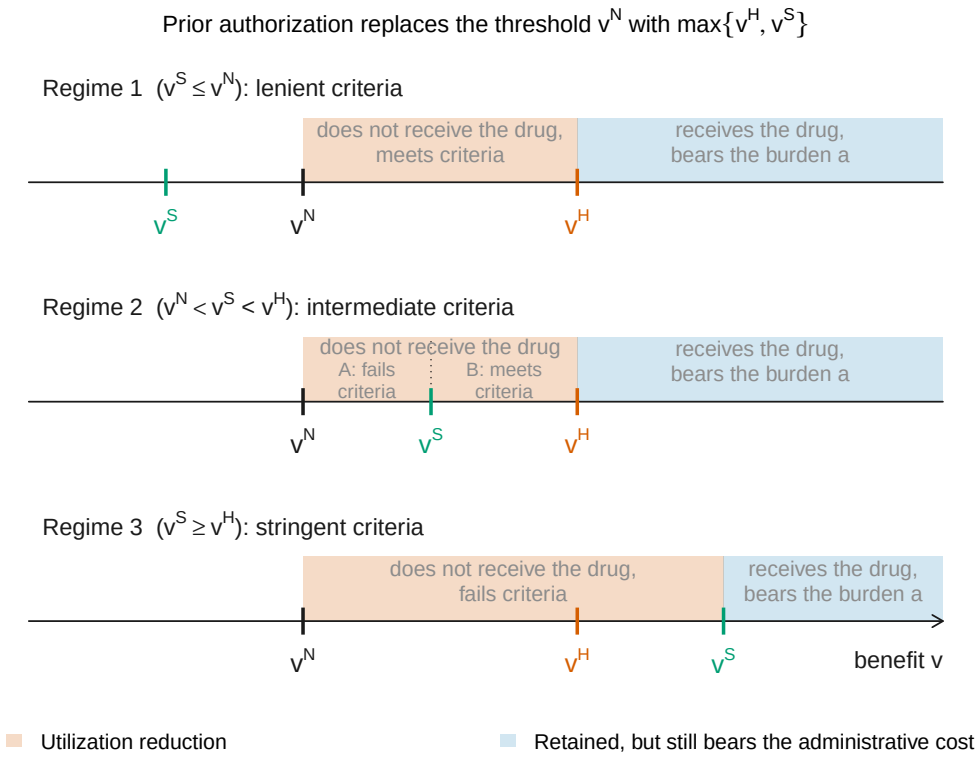



Figure B.1: Prior authorization replaces the prescribing threshold $v^N$ with $\max\{v^H, v^S\}$. Only the position of the approval threshold $v^S$ distinguishes the three regimes. In Regime 2 the patients who lose the drug divide at $v^S$ into region A, who fail the criteria, and region B, who meet them. The shaded region to the right of the new threshold—patients who keep the drug but still generate a request—is where the administrative resource cost is incurred.

## B.3 Decomposing the reduction

In R2, the reduction in utilization can be divided at vS into the two subgroup effects. Define

$$\Delta_S \equiv F(v^S) - F(v^N), \qquad \Delta_H \equiv F(v^H) - F(v^S), \tag{B.4}$$

so the treatment threshold becomes $v^S$ and the reduction in utilization shrinks to $\Delta_S$. $\Delta_H$ is therefore the part of the reduction that would disappear if the administrative burden of prior authorization could be eliminated, such as through electronic and automated prior authorization, and $\Delta_S$ is the part that would survive. In other words, reducing hassle costs would increase use among patients who meet the approval criteria, but would have no effect among patients who do not meet the criteria because they would still be screened out even in the absence of administrative burden. Therefore, the reductions we observe among patients who do and do not meet the approval criteria distinguish the hassle cost and screening effects of prior authorization.

## B.4 Welfare

The aim of this section is to define the welfare effect of prior authorization which results in the accounting identity in Eq.(B.9): The welfare effect is the sum of three terms, each a price multiplied by a quantity, and each of the three quantities is something the empirical design recovers

### The Social Objective

Three items are real resources. The first is the health the drug produces for a treated patient, $s(v_i)$, expressed in dollars. The second is the resources the drug itself consumes, $p$ per treated patient. The third is the labor the authorization process consumes, $C$ per request: staff time assembling and transmitting the request, plan time reviewing it, and the patient's delay cost. Each treated patient generates one request.

Let D=1 if the patient receives the drug and D=0 otherwise. Welfare under an allocation $D$ is therefore

$$W(D) \;=\; \underbrace{\mathbb{E}\big[D_i\, s(v_i)\big]}_{\text{health produced}} \;-\; \underbrace{p\,\mathbb{E}[D_i]}_{\text{drug costs}} \;-\; \underbrace{C\,\Pr(\text{a request is filed})}_{\text{administrative resources}}. \tag{B.5}$$

The third term is evaluated for every prior authorization request submitted. It is not proportional to the reduction in utilization and it applies to all requests, not just denied requests.

### Efficient Allocation

A planner who observed $v_i$ would require no documentation, so $\Pr(\text{a request is filed}) = 0$, and would choose $D_i$ patient by patient to maximize $D_i\,(s(v_i) - p)$. Hence $D_i = 1$ exactly when $s(v_i) \geq p$, and since $s$ is strictly increasing, this is a cutoff rule:

$$v^\star \;\equiv\; s^{-1}(p), \qquad D_i^\star \;=\; \mathbf{1}\{v_i \geq v^\star\}. \tag{B.6}$$

Treatment is efficient exactly when the health the drug produces is worth at least what the drug costs.

Prescribing does not deliver Eq.(B.6) because the physician's rule Eq.(B.1) involves $c$ rather than $p$. Even a physician whose clinical judgment coincides with the social valuation, $b = s$, prescribes down to $s^{-1}(c)$, so that $c < p$ implies

$$v^N \;=\; s^{-1}(c) \;<\; s^{-1}(p) \;=\; v^\star. \tag{B.7}$$

Baseline utilization exceeds the efficient level, and by exactly the wedge $p - c$: the drug is free to the agent making the decision. This is the case for utilization management in this setting, and

the role of prior authorization is to move the treatment threshold from $v^N$ toward $v^\star$.

We assume that $v^S = v^\star$, which means the plan's approval criteria admit exactly the patients a planner would treat. This is a strong assumption, and it is unlikely to hold in reality. In our setting, approval criteria are built plan by plan from verifiable information, and although insurers typically cite clinical evidence in support of their criteria, the ambiguity in the clinical evidence and treatment guidelines for ADHD makes it difficult to establish that the criteria are optimal. We impose the assumption as one possible scenario under which to evaluate the welfare consequences of prior authorization. Relaxing it does not affect the decomposition of the reduction into $\Delta_S$ and $\Delta_H$, which requires only that approval follow a threshold rule; it changes only the welfare values attached to the two groups. In particular, if the insurer's criteria are stricter than the social planner's threshold ($v^S > v^\star$), for example because the plan bears the cost of the drug but not the full health consequences of denying it, then part of the measured screening gain is in fact a loss, and the true welfare effect of prior authorization is more negative than our calculation.

**The Welfare Effect by Subgroup**

The welfare effect of prior authorization relative to no prior authorization is

$$\Delta W \;=\; \underbrace{\int_{v^N}^{v^S} \big[p - s(v)\big]\, dF(v)}_{\text{screening gain} \,\geq\, 0} \;-\; \underbrace{\int_{v^S}^{v^H} \big[s(v) - p\big]\, dF(v)}_{\text{burden loss} \,\geq\, 0} \;-\; \underbrace{C\,\big[1 - F(v^H)\big]}_{\text{administrative cost}}, \tag{B.8}$$

Define $\bar{g} \equiv \mathbb{E}\big[p - s(v) \mid v \in [v^N, v^S)\big]$ and $\bar{\ell} \equiv \mathbb{E}\big[s(v) - p \mid v \in [v^S, v^H)\big]$ for the average social gain per correctly screened patient and the average social loss per deterred eligible patient,

$$\Delta W \;=\; \bar{g}\,\Delta_S \;-\; \bar{\ell}\,\Delta_H \;-\; C\,U^{PA}. \tag{B.9}$$

Figure B.2 displays the three terms as areas.

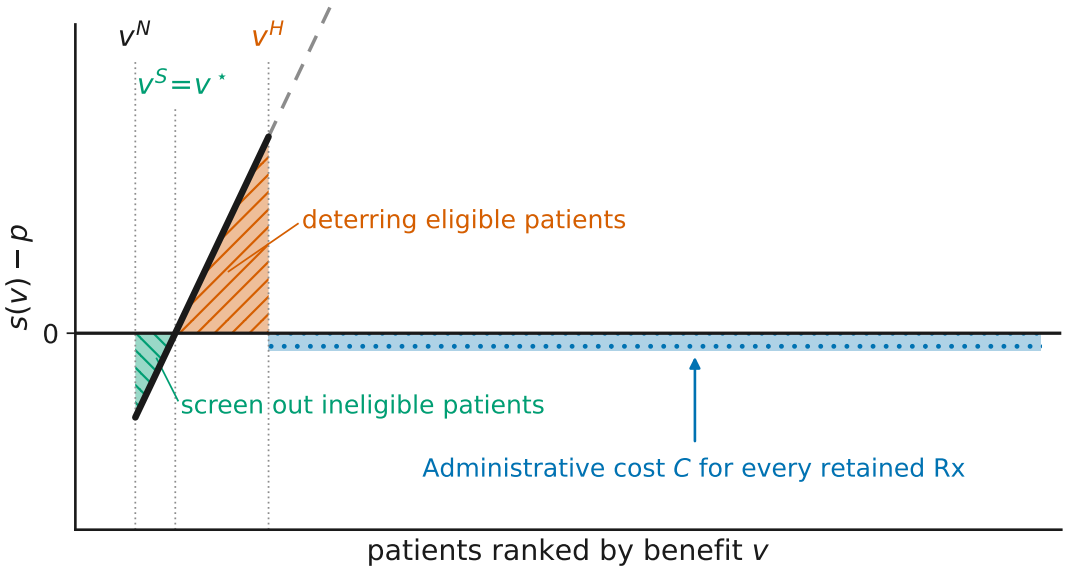



Figure B.2

The three terms of $\Delta W$. Ranking patients along the horizontal axis by clinical benefit makes horizontal distance proportional to population mass, so that each welfare term is an area. The two allocative terms are triangles adjacent to $v^\star$, where $s(v) - p = 0$: the screening gain is small because the patients it removes are only marginally below the efficiency threshold, while the burden loss extends further above it. The administrative cost is a rectangle of height $C$, which is small relative to the health stakes of an individual prescription, spanning every patient who retains the drug.

The welfare analysis underscores the importance of our main finding: most of the reduction in ADHD drug use comes from patients who would likely meet the insurer's own approval criteria. These eligible patients account for 66 to 81 percent of the decline, depending on how strictly we define eligibility. In the model, treatment lost by these patients lowers welfare, whereas treatment lost by ineligible patients raises it. Our estimates therefore imply that most of the reduction in use falls on the group for whom it lowers welfare, even if the insurer's criteria perfectly reflect social value, the case most favorable to screening. Prior authorization also imposes administrative costs beyond these changes in use, since a request must be filed for every patient who remains on the drug, roughly 85 percent of baseline users in our setting.

# C Decomposing the Reduction in Drug Use into Hassle and Screening

This appendix describes how we compute the share of the reduction in ADHD drug use attributable to eligible patients as a result of hassle costs, shown in Figure 5.

**Decomposition.** Consider a population in which a share $x$ of enrollees is eligible for treatment under the insurer's approval criteria and the remaining $1-x$ is ineligible. Let $u_E$ and $u_I$ denote baseline drug use among eligible and ineligible enrollees, and let $\beta_E$ and $\beta_I$ denote the proportional effect of prior authorization on use in each group. The reduction in use in each group equals its population share times its baseline use times the proportional effect, so the share of the total reduction attributable to eligible patients is

$$S(x) \;=\; \frac{x\,u_E\,\beta_E}{x\,u_E\,\beta_E + (1-x)\,u_I\,\beta_I}. \tag{C.1}$$

Because eligible patients would likely be approved if a request were filed, we attribute their reduction to the hassle cost effect. The reduction among ineligible patients reflects the effects of screening since they would be denied coverage if they submit a prior authorization request, so S(x) is the share of the reduction due to hassle costs.

**Inputs.** Table C.1 lists the parameters for ADHD drugs from our estimates. Baseline use is the pre-treatment mean reported in Table 4, and the proportional effects are the pooled RD estimates in Table 4. For ineligible patients, we use $u_I = 0.006$ and $\beta_I = 0.25$. For the purpose of our decomposition, we treat all enrollees who do not meet a given eligibility definition as ineligible and apply the same baseline mean $u_I$ and treatment effect $\beta_I$ to everyone in this sample.[1]

Table C.1: Parameters for the Decomposition (ADHD drugs)

| Eligibility definition | Curve | Eligible share $x$ | Baseline use $u_E$ | Effect $\beta_E$ | Share $S(x)$ |
|---|---|---|---|---|---|
| ADHD diagnosis | Red | 0.11 | 0.304 | 0.175 | 81% |
| + Prior ADHD medication use | Blue | 0.07 | 0.582 | 0.115 | 77% |
| + Specialist as primary prescriber | Purple | 0.05 | 0.598 | 0.093 | 66% |
| Ineligible patients: $u_I = 0.006$, $\beta_I = 0.25$ | | | | | |

*Note:* $u_E$ is the share of enrollees with any ADHD prescription. $\beta_E$ is the effect size of prior authorization on ADHD drug use from Table 4. $S(x)$ is the share of reduction in ADHD drug use under each definition in our sample, using Eq. (C.1).

[1] This may include patients with an ADHD diagnosis, who do not meet eligibility criteria such as prior medication use or a specialist prescriber, and also includes patients who do not have a diagnosis whom our model predicts to have ADHD. Excluding these enrollees altogether from the decomposition would raise the share attributable to eligible patients, so this choice is conservative.

**Curves and dots in Figure 5 Panel A.** Each curve plots $S(x)$ over $x \in [0, 0.3]$, holding $u_E$ and $\beta_E$ at their values for one eligibility definition. The curves differ because stricter definitions select patients with higher baseline use and smaller estimated effects. The dot on each curve marks the eligible share observed in our sample under that definition, so its height is the estimated share of the reduction in ADHD drugs attributable to eligible patients which we interpret as the hassle cost effect.

**Simulations in Figure 5 Panel B.** Panel B changes one set of parameters at a time, starting from the parameters used in the ADHD-diagnosis definition: (i) lowering the eligible share from 11% to 1%, which moves the dot along the red curve; (ii) raising $u_I$ from 0.006 to 0.05, which shifts the curve down (blue); and (iii) setting $\beta_E = 0.03$ and $\beta_I = 0.60$ (purple).