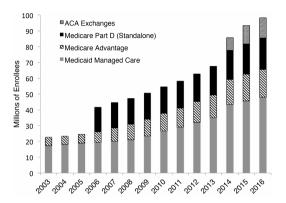
The Private Provision of Public Services: Evidence from Random Assignment in Medicaid

Danil Agafiev Macambira, Michael Geruso, Anthony Lollo, Chima D. Ndumele, and Jacob Wallace

NBER Summer Institute

Motivation

- In midst of rapid shift to private provision of social health insurance in the US
- US spends **\$1 trillion annually** on private plans in Medicaid, Medicare, and ACA Exchanges
- Privatization most prevalent in Medicaid, where 3/4 of enrollees now in private plans



The idea: Private managed care plans have strong incentives to control cost via high-powered contracts (Laffont and Tirole, 1993) and the tools to manage care more efficiently than public programs...

...but incentives for cost control can be too strong \rightarrow lower quality (Hart, Vishny, and Shleifer, 1997)

Literature review

- Private versus public provision of healthcare (e.g., in Medicare (Duggan, Starc and Vabson, 2016; Cabral, Geruso and Mahoney, 2018; Curto et al., 2021) and Medicaid (for e.g., Duggan 2004; Currie and Fahr, 2005; Aizer et al, 2007; Sparer, 2012; Duggan and Hayford, 2013; Marton et al, 2014; Van Parys, 2017; Perez, 2018; Vabson, 2018; Chorniy et al., 2018; Kuziemko et al., 2018; Lee, 2020; Dranove et al., 2021; Duggan et al., 2021; Layton et al., 2022) and at the provider-level (Knutsson and Tyrefors, 2021; Chan, Card, and Taylor, 2022; Duggan, Gupta, Jackson, and Templeton, 2023)
 - . Results are mixed as to whether privatization reduces cost, particularly in Medicaid
 - Conflicting findings on quality ranging from improved access to higher mortality
 - Challenge: Hard to estimate causal effects due to selection between private/public and potential endogeneity in the timing of privatization

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 - . Results are mixed as to whether privatization reduces cost, particularly in Medicaid
 - Conflicting findings on quality ranging from improved access to higher mortality
 - Challenge: Hard to estimate causal effects due to selection between private/public and potential endogeneity in the timing of privatization
- Effects of managed care (e.g., Glied, 2000; Cutler, McClellan, and Newhouse, 2000; Gruber and McKnight, 2016; LoSasso and Atwood, 2016, Wallace, 2023; Geruso, Layton, Wallace, 2023; Abaluck et al., 2021; Handel et al., 2021)
 - Historical focus on whether managed care tools can constrain spending rather than how
 - Challenge: Difficult to identify mechanisms but critical to understand for regulation of public insurance

Insurers Deny Medical Care for the Poor at High Rates, Report Says

Investigators found that major companies overseeing Medicaid patients' health care frequently rejected doctors' requests for approval of treatments and procedures.

Medicare Advantage Plans Often Deny Needed Care, Federal Report Finds

Investigators urged increased oversight of the program, saying that insurers deny tens of thousands of authorization requests annually.

Department of Health and Human Services Office of Inspector General



High Rates of Prior Authorization Denials by Some Plans and Limited State Oversight Raise Concerns About Access to Care in Medicaid Managed Care

Christi A. Grimm Inspector General July 2023, OEI-09-19-00350



This paper

This paper provides **novel empirical evidence** on the effects of private vs. public provision in a setting where both models operate contemporaneously with **randomization** between the two and **rich data to pinpoint mechanisms and catalog tradeoffs**

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This paper provides **novel empirical evidence** on the effects of private vs. public provision in a setting where both models operate contemporaneously with **randomization** between the two and **rich data to pinpoint mechanisms and catalog tradeoffs**

- Natural experiment: Random assignment of nearly 100,000 Medicaid enrollees to either private managed care or managed FFS in Louisiana
- Data: Detailed administrative data including denied claims, prices paid to providers, and provider network data allow us to contrast effects of privatization across services and delve into mechanisms
- Research questions:
 - **O** Does private managed care constrain healthcare spending relative to FFS? For which services?
 - What mechanisms does managed care use to constrain spending?
 - I How does managed care impact health care quality and enrollee satisfaction?

Preview of Findings

We find evidence privatization entails a cost-quality tradeoff, but terms of the tradeoff differ markedly by service

- Total spending: \downarrow 5-10pp
- Good deal for pharmacy: 25pp ↓ spending driven by quantity reductions and substitutions to lower-cost alternatives; no evidence of lower pharmacy-related health care quality
- Bad deal for medical: No savings and less primary care, more adverse health events, and lower satisfaction

We identify utilization management (observed via denials) as key mechanism

- Consistent with recent evidence on PA in Medicare Part D (Brot-Goldberg et al. (2021)) and complements Dunn et al. (2023): the managed care bureaucracy has both **costs and benefits**
- Contribute to emerging literature on the effects of managed care *mechanisms* (e.g., provider networks (Gruber and McKnight, 2016; LoSasso and Atwood, 2016, Wallace, 2023) and on prior authorization/denials (e.g., Dunn et al, 2023; Brot-Goldberg et al., 2021))

Outline

1 Data, Setting, and Empirical Framework

Does private managed care constrain spending?

Mechanisms: How does managed care reduce spending?

What effects does private managed care have on quality and enrollee wellbeing?

Conclusion

Background: FFS vs. Medicaid Managed Care (MMC)

Public fee-for-service (FFS) Medicaid:

- Patient goes to a doctor, state pays according to administrative fee schedule
- No network restrictions, but providers must accept Medicaid
- *Managed FFS:* Plans get \$10 month to setup PCP network and do basic care coordination, but all claims are paid by the state

Private Medicaid managed care (MMC):

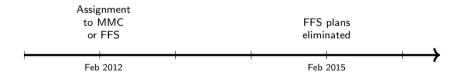
- State does not pay doctors directly; managed care plan pays provider bills
- State pays plan fixed payment regardless of how much care provided, plans profit off savings
- Plans build provider networks and pay providers, do care coordination, utilization management, customer service, etc.

Keep in mind: Medicaid is a setting with no cost sharing so plans are "at risk" for all spending and must rely exclusively on these managed care tools to shape utilization

• This helps us pinpoint effects of managed care tools, shuts down (consumer-facing) prices channel

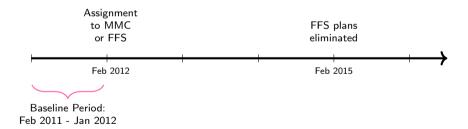
Examine transition from FFS to MMC in Louisiana in February 2012

- Pre-reform: only a state-run FFS plan
- Post-reform: Managed FFS (2 plans) and full-risk managed care MMC (3 plans)
- 2/3 of enrollees didn't choose and were randomly assigned between the models



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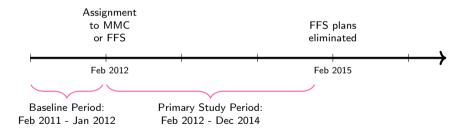
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• One year of baseline (i.e., pre-assignment) data on utilization and spending allows for balance tests

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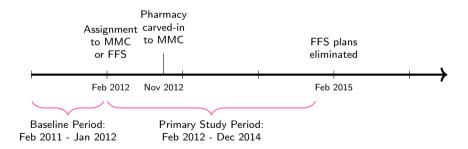
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• No differential attrition so limit sample to those continuously enrolled for all 3 years post-assignment allowing us to observe short- and medium-run effects

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• Pharmacy was carved-in to MMC after transition, creating additional variation that helps us understand heterogeneity in the effects of managed care by service

Summary Statistics

| | Mean (1) | Std Dev (2) |
|--------------------------------------|-------------|----------------|
| | (1) | (2) |
| Panel A. Enrollee Characteristics | | |
| Female (%) | 52.92 | 49.92 |
| Age at baseline | 9.36 | 7.49 |
| Panel B. enrollee-year spending (\$) | | |
| Total | 1 451.35 | 2 427.61 |
| Medical | 1 052.74 | 1815.46 |
| Inpatient | 97.48 | 747.79 |
| Outpatient | 590.29 | 820.12 |
| Pharmacy | 381.45 | 948.76 |
| Brand Drug | 229.30 | 757.06 |
| Generic Drug | 149.63 | 345.53 |

Key Takeaways

- Pre-expansion so young population; pharmacy accounts for more than 25% of spending
- Examples of common diagnoses: ADHD, asthma, upper respiratory infection...
- Examples of commonly prescribed drugs: ADHD medication, Anti-allergics, Antibiotics...

Primary Approach: Leverage random assignment in Feb 2012 to either MMC or FFS to estimate effects of MMC. Use 2SLS since assignment is not binding:

$$Y_{it} = \alpha + \beta \widehat{ManagedCare}_{it} + \phi_i^p + \delta X_{it} + \eta_{it}$$
(1)

- $\bullet~\beta$ is the coefficient of interest, on indicator for enrollment in managed care
- ϕ_i^p are fixed effects for the enrollee's pre-assignment provider (the unit of randomization)
- X_{it} is a vector of individual controls

Econometric details: Identifying Assumptions

Key identifying assumptions are simple and transparent here

- Validity: assignment to a Medicaid managed care plan must be associated with actual enrollment in Medicaid managed care
- Exclusion Restriction: assignment may only impact recipient outcomes through its effect on Medicaid managed care enrollment

Econometric details: Identifying Assumptions

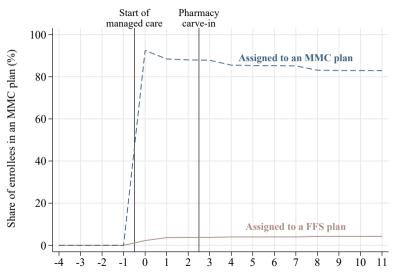
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What would violate these?

- $\textbf{ If the first stage is weak} \rightarrow \textit{Demonstrate first stage is strong}$
- \blacksquare If the state was non-randomly assigning enrollees \rightarrow Show balance on baseline covariates
- If assignment was random but caused differential attrition out of sample
- If plans in MMC vs. Managed FFS differ markedly could impact outcomes though other channel beside privatization → Second identification strategy using within-plan variation

First Stage: Assignment to MMC strong predictor of enrollment in MMC



Quarters relative to treatment ($t_0 = \text{Feb } 2012$)

Balance: Assignment to MMC (vs. FFS) does not predict characteristics

| | Mean | Coef. on Managed Care Assignment (2) | p-value (3) |
|---------------------------------------|--------|--|----------------|
| | (1) | | |
| Panel A. Enrollee Characteristics | | | |
| Age at baseline | 9.36 | 0.02 | 0.89 |
| Female (%) | 52.92 | 0.04 | 0.91 |
| Panel B. Enrollee Health Conditions | | | |
| Asthma | 6.18 | -0.02 | 0.89 |
| Serious Mental IIIness | 2.71 | 0.02 | 0.90 |
| Diabetes | 0.63 | 0.03 | 0.59 |
| Pregnancy | 1.22 | 0.01 | 0.87 |
| Cardiovascular conditions | 1.23 | 0.10 | 0.18 |
| Panel C. Enrollee-month Spending (\$) | | | |
| Total | 153.82 | 11.36 | 0.11 |
| Medical | 117.83 | 11.06 | 0.10 |
| Pharmacy | 35.99 | 0.31 | 0.81 |
| N | | 94,976 | |

Outline

Data, Setting, and Empirical Framework

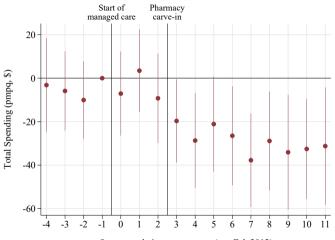


Mechanisms: How does managed care reduce spending?

What effects does private managed care have on quality and enrollee wellbeing?

Conclusion

Key Result 1: Reduced Form Event Study (preview of the IV)

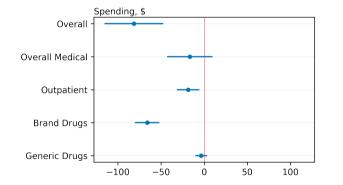


Quarters relative to treatment ($t_0 = \text{Feb } 2012$)

• Specification: assignment to managed care vs. FFS: $Y_{it} = \alpha_i + \alpha_t + \sum_{t \neq -1} \beta_t Assigned Managed Care_i + v_{it}$

• Flexibly allows for impacts to evolve over the post-period; pre-period "effects" are falsification tests

Spending effects driven by pharmacy, specifically brand drugs

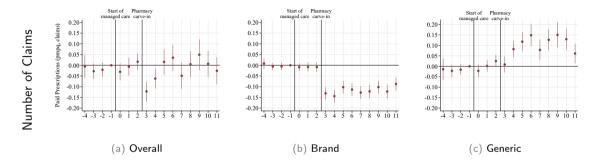


Key Takeaways:

- Pooling 2012-2014, spending ↓ 5.6%, nearly 10% after carve-in
- Effect driven by pharmacy, and particularly brand drugs
- Rest of effect from outpatient, no inpatient effect at all

Effects of Managed Care on Drug Utilization

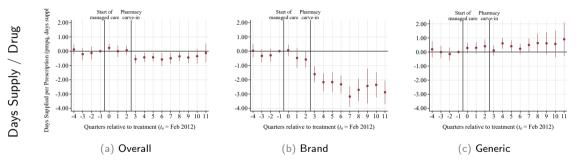
Generic Penetration



Key Takeaways:

- No reduction in medium-run quantity of prescriptions, but 1-for-1 shift from brand to generics
 - This lead to a rapid, 25% reduction in brand drug prescriptions that persisted throughout study period
- Large potential savings: Average paid amount for brand drug was \$151 and for generic drug was \$38.

Effects of Managed Care on Days Supply Per Prescription



Key Takeaways:

• Approximately a 10% decline in days supply for brand drugs, modest changes overall and for generics

Summary so far

- Private managed care generates large spending reductions (identified off of random assignment)
 - $\bullet\,$ Total spending: \downarrow 5%, 10% by the end
 - $\bullet\,$ Pharmacy spending: $\downarrow\,20\text{-}25\%$ after pharmacy carve-in
- We find evidence of several important channels for pharmacy savings, no simple formula:
 - Brand-to-generic substitution
 - $\bullet \ \downarrow$ days supply per prescription
 - \downarrow quantity for some drug classes (more on this later)
- Formal decomposition in spirit of Brot-Goldberg (2017):
 - $\bullet~78\%$ of total spending effect is Q (vs. P)
 - $\,$ $\bullet\,$ 87% of pharmacy effect is Q (vs. P) and 1/3 is brand-to-generic substitution

Second Strategy: Difference-in-Differences Exploiting Plan Transition

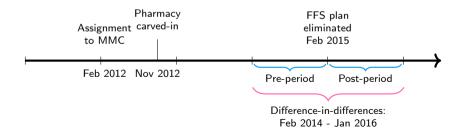
Potential challenge: Estimates are local to auto assignee population (i.e., people who don't pick a plan are different) or biased based on which plans selected for MMC vs. FFS.

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Potential challenge: Estimates are local to auto assignee population (i.e., people who don't pick a plan are different) or biased based on which plans selected for MMC vs. FFS.

Solution: Elimination of FFS allows for 2nd identification strategy using within-plan variation

- Enrollees and ownership remained the same, but model changed from state to plan being at-risk
- Sample: All enrollees in transitioned plan (i.e., auto assignees and choosers) and existing MCOs

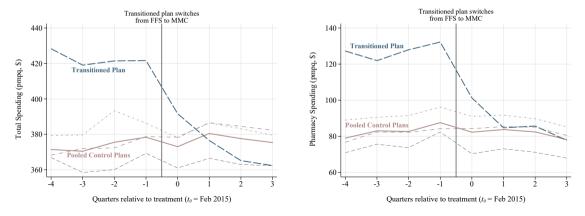


Second Strategy: Difference-in-Differences Exploiting Plan Transition

• We leverage this natural experiment, as diff-in-diff:

Figure: A. Overall Spending





Despite different samples, time frame, and identifying variation the effects were similar:

- Random assignment of people to MMC vs FFS plans
 - 10% overall reduction in spending
 - driven by a 25% reduction in pharmacy
- Plan transition from FFS to MMC
 - $\bullet~12\%$ overall reduction in spending
 - driven by a 32% reduction in pharmacy

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Image: Mechanisms: How does managed care reduce spending?

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• Glied (2000) hypothesizes a range of mechanisms:

Lower prices?

• Some. Following Brot-Goldberg et al. (2017) decompose P v Q by repricing services to common schedule. Prices explained 1/5 of spending effects overall, and less in drugs.



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 - Not provider steering: Sweeping out attributed provider fixed effects leaves results unchanged.
 - Not provider network breadth Adjusting for assigned primary care provider network breadth at the plan \times ZIP level leaves results unchanged.



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Better care management leading to offsets?

• Don't observe directly, but not consistent with facts, e.g., we find no reduction inpatient spending and will show lower use of primary care and increased avoidable emergency department use



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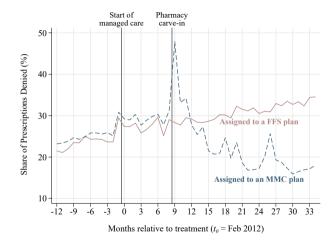
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O Utilization management

• Key mechanism. Show next that: There is a short-term increase in denials (in rx) for enrollees assigned to MMC with spending reductions concentrated in the therapeutic classes targeted by denials.

How is drug spending curtailed? Utilization management via claims denials



Key Takeaways: FFS denial rates not 0; initial peak in MMC denial rates but then fall to lower than FFS.

Utilization management in pharmacy via denials

What does a pharmacy denial look like?

- Real time adjudication: the insurer refuses to pay; patient doesn't get the drug
- Denials may be due to several reasons:
 - Lack of prior authorization, step therapy/fail first, quantity limits (e.g., days supply), non-covered-service Aggregate trends in PA, step therapy, and fail first
 - Incomplete information, errors

Contrast with medical denial: service may be rendered, only payment is in dispute

- Potentially different from story of cost of incomplete payments for physicians (e.g., Dunn et al., 2023) in terms of impact on providers
- Two other advantages:
 - Don't need to change prescribing behavior to generate savings, get to say no before rx is filled
 - Availability of close substitutes in pharmacy vs. medical

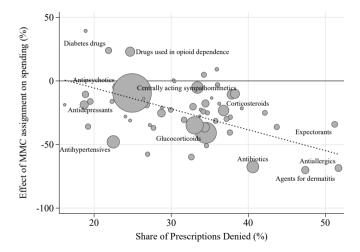
Are strategic claims denials driving the reductions in spending?

Already showed pharmacy spending reduction coincides with spike up in denials and persists...but could be a spurious correlation

Test for dose-response: Are the families of drugs subject to more aggressive utilization management where the spending reductions are concentrated?

- Groups drugs into therapeutic classes (e.g., antibiotics, antidepressants, etc.)
- Plot IV estimates of the spending reductions by therapeutic class vs. claims denial rates
- Use denial rate in first 3 months (the "peak") post pharmacy carve-in, to avoid encoding endogenous provider/enrollee responses
- Exclude drug spending in first 3 months to avoid mechanical effect of denials on spending...

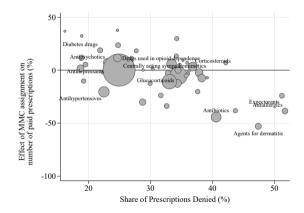
Key Result 2: Savings concentrated in classes subject to denials



Key Takeaways: Large reductions in spending for antibiotics/antiallergics. Smaller reductions (or increases) in for, e.g., diabetes and opioid dependence drugs. 1pp \uparrow denials \rightarrow 1.7pp \downarrow spending

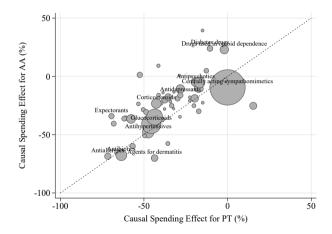
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Denials caused within-class substitutions, not outright reductions for most drug classes



Key Takeaways: Cloud of points centered around 0 on y-axis. Exception is highly-denied services where points below the line — tend to be drug classes where overuse is a concern.

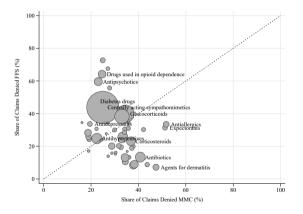
Aside: Spending Reductions Concentrated in Same Drugs for the two natural experiments



Key Takeaway: Further evidence of concordance between the two natural experiments.

FFS doesn't deploy utilization management in same manner

Unique feature of our study: We can contrast how public and private models deploy managed care tools, since we observe claims denials in both



Drugs used in opioid dependence:
MMC denial rate: 25%
FFS denial rate: 60%

- Antibiotics:
 - MMC denial rate: 40%
 - FFS denial rate: 10%

One interpretation: FFS focused on documenting medical necessity, MMC using strategic denials to shape utilization. Does not appear to be driven by differences in incentives due to rebates.

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Does private managed care constrain spending?

Mechanisms: How does managed care reduce spending?



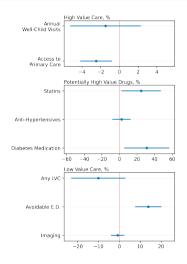
What effects does private managed care have on quality and enrollee wellbeing?



Tradeoffs: Impact of private managed care on quality and wellbeing

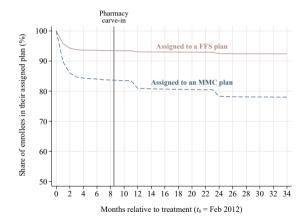
- Recap: Managed care generates reductions in health care spending (relative to FFS) without exposing enrollees to any additional financial risk Great, now ask "what's the catch?"
- Check whether spending reductions come at the cost of quality/wellbeing (e.g., Geruso et al., 2020; Curto et al., 2019; Wallace, 2023).
 - Are there tradeoffs associated with spending reductions, either in pharmacy or beyond?
 - If yes, are quality/satisfaction results driven by same mechanism as spending effects?
- We look at a broad set of measures:
 - Population is young and healthy, so mortality isn't a usable outcome (fortunately)
 - Instead look at wide range of high and low value services? (as in Brot-Goldberg et al. (2017); Curto et al. (2019); Geruso et al. (2020)), show a few
 - Also examine how managed care impacts well-being using an (imperfect) revealed-preference measure of enrollee satisfaction

Key Result 3: Assignment to managed care led to mixed effects on quality, adverse effects concentrated on medical side



- Medical: Reduced access to primary care and large (15%) increase in avoidable emergency department visits
- Drugs: Null or *increased* use of select high-value drug classes *despite* large reductions in drug spending
- Key takeaway: Mixed, but adverse health effects seem disconnected from pharmacy utilization management

Key Result 4: Large differences in disenrollment rates between those assigned to MMC and FFS; revealed preference measure of "satisfaction"



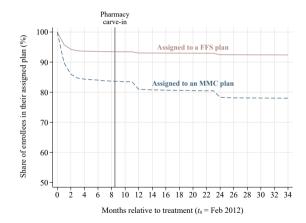
Key takeaway: Enrollees assigned to MMC were 14.54pp (200%) more likely to switch out of plans

Satisfaction effects are huge, are they driven by the key mechanism: pharmacy utilization management?

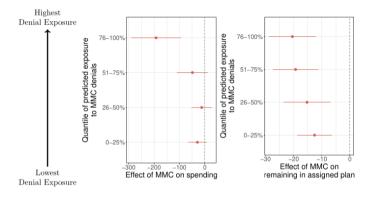
Goal is to get at the spending-satisfaction tradeoff — Assess this in two ways:

- Examine the timing of disenrollments
- Examine heterogeneity based on exposure to utilization management—group enrollees based on pre-carve-in use of drugs targeted by the denial regime
 - Take distribution of enrollees' drug spending across NDCs during pre-carve-in period and ask what % of pharmacy spending would be denied based on denial rates by NDC during "peak-period"?

Much of the differences in disenrollment rates materializes pre-carve-in, but no spending effects until the carve-in



Spending effects driven by exposure to denials, disenrollment effects less so



Key takeaways:

- Spending reductions driven by highest quartile of exposure to the managed care denial regime—no other significant effects
- Large disenrollment rates even among the lowest quartile of exposure to managed care denial regime, though there is a gradient

Outline

Data, Setting, and Empirical Framework

2 Does private managed care constrain spending?

Mechanisms: How does managed care reduce spending?

What effects does private managed care have on quality and enrollee wellbeing?

5 Conclusion

Conclusion

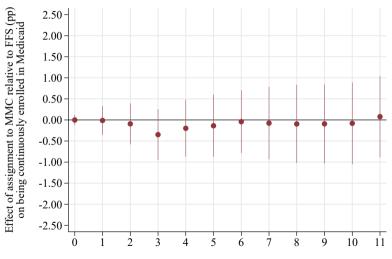
• MMC generates large reductions in spending

- ${\scriptstyle \bullet}$ Total spending: \downarrow 5-10pp driven primarily by quantity, not price, in pharmacy
- But there is no free lunch: MMC reduces use of primary care, increases adverse events, and substantially lowers satisfaction
 - But, interestingly, despite large drug spending reductions, enrollees assigned to MMC continued to use high-value drugs (if anything, we see increases there)
- Effects depend on the services being studied: managed care seems to have sharp tools to manage drugs, but blunter tools on medical side
 - Results may help resolve conflicting results in the literature that split along pharmacy/medical lines
 - Understanding this heterogeneity is important for policy—states have tended to *carve out* rx drugs from managed care (NY/CA moving in that direction...)
- Contribute to growing literature focused on mechanisms, shows that utilization management can have both costs and benefits → tradeoff depends on the tool (i.e., real-time adjudication)

References I

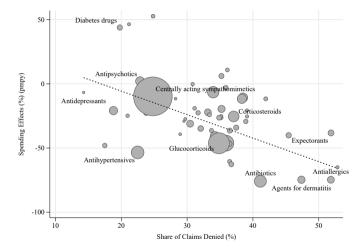
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Attrition: Assignment to MMC (vs. FFS) does not predict attrition •••••



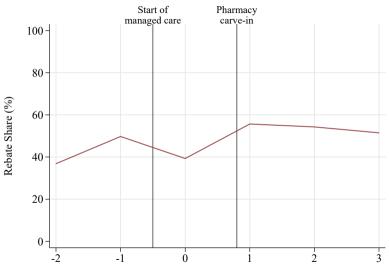
Quarters relative to treatment (t_0 = Feb 2012)

Sample is largely kids, story looks the same if we restrict to them •••••



Key Takeaways: Similar but some categories smaller (e.g., drugs for use in opioid dependence)

Rebates share ••••



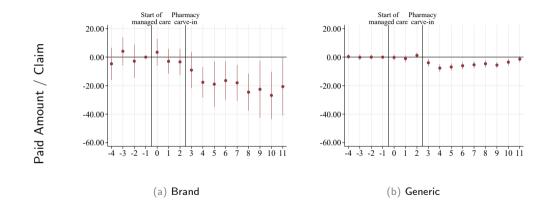
Years relative to treatment ($t_0 = \text{Feb } 2012$)

Mechanisms: Prices account for some (esp. outpatient); Providers and networks matter less than zero

| | Original Spending | | Repriced Spending | | | |
|--|---------------------|-------------------------|----------------------|----------------------|----------------------|----------------------|
| | \overline{Y} (1) | 2SLS (2) | 2SLS (3) | 2SLS (4) | 2SLS (5) | 2SLS (6) |
| Panel A. Spending by comp | oonents of care (\$ | ;) | | | | |
| Total Spending | 1 451.37 ` | | —56.78*** (16.90) | -82.92*** (17.65) | —72.58*** (14.85) | —90.81*** (16.28) |
| Inpatient Spending | 98.61 | 3.12 (4.85) | 1.20 (5.08) | 1.58 (5.71) | -3.96 (4.51) | —3.30 (5.11) |
| Outpatient Spending | 590.17 | -18.58^{**} (6.60) | -2.15 (6.92) | -6.29 (6.43) | -4.92 (6.55) | —7.78 (6.66) |
| Pharmacy Spending | 380.19 | -68.66*** (8.79) | -61.45*** (8.23) | -71.24*** (9.46) | -56.13*** (8.56) | -66.45*** (9.97) |
| Repriced Claims | | No | Yes | Yes | Yes | Yes |
| Plan Network Breadth Provider Fixed Effects | | No No | No No | Yes No | No Yes | Yes Yes |

So why isn't generic drug spending increasing?

There is also a compositional shift toward lower cost brand and generic prescriptions:



Formal decomposition in style of Brot-Goldberg et al. (2017) finds that prices play a small role, this is about the changing composition of drugs within brand/generic.

Decomposition of Main Spending Results: Framework

- Follow Brot-Goldberg et al. (2017) to decompose spending results into *price* and *quantity* terms (in the spirit of Kitagawa (1955), Oaxaca (1983), and Blinder (1973))
- Result: Four mutually exclusive and collectively exhaustive terms, focused on pharmacy

$$\Delta TS_{MMC,FFS} \equiv \underbrace{\Delta P_{MMC,FFS}}_{\text{Price diff for same services}} + \underbrace{\Delta Q_{MMC,FFS}^{Steering}}_{\text{Steering within brand/generic}} + \underbrace{\Delta Q_{MMC,FFS}^{Generic}}_{\text{Substitution from brands to generics w/in ATC-4 groups}} + \underbrace{\Delta Q_{MMC,FFS}^{Residual}}_{\text{differences}}$$

 Restrict to services we observe at least 5 times in both the MMC and Managed FFS models in each year (93% of overall spending)

Price Differences: $\Delta P_{MMC,FFS}$

- **Question:** How much is spending effect due to lower MMC prices for the *same service* at the same provider or steering to lower priced providers?
- 3 steps to estimates:

 - Solution Estimate MMC effects on repriced enrollee spending (i.e., quantity) call that $\hat{\beta}^{\overline{P}}$ (price fixed)
 - () Then $\beta \hat{\beta}^{\overline{P}}$ isolates price term in decomposition, $\Delta P_{MMC,FFS}$
- Illustrative example:
 - ${\scriptstyle \bullet}\,$ Effect of MMC on total spending = \$100
 - ${\scriptstyle \bullet}\,$ Effect of MMC on repriced spending = \$90
 - $\Delta P_{MMC,FFS} \equiv \beta \hat{\beta}^{\overline{P}} = \$100 \$90 = \10

Decompose quantity effect into three, mutually exclusive terms

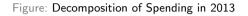
• Steering to lower cost brand/generic within class: $\Delta Q_{MMC,FFS}^{Steering}$

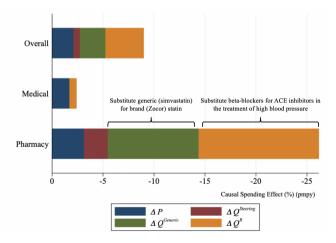
- Assign drugs to ATC-4 therapeutic classes to identify clinical substitutes, e.g., diabetes drugs
- Reprice at the rapeutic class imes brand/generic level and reestimate MMC effects — call that $\hat{eta}^{\overline{Steering}}$
- $\hat{\beta}^{\overline{P}} \hat{\beta}^{\overline{Steering}}$ isolates steering within brand/generic term: $\Delta Q_{MMC,FFS}^{Steering}$
- Substitution from brand to generic within class: $\Delta Q_{MMC,FFS}^{generic}$
 - Next reprice at the rapeutic class level, e.g., all diabetes drugs have exact same price \rightarrow eliminates advantage to higher share of generics
 - Estimate MMC effect on repriced spending, call that $\hat{\beta}^{\overline{\text{Generic}}}$ and subtract from $\hat{\beta}^{\overline{\text{Steering}}}$ to get brand-to-generic term: $\Delta Q_{MMC,FFS}^{\text{Generic}} \equiv \hat{\beta}^{\overline{\text{Steering}}} \hat{\beta}^{\overline{\text{Generic}}}$

Sesidual quantity differences: $\Delta Q^R_{MMC,FFS}$

- $\, \bullet \,$ Final term is recovered by $\hat{\beta}^{\,\overline{Generic}}$, applies to both pharmacy and medical spending
- Residual that captures both outright quantity reductions and substitutions between services

Decomposition: Spending effects come largely from quantity

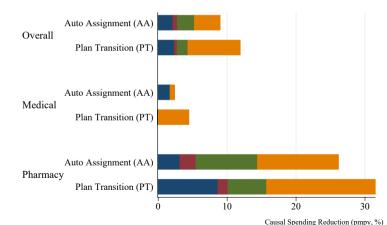




- Price not the main driver
- Out of the overall spending reduction of 9.3%, 4/5 is Qty
- For pharmacy spending reduction, 87% is Qty and 1/3 is brand-generic substitutions
- Pharmacy reduction similar to 21.3% in Dranove et al. (2021)

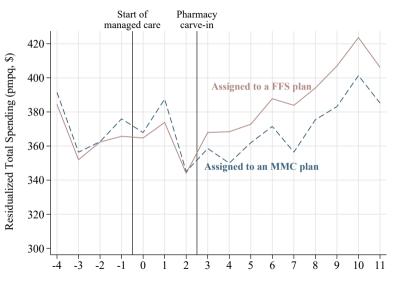
Decomposition: Decomposition reveals spending reductions generated in similar ways across different populations/natural experiments

Figure: Decomp of spending in 2013 for AA and 2015 for PT



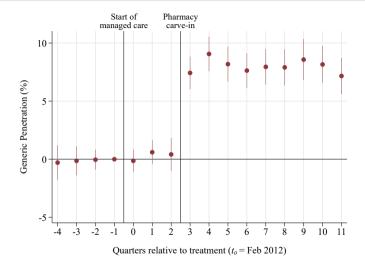
- Price not the main driver
- Brand-generic substitution and quantity residual is important in pharmacy
- Pharmacy reductions similar to 21.3% reported in Dranove et al. (2021) in both natural experiments

Key Result 1: Reduced form time series for total spending



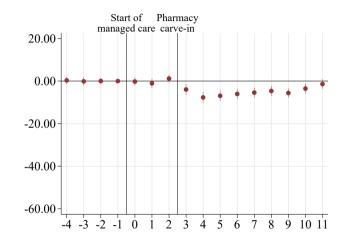
Quarters relative to treatment ($t_0 = \text{Feb } 2012$)

Assignment to MMC (vs. FFS) increased generic penetration rates



Generic penetration rate prior to the pharmacy carve in was 69%.

Assignment to MMC (vs. FFS) led to lower paid amounts per generic claim



Share of prescription drug claims subject to PA, step therapy, fail first started high and decreased quickly after the pharmacy carve-in

