Participation and Spending in the Medicare Shared Savings Program

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September 11, 2025

Outline

Introduction

Institutional Setting

Data and Reduced Form Evidence

Single Agent Dynamic Model

Estimation Strategy and Results

Counterfactuals

Motivation

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- Pay-for-Performance contracts in healthcare

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  - Ratchet Effect

Policy Relevance

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The policy maker is concerned about the impact of the benchmarking rules:

> *"[providers] that lower their spending are effectively penalized with lower subsequent benchmarks [...] The explicit reduction (known as a ratchet effect) greatly weakens [providers'] incentives to reduce their spending."*
>
> *"[...regional average based] benchmarks favor providers with baseline spending levels that are lower than the regional average because those providers would find it easier to stay below their benchmarks and earn [bonus payments]."*

– Congressional Budget Office, April 2024

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  Gaynor, Rebitzer, Taylor, 2004; Ho and Pakes, 2014; Eliason et al., 2018. Zhang et al. (2018) Einav, Finkelstein et al., 2021;

- MSSP:
  - study both participation and performance
  - estimate the impact of Adverse Selection and Ratchet Effect
  - propose benchmark rule that could improve savings

  Reddig, 2020; Aswani, Shen, Siddiq, 2019;

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- Data and Reduced Form Evidence
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- Counterfactuals

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- MSSP contract makes ACO internalize the benefits of reducing low-value care.

MSSP Contract

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One-Sided Shared Savings Contract: details

$$\text{Shared Savings} = \begin{cases} \frac{1}{2} q \cdot (b - y) & \text{if } \frac{b-y}{b} > \underline{s} \\ 0 & \text{otherwise} \end{cases}$$

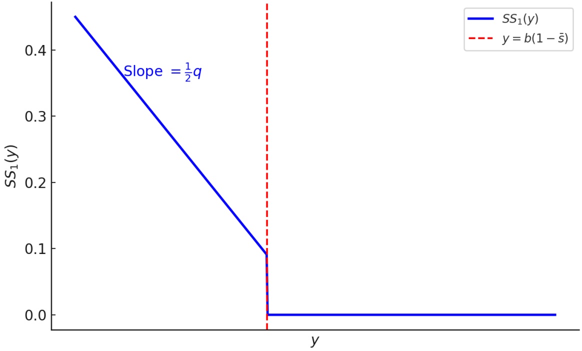

Figure 1: One-sided contract

Benchmarking Rules

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- **Adverse Selection**: ACOs with spending below $\overline{y}_t^R$ can earn shared savings without changing behavior.

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  - ACOs financial data: benchmark, spending, quality score, regional expenditure.
  - ACOs characteristics: participants list, beneficiaries
- To study participation in counterfactual scenarios
  - Construct artificial ACOs from the Shared Patients Database
  - Obtain characteristics of ACO providers from Physician Compare Database and AHA database

Participation in the MSSP

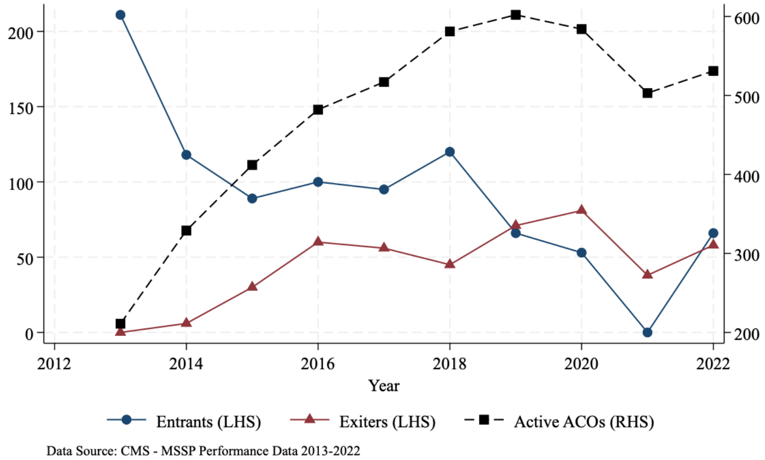

Figure 2: Entry, Exit and Active ACOs from 2013 to 2022

Ratchet Effect - Reduced Form Evidence

- Two policy induced Non-Rebasing Years:
  (i) **Deferral Option**: Between 2016 and 2018, ACOs had the option to defer the start of the next AP by one year, and only the last three years of the AP are included in the rebasement.
  (ii) **5-Year AP cycles**: AP starting from 2019 last 5 years and first two PY are not used to rebase the benchmark.
- Define Deferral and Non-Rebasing Years treatment indicators

$$\mathrm{DF}_{it} = \begin{cases} 1 & \text{if ACO } i \text{ in year } t \text{ is in (i)} \\ 0 & \text{otherwise} \end{cases}$$

and

$$\text{Non-RY}_{it} = \begin{cases} 1 & \text{if ACO } i \text{ in year } t \text{ is in (ii)} \\ 0 & \text{otherwise} \end{cases}$$

- Estimate

$$\text{Savings Rate}_{it} = \alpha_i + \lambda_t + \beta_1 \cdot \text{Non-RY}_{it} + \beta_2 \cdot \mathrm{DF}_{it} + X_{it}'\delta + \varepsilon_{it}$$

Ratchet Effect - Reduced Form Evidence

Table 1: Ratchet Effect: Two Way Fixed Effects Regressions

	Full Sample		Entry Year < 2019	
	ACO FE	No ACO FE	ACO FE	No ACO FE
Non-RY	0.943***	0.341*	0.907***	0.248
	(0.210)	(0.189)	(0.227)	(0.206)
Deferral	1.792***	0.533*	1.798***	0.605**
	(0.472)	(0.290)	(0.497)	(0.308)
R-squared	0.180	0.154	0.186	0.163
Mean	2.324	2.324	2.235	2.235
SD	4.173	4.173	4.207	4.207

Dependent Variable: CMS savings rate

Year FE and Age FE are included

Standard errors clustered by ACO

Selection on Levels - Reduced Form Evidence

- Regional adjustment was introduced from the 3rd AP for ACOs entered in 2013, and from the 2nd AP for all other ACOs.
- We define:

$$\text{Regional Adj}_{it} = \begin{cases} 1 & \text{if ACO } i \text{ regional adjustment is applied} \\ 0 & \text{otherwise} \end{cases}$$

and

$$\text{Positive Adj}_{it} = \begin{cases} 1 & \text{if ACO } i \text{ positive adjustment is applied} \\ 0 & \text{otherwise} \end{cases}$$

and estimate a logistic regression

$$\Pr(\text{Exit}_{it} = 1) = \Lambda\Big(\lambda_t + \beta_1 \cdot \text{Regional Adj}_{it} + \beta_2 \cdot \text{Positive Adj}_{it} + X'_{it}\delta\Big)$$

Selection on Levels - Reduced Form Evidence

Table 2: Selection on Level: Fixed Effects Logistic Regressions

	(1)	(2)	(3)	(4)
Positive Adj	0.257***	0.266***	0.299**	0.296***
	(0.077)	(0.036)	(0.146)	(0.037)
Regional Adj	3.641**	3.693***	3.735*	3.773***
	(1.159)	(0.739)	(2.615)	(0.740)
McFadden R^2	0.157	0.155	0.141	0.139
AP FE	Yes	No	Yes	No
Year FE	Yes	Yes	No	No

Dependent Variable: Indicator for Exit from MSSP

Coefficients represents the odds ratio of Exit = 1

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- FFS spending y_{it}^{FFS} evolves over time as follows

$$y_{it}^{FFS} = y_{it-1}^{FFS} \cdot \mathrm{tf}_{it} \cdot \mathrm{rr}_{it} + u_{it}$$

  where
  - tf_{it} is the national trend and regional FFS trends factor,
  - rr_{it} is the risk ratio,
  - $u_{it} = \epsilon_{it} - \epsilon_{it-1}$ with ϵ_{it} i.i.d. from $N(0, \sigma_{it}^2)$.
  - $\sigma_{it} = \rho \cdot \mathbb{E} y_{it}^{FFS}$

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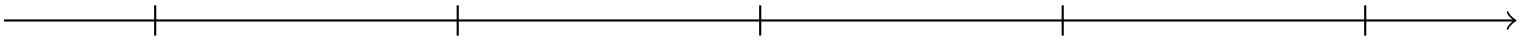
  - $\sigma_{it} = \rho \cdot \mathbb{E} y_{it}^{FFS}$

- State variables Ω_{it}: (i) historical rebased benchmark b_{it}^h, (ii) rolling average spending $\tilde{y}_{it}$, (iii) average regional spending y_{it}^R. dynamics

ACOs' Dynamic Problem

- Timing of the model



$\{\Omega_{it}, \varepsilon_{it}^{d}\}$

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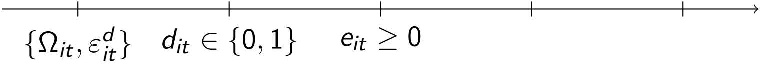

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$$\{\Omega_{it}, \varepsilon^d_{it}\} \quad d_{it} \in \{0,1\} \quad e_{it} \geq 0 \quad \epsilon_{it} \quad y_{it}, \pi_{it}$$

- The MSSP participation condition is given by

$$d_{it} = 1 \iff v^M_{it}(\Omega_{it}) + \varepsilon^M_{it} > v^F_{it}(\Omega_{it}) + \varepsilon^F_{it}$$

where v^M_{it} is the Choice Specific Value Function of MSSP

$$v^M_{it}(\Omega_{it}) + \varepsilon^M_{it} = \max_{e_{it}} \left\{ \pi^M_{it}(e_{it}) + \delta \mathbb{E} V_{it+1}(\Omega_{it+1}) \right\} + \varepsilon^M_{it}$$

where ε^M_{it} is a TIEV choice-specific shock.

Functional Form Assumptions

- Profits of ACO i in year t

$$\pi_{it}^{M}(e_{it}) = N_{it}\Big[\underbrace{SS(y_{it}, b_{it})}_{\text{shared savings}} - \underbrace{C(e_{it})}_{\text{variable costs}} - \underbrace{F_i}_{\text{fixed costs}}\Big]$$

  where N_{it} is the number beneficiaries.

- Effort cost

$$C(e_{it}) = \frac{1}{2}\gamma_{it}\frac{e_{it}^2}{\mu_{it}} \quad \text{with} \quad \mu_{it} = \mathbb{E}y_{it}^{FFS}$$

  depends on an unknown ACO specific cost parameter γ_{it}.

- Parametric Assumptions

$$\log\gamma_{it} \ = \ x_{it}'\beta_C \ + \ \nu_i'\alpha_C, \qquad \log F_i \ = \ x_{it}'\beta_F \ + \ \nu_i'\alpha_F,$$

  where x_{it} are observed ACO characteristics, and ν_i' is a vector of indicators for ACO unobserved types.

Efficient and Inefficient Selection

- ACO i efficiently selects into MSSP if the total cost under the MSSP is lower the than the cost under FFS

$$\underbrace{\left(y_i^{FFS} - e_i\right)}_{\text{MSSP spending}} + \underbrace{\text{ssr} \cdot \max\left\{ \left(b_i - (y_i^{FFS} - e_i)\right), 0\right\}}_{\text{shared savings payments}} \quad < \quad y_i^{FFS}$$

- *Efficient* - *Inefficient* threshold:

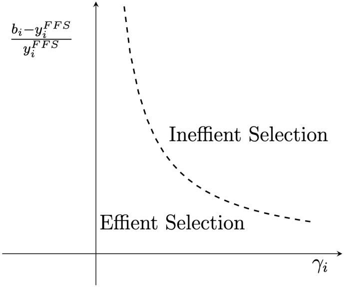

Figure 3: Selection Frontier

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- The likelihood function for ACO i:

$$L_i(\theta) = \sum_k q_{ik} \left[\prod_{t=1}^{T_i - 1} \phi(y_{it}, \Omega_{it}, k; \theta) \Pr(d_{it} = 1 | \Omega_{it}, k; \theta) \right] \times \Pr(d_{iT_i} = 0 | \Omega_{iT_i}, k; \theta)$$

where q_{ik}s are the unobserved type probabilities , and

$$\phi(y_{it} | \Omega_{it}, k) = \frac{1}{\sqrt{2\pi\sigma_{it}^2}} \exp\left(-\frac{(y_{it} - \mu_{it} - e_{it})^2}{2\sigma_{it}^2} \right), \quad \mu_{it} = y_{it-1}^{FFS} \cdot \eta_{it} \cdot rr_{it}$$

and

$$Pr(d_{it} = 1 | \Omega_{it}, k; \theta) = \frac{1}{1 + \exp(v_{it}^F - v_{it}^M)}$$

SVF

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SVF

- I estimate θ with an EM algorithm (Arcidiacono Miller 2011). EM

Estimation Results: Variable Costs

	K=1	K=2	K=3	K=4
Risk Score	0.541**	0.493***	0.435*	0.451***
	(0.156)	(0.137)	(0.053)	(0.061)
Beneficiaries	−0.241***	−0.193***	0.135*	0.173***
	(0.059)	(0.039)	(0.035)	(0.040)
Hospital	1.641**	1.523**	1.735**	1.613**
	(0.316)	(0.358)	(0.415)	(0.421)
Type 1		0.302***		
		(0.045)		
Type 2		0.217***	0.134**	
		(0.052)	(0.043)	
Type 3		0.147**	0.094**	0.056
		(0.042)	(0.028)	(0.053)
GOF	0.852	0.881	0.936	0.904

(i) Coefficients represent the dollar change in the cost of reducing spending by 1%. (ii) Standard errors are computed with bootstrapping method

Estimation Results: Fixed Costs

	K=1	K=2	K=3	K=4
Beneficiaries	0.142**	0.194**	0.136**	0.154**
	(0.059)	(0.039)	(0.042)	(0.041)
Hospital	0.640**	0.554**	0.637**	0.643**
	(0.116)	(0.158)	(0.135)	(0.121)
Type 1		0.252***		
		(0.045)		
Type 2		0.253***	0.216***	
		(0.052)	(0.043)	
Type 3		0.247**	0.214**	0.156*
		(0.068)	(0.057)	(0.083)
GOF	0.852	0.881	0.936	0.904

(i) Coefficients represent the dollar change in the cost of reducing spending by 1%. (ii) Standard errors are computed with bootstrapping method

Selection into MSSP

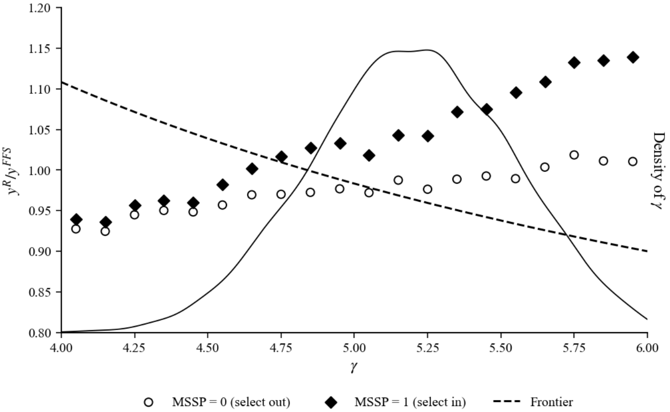

Figure 4: Model-based Selection into MSSP

Outline

Introduction

Institutional Setting

Data and Reduced Form Evidence

Single Agent Dynamic Model

Estimation Strategy and Results

Counterfactuals

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- Change in total per-capita spending Y_j:

$$\Delta Y = \sum_j Y_j^{\text{counterf}} - Y_j^{\text{status quo}}$$

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  - Rebased Benchmark to Regional Spending ratio $b_t^h / \overline{y}_t^R$

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Estimation of Adverse Selection

- Status Quo Benchmark:

$$b^{r}_{it} = (1-\lambda)\frac{y_{it-1} + y_{it-2} + y_{it-3}}{3} + \lambda \overline{y}^{R}_{it}$$

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- Counterfactual Benchmark sets $\lambda = 0$ (No regionalization):

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- Changes in participation: chart
  - fewer ACOs with $b_t^h/\overline{y}_t^R < 1$
  - more ACOs with $b_t^h/\overline{y}_t^R > 1$

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- Changes in participation: chart
  - fewer ACOs with $b_t^h / \overline{y}_t^R < 1$
  - more ACOs with $b_t^h / \overline{y}_t^R > 1$
- Changes in spending: table
  - SS $\downarrow$ by 0.71% points.
  - Total spending -0.58% points $\Rightarrow$ 48\$ per-capita (1.367 bln \$)

Estimation of Ratchet Effect

- Status Quo Benchmark:

$$b_{it}^{r} = (1-\lambda)\frac{y_{it-1} + y_{it-2} + y_{it-3}}{3} + \lambda \overline{y}_{it}^{R}$$

Estimation of Ratchet Effect

- Status Quo Benchmark:

$$b_{it}^{r} = (1-\lambda)\frac{y_{it-1} + y_{it-2} + y_{it-3}}{3} + \lambda \overline{y}_{it}^{R}$$

- Counterfactual Benchmark (No rebasement):

$$b_{it}^{r} = (1-\lambda)\underbrace{\frac{y_{i0} + y_{i-1} + y_{i-2}}{3}}_{\text{initial benchmark}} \cdot \mathrm{uf}_{t} + \lambda\left(\overline{y}_{it}^{R} - \underbrace{\frac{y_{it-1} + y_{it-2} + y_{it-3}}{3}}_{\text{rolling average spending}}\right)$$

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- Changes in participation: ⏩ chart
  - Participation ↑: lower exit rate
  - Selection is similar to the actual MSSP

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- Changes in participation: chart
  - Participation ↑: lower exit rate
  - Selection is similar to the actual MSSP
- Changes in spending: table
  - FFS Spending by −2.12%, SS Payments +0.58%
  - Total spending −1.54% → 104$ per-capita (2.962 bln $)

Alternative Policy

Alternative Policy

- Conditional Regionalization:
  - Regional adjustment to mitigate Ratchet Effect as in the status quo
  - To address adverse selection:

  (i) ACOs must achieve savings to qualify for a positive regional adjustment.
  (ii) Negative regional adjustment is waived only for ACOs that achieve savings.

- Changes in participation: chart
  - fewer ACOs with $b_t^h / y^R < 1$
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- Changes in participation: chart
  - fewer ACOs with $b_t^h / y^R < 1$
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- Changes in spending: table
  - FFS Spending -2.86%, SS Payments $+0.73\%$
  - Total spending $-2.13\% \rightarrow 156\$$ per-capita (4.225 bln \$)

Conclusions

- This paper studies how the current MSSP benchmarking rules affect the overall savings of the program.
- Main findings:
  - benchmark rebasement
    - (i) induces ACO to delay spending reduction.
    - (ii) reduces potential savings by 1.54% points relative to the status quo.
  - regionalizal adjustment
    - (i) induces adverse selection into the MSSP.
    - (ii) causes excessive SS payments by 0.71% points relative to the status quo.
  - conditional regionalization:
    - (i) is able to prevent adverse selection and mitigate the ratchet effect.
    - (ii) improves savings by 2.13% points relative to the status quo.

Thank You!

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[4] Frandsen, B. and Rebitzer, J. B. (2015). Structuring incentives within accountable care organiza- tions. The Journal of Law, Economics, and Organization, 31(suppl 1):i77–i103.

[5] Gaynor, M., Rebitzer, J. B., and Taylor, L. J. (2004). Physician incentives in health maintenance organizations. Journal of Political Economy, 112(4):915–931.

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Two-Sided Shared Savings Contract

Penalty for overspending, but has higher shared savings rate

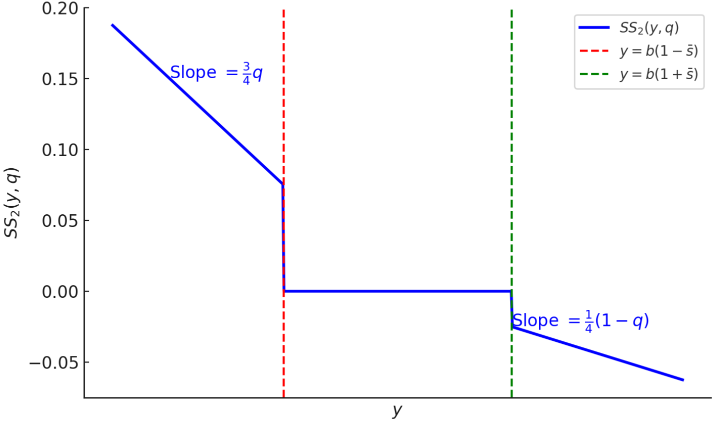
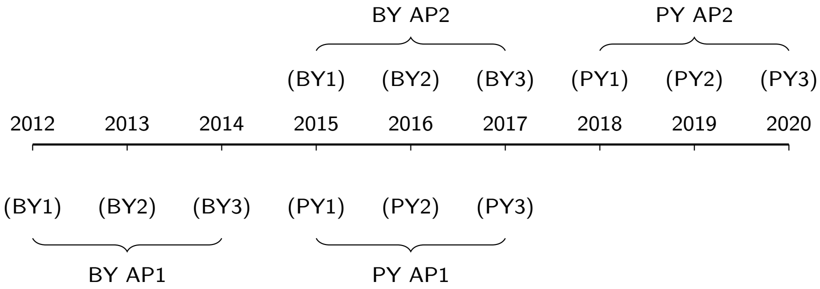


Figure 5: Two-sided contract

details

Benchmark over time

- Consider an ACO that joined in 2015 [back]



Benchmark over time

- Consider an ACO that joined in 2015 ⏩ back

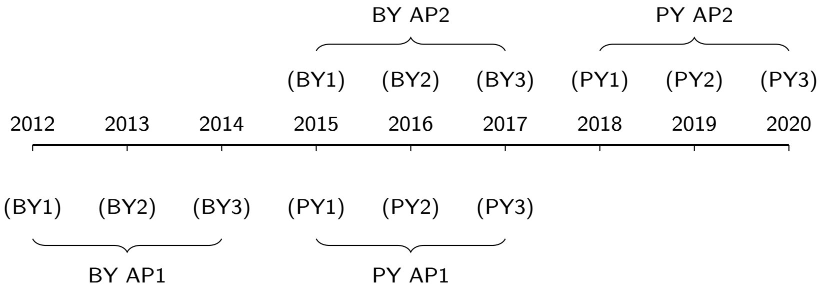
	2012	2013	2014	2015	2016	2017	2018	2019	2020
				BY AP2			PY AP2		
				(BY1)	(BY2)	(BY3)	(PY1)	(PY2)	(PY3)
	(BY1)	(BY2)	(BY3)	(PY1)	(PY2)	(PY3)			
	BY AP1			PY AP1					

The 1st AP **historical** benchmark is

$$b^h_{AP1} = \underbrace{0.6y_{2014} + 0.3y_{2013} + 0.1y_{2012}}_{\text{average spending prior to joining MSSP}}$$

Benchmark over time

- Consider an ACO that joined in 2015 back

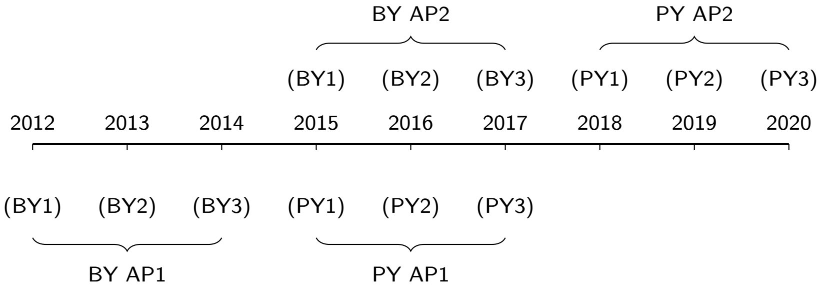


In the 2nd AP benchmark is **rebased**

$$b^h_{AP_2} = \underbrace{\frac{1}{3}y_{2015} + \frac{1}{3}y_{2016} + \frac{1}{3}y_{2017}}_{\text{average spending in the 1st AP}}$$

Benchmark over time

- Consider an ACO that joined in 2015 ⏩ back



and **regionalized**

$$b^r_{AP2} = (1-\lambda) \underbrace{b^h_{AP2}}_{\substack{\text{rebased} \\ \text{benchmark}}} + \lambda \underbrace{y^R}_{\substack{\text{regional} \\ \text{spending}}}$$

Euler Equation

The optimal level of effort at time t satisfies the FOC

$$\frac{\partial \pi_t^M}{\partial e_t} = \begin{cases} 0 \quad \text{if } t \text{ is non benchmark year} \\ \delta \Pr\left(d_{t+1} = 1 \mid \tilde{y}_{t+1}, b_{t+1}\right) \frac{\partial v_{t+1}^M}{\partial \tilde{y}_{t+1}} \frac{\partial \tilde{y}_{t+1}}{\partial y_t} \frac{\partial y_t}{\partial e_t} \quad \text{otherwise} \end{cases}$$

where $\frac{\partial y_t}{\partial e_t} = -1$

$$\frac{\partial \pi_t^M}{\partial e_t} = \begin{cases} 0 \quad \text{if } t \text{ is non benchmark year} \\ \delta P_{1t+1} \left[\frac{\partial \pi_{t+1}^M}{\partial e_{t+1}} \mathbb{1}(\text{PY}_{t+1} \neq 1) + \frac{1}{3} \frac{\partial \pi_{t+1}^M}{\partial b_{t+1}} (1 - \lambda_{t+1}) \mathbb{1}(\text{PY}_{t+1} = 1)\right] \end{cases}$$

where $P_{1t+1} = \Pr\left(d_{t+1} = 1 \mid \tilde{y}_{t+1}, b_{t+1}\right)$. back

State Variables Evolution

- **Rolling Average Spending** $\tilde{y}_t$

$$\tilde{y}_{it+1} = \begin{cases} y_{it} & \text{if } \mathrm{PY}_t = 1 \\ \frac{1}{2}\tilde{y}_{it} \cdot \tilde{\mathrm{uf}}_{it} + \frac{1}{2} y_{it} & \text{if } \mathrm{PY}_t = 2 \\ \frac{2}{3}\tilde{y}_{it} \cdot \tilde{\mathrm{uf}}_{it} + \frac{1}{3} y_{it} & \text{if } \mathrm{PY}_t = 3 \end{cases}$$

The value of $\tilde{y}_{it+1}$ in the 3rd PY of each AP is used to rebase the benchmark for the subsequent AP.

- **Updated Historical Regionalized Benchmark** b_{it+1}

$$b_{it+1} = \begin{cases} \left[(1-\lambda_{it+1})\tilde{y}_{it+1} + \lambda_{it+1} y_{it}^{R}\right] \cdot \mathrm{uf}_{t+1}^{1} & \text{if } \mathrm{PY}_{t+1} = 1 \\ b_{it} \cdot \mathrm{uf}_{t+1}^{2} & \text{if } \mathrm{PY}_{t+1} = 2 \\ b_{it} \cdot \mathrm{uf}_{t+1}^{3} & \text{if } \mathrm{PY}_{t+1} = 3 \end{cases}$$

where uf_{t+1}^{j} is the updated factor applied to set the historical benchmark in PY j terms. back

Expectation Maximization

- Expectation Step:

back

Expectation Maximization

- Expectation Step:
  (i) Use Bayes' Rule to update q_{ik}

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back

Expectation Maximization

- Expectation Step:
  - (i) Use Bayes' Rule to update q_{ik}
  - (ii) Update the population probability of each type, w_k
  - (iii) Using $\theta^{(m)}$ and $p^{(m)}$, update the CCP

$$p_1^{(m+1)} = \frac{1}{1 + \exp\left[v_{it}^F(\Omega_{it}, k; p^{(m)}, \theta^{(m)}) - v_{it}^M(\Omega_{it}, k; p^{(m)}, \theta^{(m)})\right]}$$

back

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- Maximization Step: simulated value function

$$\theta^{(m+1)} = \underset{\theta}{\operatorname{argmax}} \sum_i \sum_k q_{ik} \log L_{ik}(\theta | q_{ik}^{(m+1)}, p_1^{(m+1)}, \Omega_{it}, k))$$

back

Simulated Value Function

To evaluate v_{it}^{M}, we use forward simulation to simulate S paths of participation effort, spending and profits

$$v_{it}^{M} \approx \frac{1}{S} \sum_{s=1}^{S} \sum_{h=0}^{H} \delta^{h} \pi_{i,t+h}^{(s)}$$

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Given some value of the parameters θ, each simulated path uses:

- d_{it} draws from Kernel probabilities $\hat{\Pr}(d_{it} = 1 | \Omega_{it})$
- e_{it} from the Euler equation euler equation
- y_{it} from the spending equation
- $\tilde{y}_{it}$ and b_{it} move forward according to the MSSP rules. back

Identification of variable costs

- From the model assumptions $y_{it}|e_{it} \sim N\left(\mathbb{E}y_{it}^{FFS} - e_{it}, \sigma_{it}\right)$

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$$MB(\Omega_{it}) = \gamma(x_{it}, \nu_i; \theta)e_{it}$$

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- Hence,

$$\Delta y_{it} = \max\left\{0, \frac{MB(\Omega_{it})}{\gamma(x_{it}, \nu_i; \theta)}\right\} + \epsilon_{it}$$

- The Normal likelihood ties variation in Ω_{it} and x_{it} to the observed Δy_{it} , which identifies $(\beta_\gamma, \alpha_\gamma)$. FC

Identification of Fixed Costs

- Let Δv_t be the value difference between stay and exit net of the fixed cost:

$$\Delta v_t \ \equiv \ \widetilde{v}_t^{\text{stay}}(\gamma; S_t) \ - \ v_t^{\text{exit}}$$

- Under logit, the log(Odds Ratio) is

$$\log \frac{P_t(\text{stay})}{1 - P_t(\text{stay})} \ = \ \underbrace{\Delta v_t}_{\text{offset}} - \ \underbrace{G_t}_{\text{horizon}} \cdot F$$

  where G_t is the expected discounted number of future active periods if stay.

- We choose F so that the model-implied probabilities $P_t(\text{stay})$ fit the observed dt best (maximum likelihood). back

Counterfactual Results

Table 3: COUNTERFACTUALS
(Percentage change relative to status quo)

	Part Rate P	%Δ Spending Gross SS Δy	SS Payments Δss	%Δ Spending Net of SS ΔY
Simul MSSP	56.2	0	0	0
No Regn	46.4	0.13	-0.71	-0.58
No Rebas	65.5	-2.12	0.58	-1.54
Cond Regn	58.7	-2.86	0.73	-2.13

Notes: (1) P is the MSSP participation rate, (2) Δy is the % change in spending per-capita among all ACOs, (3) Δss is the % change in Shared Savings Payments, and (4) ΔY is the % change in spending per-capita net of Shared Savings Payments among ACOs.

back

Counterfactual Results

Table 4: COUNTERFACTUALS
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back

Counterfactual Results

Table 5: COUNTERFACTUALS
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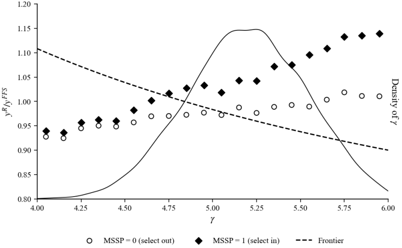
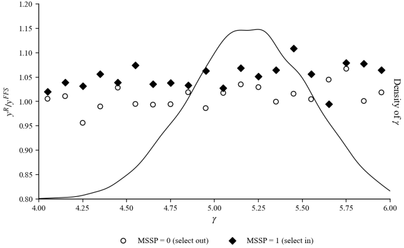
back

Selection under No Regionalization



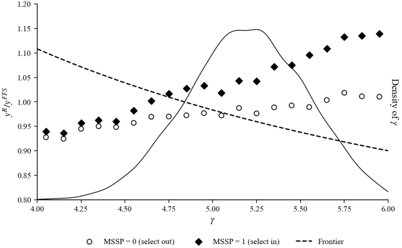
(a) Simulated MSSP



(b) No Regionalization

back

Selection under No Rebasement



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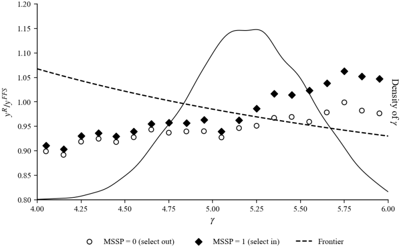
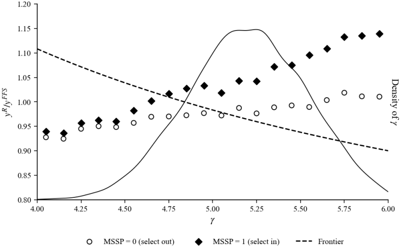


(b) No Rebasement

back

Selection under Conditional Regionalization



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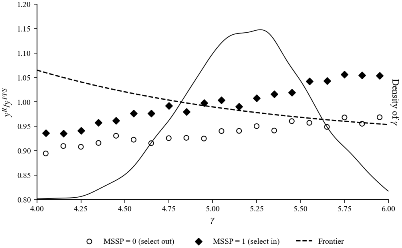

(b) Conditional Regionalization

back