# RATIONING MEDICINE THROUGH BUREAUCRACY: AUTHORIZATION RESTRICTIONS IN MEDICARE
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# Background

- Administrative costs make up a substantial portion of healthcare spending in the United States
- half of administrative effort is spent on activities that aim to reduce healthcare utilization and spending
- evaluate the trade-off between administrative burden for potential reductions in moral hazard and lower costs of insurance provision
- specifically, of **prior authorization restrictions** in healthcare, specifically focusing on their impact on drug utilization and healthcare costs

# Innovation

- comprehensive analysis of the effects of prior authorization on drug utilization using a large dataset and advanced statistical techniques
- examines the efficiency and equity implications of prior authorization policies, shedding light on their broader impacts on the healthcare system.

# Outline

# Prior Authorization Restrictions in Practice

- Prior Authorization Restrictions: insurers require approval from providers before covering certain medical services or prescription drugs
- Purpose: ensures appropriate utilization of healthcare resources, control costs
  - The physician's willingness to complete the forms implicitly signals to the payer that the value of the drug or treatment to the patient is high enough to justify going through the process.

# A Model of Prior Authorization Restriction

**without** Prior Authorization Restriction

- $\triangle v_{id} = v_{id} - v_{i(-d)}$ the incremental value; $\triangle c_{id}$ the incremental cost
- consumer type $\theta \in [0, 1]$
- The patient will receive the drug if $u(\theta_{id}) \geq 0$
- social welfare

$$W(0) = \int_{\Theta_0} [V_d(\theta) - C_d(\theta)] d\theta$$

, where $\Theta_0 = \{\theta : u(\theta_{id}) \geq 0\}$

# A Model of Prior Authorization Restriction

**with** Prior Authorization Restriction

- new choice utility function $u_A(\theta_{id})$
- administrative cost $a$
- social welfare

$$W(1) = \int_{\Theta_1} [V_d(\theta) - C_d(\theta)]d\theta - a$$

, where $\Theta_1 = \{\theta : u_A(\theta_{id}) \geq 0\}$

Welfare Impact of Prior Authorization Restriction:

$$W(1) - W(0) = -\int_{\Theta_M} V_d(\theta) + \int_{\Theta_M} C_d(\theta)d\theta - \int_{\Theta_1} a$$

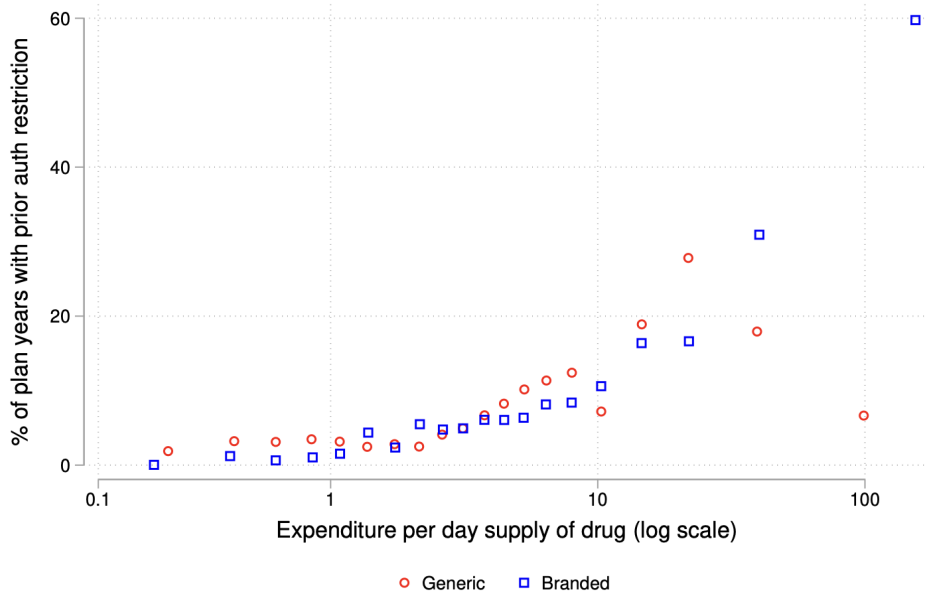
, where $\Theta_M = \Theta_0 \backslash \Theta_1$

# Model: When Should Policymakers Restrict Drugs?

this model implies drugs under the restriction should be:

- Optimizing Administrative Costs: few inframarginal users
- Addressing Moral Hazard: incremental value is low
- Ideal drugs for restriction are expensive, niche-branded drugs, particularly new entrants in established therapeutic classes

**Figure 2:** Prior Authorization Restrictions by Drug Price



# Data

utilizes administrative datasets from the Centers for Medicare and Medicaid Services (CMS) from 2007 to 2015.

1. Beneficiary Demographics, Enrollment, and Choice Status
   - tracks whether enrollment was initiated through active choice or the default auto-assignment mechanism.
   - allows us to observe the *assigned* plan and the *enrolled* plan for each beneficiary, even when the two differ.
2. Plan Characteristics
3. Formulary Data: drug-level, the set of drugs covered by each plan each year
4. Outpatient Prescription Drug Data
5. Other Drug Information: rebates etc.

# Data: Sample Selection

- restriction to full Low Income Subsidy (LIS) Beneficiaries
  - they effectively pay nothing out of pocket for covered drugs, making prior authorization the primary feature of the insurance contract that shapes drug demand
  - they frequently face default rules which assign them to a randomly-chosen plan if they do not make an active plan choice
- restrict to those who were automatically reassigned to a benchmark plan
- data from the year before their reassignment to two years after reassignment

# The Effect of Authorization Restrictions on Drug Utilization

the treatment effect of moving a drug from being covered with no restrictions to being covered with restrictions, all else equal.
identification challenges:

1. beneficiaries are free to choose plans, beneficiaries intending to take specific drugs may be inclined to avoid plans that restrict the drugs they want, introducing reverse causality between propensity to use a drug and whether a beneficiary faces prior authorization
2. plans do not randomly select which drugs to restrict

# Effect of on Drug Utilization: Research Design

solutions:

1. restrict to *only* beneficiaries who faced random assignment to default plans.
2. use an indicator for whether the drug was restricted under the beneficiary's **assigned plan** as an **instrument** for whether the drug was restricted under the beneficiary's **enrolled plan**, for each beneficiary-drug pair
3. rich controls: drug-by-market fixed effects; assigned-plan-by-market fixed effects; whether the drug was excluded in the enrolled plan; formulary status of substitutes

# Effect of on Drug Utilization: Research Design

estimating equations

$$\begin{aligned} Y_{idt} = \beta_1 Auth_{idt}^{Enrolled} + \beta_2 Excl_{idt}^{Enrolled} + \kappa_{dm(it)} + \lambda_{j(it)m(it)} \\ \gamma_1 Auth_{j(it)dt}^{Sub,Assigned} + \gamma_2 Excl_{j(it)dt}^{Sub,Assigned} + \nu_{idt} \end{aligned} \tag{1}$$

$$\begin{bmatrix} Auth^{Enrolled} \\ Excl_{idt}^{Enrolled} \end{bmatrix} = \begin{aligned} \delta_1 Auth_{idt}^{Assigned} + \delta_2 Excl_{idt}^{Assigned} + K_{dm(it)} + \Lambda_{j(it)m(it)} \\ \Gamma_1 Auth_{j(it)dt}^{Sub,Assigned} + \Gamma_2 Excl_{j(it)dt}^{Sub,Assigned} + u_{idt} \end{aligned} \tag{2}$$

where the utilization outcome is a binary indicator for whether the beneficiary filled the drug at least once in the year.

# Effect of on Drug Utilization: : Main Estimates

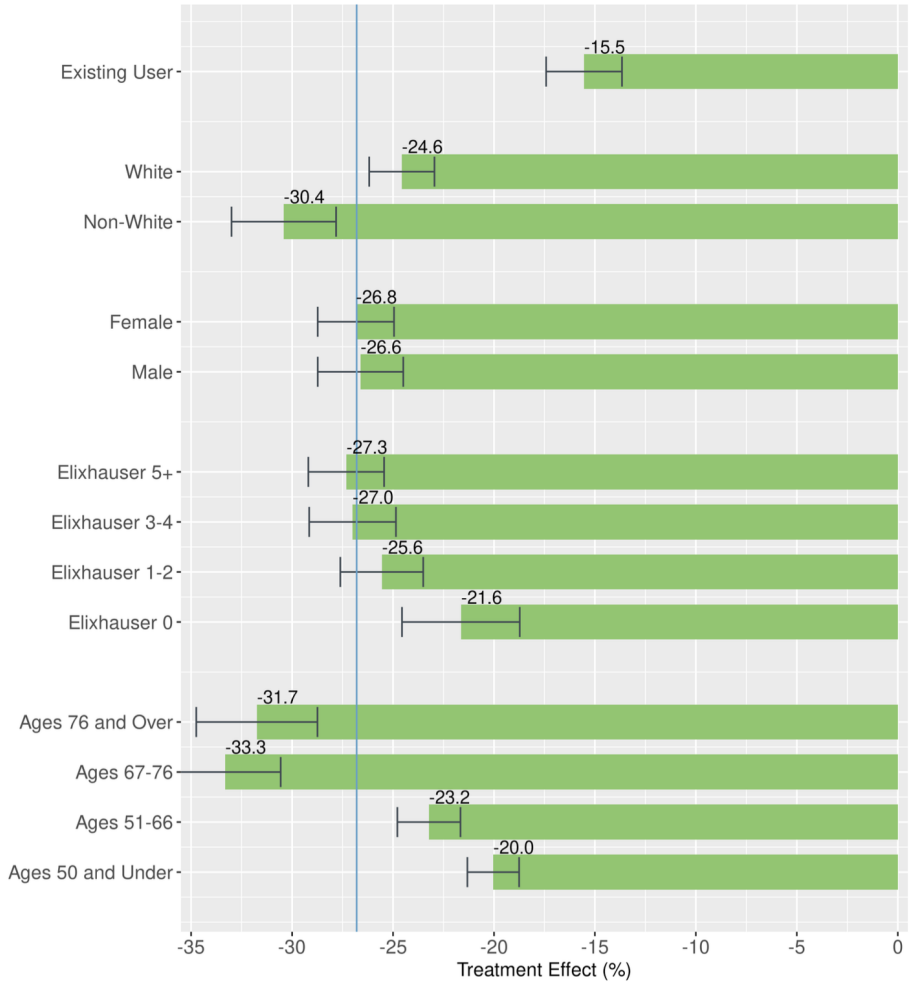
**Table 5:** Estimates of the Effect of Prior Authorization Status on Drug Utilization

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $\text{Auth}^{\text{Enrolled}}$ | -1.169 | -0.136 | -0.098 | -0.099 | -0.101 | -0.108 |
| | ( 0.012) | ( 0.005) | ( 0.004) | ( 0.003) | ( 0.003) | ( 0.004) |
| $\text{Auth}^{\text{Sub}}$ | | | | | | 0.049 |
| | | | | | | (0.0036) |
| PA % Effect | -290.0 | -33.7 | -24.3 | -24.5 | -25.1 | -26.8 |
| Control Mean | | | 1.299 | | | |
| Reweighted Control Mean | | | 0.403 | | | |
| Drug FEs | | X | | | | |
| Drug-year FEs | | | X | | | |
| Drug-market-year FEs | | | | X | X | X |
| Plan-market-year FEs | | | | | X | X |
| Substitution Controls | | | | | | X |
| Number of drug × beneficiary-years | | | 1,723,975,571 | | | |
| Number of market years | | | 210 | | | |
| Average plans per market-year | | | 6.6 | | | |
| Average beneficiaries per plan | | | 51 | | | |
| Average drugs per year | | | 1569.2 | | | |

Figure 1: %PA effect = coefficient estimates divided by reweighted control mean

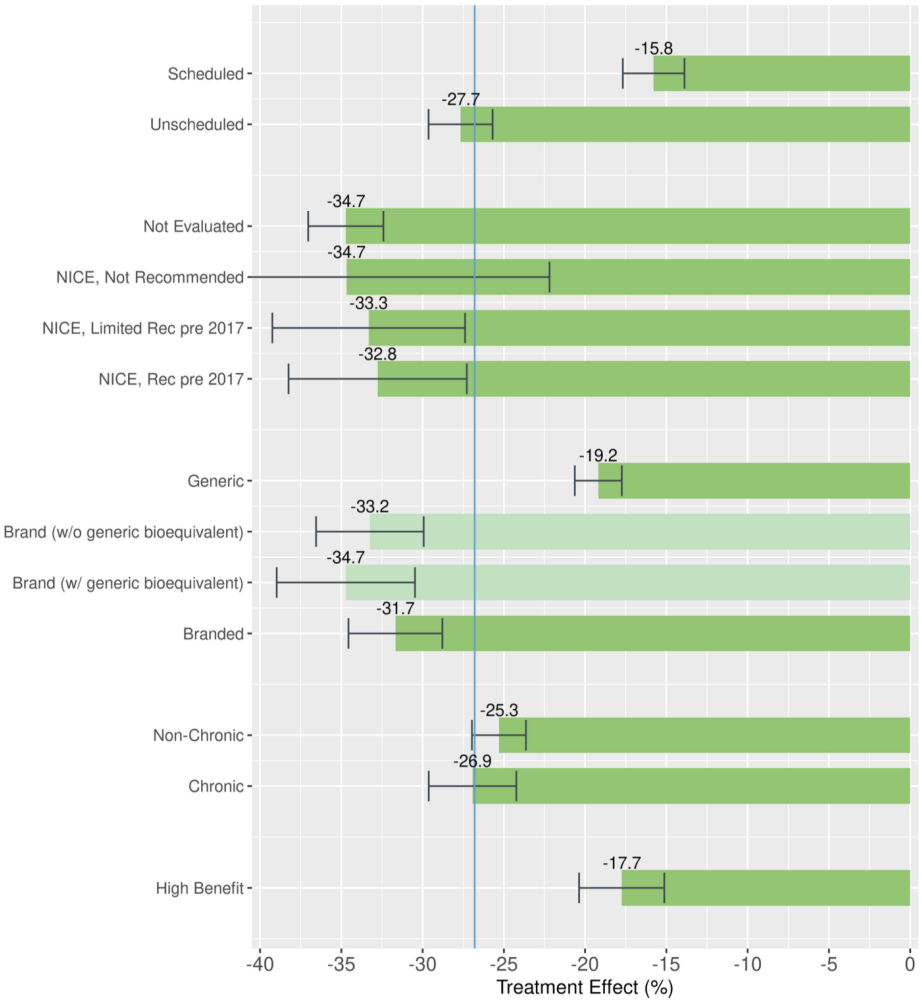
# Effect of on Drug Utilization: Heterogeneous Effects

**Figure 5:** Heterogeneous Effects of Prior Authorization on Utilization by Beneficiary Characteristics



# Effect of on Drug Utilization: Heterogeneous Effects

**Figure 6:** Heterogeneous Effects of Prior Authorization on Utilization by Drug Characteristics



# Spending Effects: Estimating Substitution Patterns

a discrete choice of a single drug within a therapeutic class for a given year:

$$u_{idt} = \underbrace{\beta_C Auth_{idt} + \delta_C Excl_{idt} + \kappa_{dm(it)}}_{V_{idt}} + \xi_{iCt} 1\{d \neq 0\} + \lambda_{C\epsilon idt}$$

which implies a nested logit demand system. The probability of taking a drug is

$$P_{id} = \frac{\exp \frac{V_{idt}}{\lambda_C} (\Sigma_{k \in C} \exp \frac{V_{idt}}{\lambda_C})^{\lambda_C - 1}}{1 + (\Sigma_{k \in C} \exp \frac{V_{idt}}{\lambda_C})^{\lambda_C - 1}}$$

with $1 - \lambda_C$ governing the within-nest correlation of unobserved preferences

# Spending Effects: Estimating Substitution Patterns

primary parameters of interest are

- $\beta_C$, the effect of prior authorization on choice utility
  identified from differences in a drug's market share among beneficiaries enrolled in plans that restrict it versus the market share among beneficiaries in plans that do not restrict it
- $\lambda_C$, governs the extent of intensive margin substitution
  compare the relative market shares of *all other drugs* from beneficiaries in plans that restrict a given drug, compared to the market shares of those drugs from beneficiaries in plans that do not restrict a given drug

Poisson pseudo-maximum-likelihood estimation method

# Spending Effects

with the estimated parameters, simulate demand for drugs under (1) status quo of beneficiary plan assignment (2) alternative where drugs that were previously under restrictions are now unrestricted.
Then measure the effects of moving from simulation (2) to (1)

**Table 6:** Spending and Utilization Effects of Status Quo Relative to Ban on Prior Authorization Restrictions

| | Total | Restricted Drugs | Unrestricted Drugs | No Drug |
|---|---|---|---|---|
| Change in | -3.57% | -21.8% | +0.72% | - |
| Spending | -95.88 | -111.57 | +15.69 | - |
| Per Capita | | | | |
| Change in | -0.65% | -28.9% | +0.58% | +0.06% |
| # Users | -0.065 | -0.120 | +0.056 | +0.065 |
| Per Capita | | | | |
| Diversion | - | -100% | 46.2% | 53.8% |

# Administrative Cost Burden

relevant parameters:

- joint cost to both the physician (submit requests) and the insurer (process requests): $a$
- constant rejection rate across all drugs and years: $r$
- # of patients taking the drug: $N$

then there will be $\frac{N}{1-r}$ requests and the administrative cost is $\frac{aN}{1-r}$

# Administrative Cost Burden– Calibration

- estimates $N$ using simulation under status quo in the previous section
- estimates cost $a$ based on previous literature: provider-side paperwork cost is \$18.53 per application; processing cost is \$3.95 per application

**Table 7:** Per Capita Administrative Burden of Authorization Restrictions

| | | Request Rejection Rate | | | | |
|---|---|---|---|---|---|---|
| | | 0% | 1.5% | 4% | 7.5% | 15% |
| Paperwork Cost | \$11.62 | \$4.84 | \$4.92 | \$5.04 | \$5.24 | \$5.70 |
| | \$18.19 | \$7.58 | \$7.70 | \$7.90 | \$8.20 | \$8.92 |
| | \$21.72 | \$9.05 | \$9.19 | \$9.43 | \$9.79 | \$10.65 |
| | \$22.48 | \$9.37 | \$9.51 | **\$9.76** | \$10.13 | \$11.02 |
| | \$31.30 | \$13.04 | \$13.24 | \$13.59 | \$14.10 | \$15.35 |
| | \$50 | \$20.84 | \$21.16 | \$21.71 | \$22.53 | \$24.52 |
| | \$100 | \$41.68 | \$42.31 | \$43.41 | \$45.06 | \$49.03 |
| | \$200 | \$83.35 | \$84.62 | \$86.83 | \$90.11 | \$98.06 |

Figure 2: subtracting from \$96, a net saving of around \$86

# Welfare Effect: a Revealed Preference Approach

aim: estimate the total loss in consumer surplus due to being turned away from a drug

$$\triangle CS_d = -\int_{\Theta_M} V_d(\theta) d\theta$$

denote the WTP for drug $d$ for $\theta$ type consumer as $W_d(\theta_{id})$
the market demand curve is $D_d(P_d) = \int 1\{W_d(\theta) \geq P_d\} d\theta$
use the exogenous variation in $P_d$ to trace out $D_d(\cdot)$ and the distribution of $W_d$
if $W_d(\theta) = V_d(\theta)$, can get the distribution of $V_d$

# Welfare Effect: a Revealed Preference Approach

leverage the transitions of 62,785 beneficiaries into the LIS as a source of exogenous variation in price

$$\log(E[Y_{idt}]) = \frac{\epsilon}{100} P_{dt} \times NotLIS_{it} + \alpha_i + \gamma_{dmt} + \epsilon_{it} \tag{3}$$

where $P_{dt} \times NotLIS_{it}$ is equal to the price of the drug d in year t for those not yet enrolled in the LIS program ($NotLIS_i t = 1$) and zero for those enrolled ($NotLIS_i t = 0$)
estimated by Poisson regression, the estimated $\epsilon = 0.15$
assume the demand curve is $D_d(P_d) = D_d(0)e^{\frac{\epsilon}{100}P_d}$ then the distribution of $W_d$ is

$$F_d(W) = 1 - D_d(0)e^{\frac{\epsilon}{100}W}$$

estimate $D_d(0)$ in simulation absent of restriction

# Welfare Effect: a Revealed Preference Approach

with 28.9% of users deterred by the restriction,

- if marginal beneficiaries screened away are those with the lowest WTP

$$\triangle CS_d^{best-case} = -\int_{(1-0.289)D_d(0)}^{D_d(0)} D_d^{-1}(\theta)d\theta$$

- if screening is random

$$\triangle CS_d^{random} = -0.289\int_{0}^{D_d(0)} D_d^{-1}(\theta)d\theta$$

# Welfare Effect: a Revealed Preference Approach

**Table 9:** Revealed Preference Estimates of Consumer Surplus Loss

| | (1) | (2) |
|---|---|---|
| Best-Case Screening | 3.83 | 13.05 |
| Random Screening | 23.80 | 80.91 |
| Beneficiary FEs | | X |
| Net Financial Savings from Prior Authorization | 86.58 | |

Figure 3: two columns represent two amounts under the two estimates of semi-elasticity demand. Under the best-case screening, the amount consumers are willing to pay for the forgone drugs is around 15% of the net savings. In the random screening case, the amount consumers are willing to pay for the forgone consumption is in the same general range as the net savings.

# Health Effects: Case Study of Oral Anticoagulants

understand the impact of prior authorization restrictions on access to non-Vitamin K oral anticoagulants (NOACs) compared to warfarin, a low-priced generic alternative, with:

$$Y_{it} = \beta AuthAllNOACs_{j(it)t} + \gamma OtherFormulary_{j(it)t} + \delta_{m(it)} + \epsilon_{it}$$

, where

- *AuthAllNOACs* is a dummy variable indicating whether assigned to a plan $j$ where all NOACs were restricted;
- $Y$ is an indicator of a beneficiary's health outcomes

health outcomes such as strokes, bleeding events, and death yield inconclusive results

# Health Effects: Aggregate Health Effects

the effect of prior authorization aggregated across drug classes
construct two indicators:

- $AuthExposureQ5_i$ whether the beneficiary's assigned plan was in the quantile with the most exposure to prior authorization
- $ExclExposureQ5_i$ assignment to the worst plans in terms of their exclusion of previously-taken drugs

$$Y_{it} = \beta AuthExposureQ5_i + \gamma ExclExposureQ5_i + \delta_{m(i)} + \epsilon_i$$

$\beta$ thus represents the health consequences of greater exposure to prior authorization. The result is still inconclusive.

# Health Effects: Aggregate Health Effects

**Table 12:** Effects of Aggregate Prior Authorization Restriction Exposure on Utilization and Health Outcomes

| | All Beneficiaries | | | |
|---|---|---|---|---|
| | Spending | % Died in Year | Inpatient Spending | Non-Drug Medical Spending |
| AuthExposureQ5 | -64.825 | 0.058 | 68.446 | 78.948 |
| | (29.508) | (0.065) | (87.435) | (120.543) |
| Control Mean | 4,210.39 | 2.253 | 12,196.71 | 1,579.28 |
| N (beneficiary-years) | | | 609,316 | |
| | Top 25% of Beneficiaries by Spread in Fit | | | |
| | Spending | % Died in Year | Inpatient Spending | Non-Drug Medical Spending |
| AuthExposureQ5 | -192.499 | -0.051 | -162.382 | -309.17 |
| | (43.018) | (0.115) | (145.638) | (201.224) |
| Control Mean | 3,909.49 | 2.151 | 5,429.84 | 11,090.72 |
| N (beneficiary-years) | | | 152,385 | |

*Notes*: This table presents coefficient estimates from a set of regressions of a beneficiary's utilization and health outcomes in a given year on an indicator for whether their assigned plan was in the bottom quintile of benchmark plans in terms of putting authorization restrictions on their previously-taken drugs. Regressions include market fixed effects and a control for exclusion exposure.

Figure 4: second panel restrict to a subset of beneficiaries who face the greatest variation across plans in terms of exposure to prior authorization

# Conclusion

- reducing drug spending by \$96 per beneficiary-year, while only generating approximately \$10 in paperwork costs. The cost savings likely exceed beneficiaries' willingness to pay for foregone drugs.
- Despite its benefits, prior authorization policies may not be optimal if implemented more widely.