Participation and Spending in the Medicare Shared Savings Program

Job Market Paper

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Abstract

The Medicare Shared Savings Program (MSSP) is a voluntary program that provides incentive payments to healthcare providers that form integrated healthcare organizations, known as Accountable Care Organizations (ACOs). The MSSP rewards ACOs for keeping average per capita spending below a benchmark based on historical spending by ACO providers under the fee-for-service (FFS) system. I provide reduced-form and model-based evidence that benchmarks affect ACOs' participation and performance in the MSSP. I show that blending the ACOs' historical spending with a regional adjustment factor induces adverse selection, enabling some ACOs to earn incentive payments without reducing spending below the FFS level. Moreover, the benchmark rebasement, which updates the benchmark over time to reflect observed healthcare spending among ACOs providers, incentivizes ACOs to delay spending reductions to avoid lowering future benchmarks. I propose a revised benchmarking methodology to address these inefficiencies. Counterfactual analyses demonstrate that this alternative policy mitigates adverse selection and significantly increases Medicare savings.

Key Words: Health Economics, Medicare, Pay-for-Performance, Accountable Care Organizations, Ratchet Effect, Adverse Selection

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1 Introduction

There is a broad consensus among health economists that the high costs and inefficiencies in the U.S. healthcare system are largely due to the fragmented nature of healthcare delivery and misalignment of incentives between Medicare and healthcare providers (Cebul et al., 2008). Medicare patients are frequently treated by numerous care providers who have only weak organizational ties with one another and often little expertise in coordinating care. This results in duplicate and unnecessary services, heightened error rates, and inadequate care coordination.

Medicare payments operate under a fee-for-service (FFS) system, which lacks incentives for cost-efficient healthcare delivery. Under this model, providers are reimbursed based on the cost and volume of services rendered. As a result, healthcare providers may find it profitable to deliver excessive services or opt for unnecessarily expensive procedures, even when doing so does not necessarily improve patient outcomes (Hendee et al., 2010, Chatterji et al., 2022).

Value-based programs and pay-for-performance contracts are increasingly popular forms of government regulation aimed at correcting the FFS system's adverse incentives and at improving the efficiency of healthcare delivery. The Medicare Shared Savings Program (MSSP) is an incentive payment program administered by the Centers for Medicare and Medicaid Services (CMS) since 2012. The goal of the MSSP is to encourage the formation of integrated provider organizations and make it financially viable for providers to reduce spending through improved care coordination and proper use of preventive care and care monitoring. To participate in the MSSP, a group of independent Medicare providers, including hospitals, physician groups, and individual practices, must form a joint venture referred to as an Accountable Care Organization (ACO). Under the MSSP, ACOs are held accountable for the per capita expenditure (Medicare Part A and Part B) and quality of care for a defined population of Medicare beneficiaries.

The MSSP contract rewards a bonus payment to ACOs based on the overall group performance. ACOs qualify for the bonus payment, known as shared savings, if their per capita FFS spending falls below a predetermined benchmark. This payment is calculated as a fraction of the difference between the benchmark and actual spending. Moreover, ACOs can opt for either a one-sided or two-sided shared savings contract. Under the two-sided contract, ACOs receive a larger share of the savings compared to the one-sided contract, but are also subject to financial penalties if their spending exceeds the benchmark.

The primary focus of this paper is on the MSSP rules for setting and updating the benchmark and how the latter affect ACOs' participation and spending. When an ACO enters the MSSP, the historical benchmark is calculated as the average per capita FFS spending of the Medicare beneficiaries assigned to the ACO. As the ACO progresses in the MSSP, the two adjustments are applied to the historical benchmark. First, the ACO benchmark is recalculated every three years using the average spending of the previous three years (rebased benchmark). Secondly, a regional adjustment factor is applied to the benchmark in proportion to the difference between the ACO rebased benchmark and average regional Medicare spending (regionalized benchmark).

From Medicare's perspective, it may be ideal for ACOs to act myopically, that is, to achieve the largest possible spending reduction each year. However, due to the MSSP rebasement mechanism, which recalculates future benchmarks based on an ACO's previous spending, ACOs may find it advantageous to reduce their efforts in earlier years to secure more favorable benchmarks in subsequent periods. This behavior is known as the ratchet effect and leads to a lower spending reduction than what would be observed under a static benchmark. I exploit variations in the MSSP benchmarking rules to provide reduced-form evidence of the ratchet effect. Years in which spending is not counted for the benchmark rebasement are associated with a 40% increase in the average savings rate.

To reduce the influence of an ACO's past spending on its benchmarks, Medicare began blending the ACO's rebased benchmark with the average FFS spending of the region where the ACO operates. The benchmark regionalization can result in adverse selection of ACOs in the MSSP. ACOs with baseline FFS spending below the regional average can participate in the MSSP and obtain shared savings without reducing their spending relative to the FFS level. I present empirical evidence of adverse selection showing that ACOs with a positive regional adjustment are about 70% less likely to exit the MSSP compared to ACOs with a negative regional adjustment.

To estimate the full effect of benchmark ratcheting and adverse selection on MSSP savings and evaluate alternative policies, I build a dynamic model of ACO behavior. Each year, an ACO chooses whether to participate in the MSSP and how much effort to invest in reducing spending. This allows the model to capture both intensive (effort) and extensive (participation) margins. I assume that the observed MSSP spending equals the underlying fee-for-service (FFS) spending minus effort. The per-period payoff of an ACO is the expected shared savings net of a variable effort cost and a fixed participation cost. Since reduced-form evidence reveals a large unexplained variation in savings and participation after accounting for ACO observables, I allow both variable and fixed costs to depend on observables and persistent unobserved heterogeneity.

The model primitives and the unobserved types are estimated through an Expectation-Maximization algorithm. The estimated model is then used to perform counterfactual analysis. I find that removing the benchmark regionalization reduces Medicare spending by 48$ per capita relative to the status quo, and almost of this reduction is the result of lower shared savings payments. This indicates that Medicare could improve MSSP savings by avoiding paying shared savings to those ACOs that do not reduce their spending relative to their FFS level.

Secondly, to assess the impact of benchmark rebasement, I simulated a counterfactual scenario where the ACOs' spending contributes to the regional adjustment, but does not directly influence future benchmarks. Under this scenario, Medicare per capita spending decreases by 104$ (approximately 1% of Medicare average spending per capita). This confirms the reduced-form evidence that benchmark rebasement induces ACOs to delay cost-containment efforts.

When the benchmark places greater weight on an ACO's own past spending, incentives to reduce spending are attenuated (ratchet effect). Conversely, when the benchmark leans toward regional spending, some ACOs can receive payments even with little or no spending reduction (adverse selection). Motivated by the need to better balance the trade-off between rebasement and regionalization, I propose an alternative benchmarking rule called Conditional Regionalization. Under this rule, a positive regional adjustment is awarded only if the ACO generates savings relative to its benchmark (curbing adverse selection). In parallel, to encourage participation of ACOs whose historical spending exceeds the regional average, negative regional adjustments are waived for ACOs that achieve savings.

Counterfactual results indicate that this approach effectively leverages benchmark regionalization to mitigate the ratchet effect while simultaneously addressing the problem of adverse selection. Medicare savings increase by 2.13% relative to the status quo, which is approximately 4.225 billion dollars (0.9% of the total annual Medicare cost). Moreover, shared savings payments increase, but selection into MSSP is more efficient as these payments are concentrated on ACOs that persistently reduce spending over time.

This paper contributes to the vast economics literature on the impact and optimal design of financial incentives for healthcare providers (e.g., Cutler, 1993; Gaynor et al., 2004; Clemens and Gottlieb, 2014; Ho and Pakes, 2014; Einav et al., 2022; Eliason et al., 2018; Hackmann, 2019). Previous works have analyzed specific Medicare programs with objectives similar to the MSSP. In particular, the Bundled Payments for Care Improvement Initiative (BPCI) is a payment model in which Medicare providers receive a single payment (benchmark) for a collection of services related to a specific episode of care. Einav et al. (2022) show the impact of adverse selection in the context of the BPCI and investigate the effects of alternative benchmarking policies. Zhang et al. (2016) studied the behavior of hospitals under the Hospital Readmissions Reduction Program, a mandatory program that penalizes hospitals that do not reduce readmissions below target levels.

More narrowly, this paper contributes to the literature on the effect of the Medicare Shared Savings Program. Reddig (2023) estimates a static model of ACOs' optimal savings and quality choices and shows a substantial trade-off between reducing costs and increasing quality. Frandsen and Rebitzer (2015) calibrate a simple model of ACO performance and find free-riding incentives that significantly reduce ACO providers' efforts to reduce spending. Aswani et al. (2019) examine the role of asymmetric information between Medicare and ACOs and propose an alternative contract design. They consider both selection on the cost of spending reduction and selection on the historical spending. However, since they only use data for 2015, which is two years before the benchmark regionalization becomes effective, they cannot account for the negative impact that adverse selection will have on Medicare spending when the regionalization takes effect. Furthermore, their single-period model cannot capture the dynamic implications of benchmark rebasement. Hence, we cannot tell how their alternative contract affects participation and the incentives to generate savings over time.

Compared to the existing literature, this paper makes three key contributions. First, it develops a multi-period model to analyze ACOs' participation and spending decisions over time. Second, it is the first to estimate and evaluate the dual effects of the ratchet effect caused by benchmark rebasement and adverse selection arising from benchmark regionalization. Finally, it proposes an alternative benchmarking rule that can mitigate the ratchet effect and prevent adverse selection, while also substantially improving the savings generated by the MSSP.

The rest of this paper is organized as follows: Section 2 gives an overview of the Medicare Shared Savings Program and describes how benchmark rebasement and regionalization work. Section 3 describes the data sources and presents some reduced-form evidence of ratchet effect and adverse selection. In Section 4, I present the ACOs' behavioral model and describe the role that the model primitives and the MSSP policy parameters play in the trade-off between ratchet effect and adverse selection . In Section 5, I present my estimation strategy and discuss the identification of the model primitives. In Section 6, I show the results of the counterfactual analysis, and Section 7 concludes.

2 Institutional Setting

Proponents of the MSSP argue that providing a financial incentive to reduce spending below the FFS level will improve care coordination among providers and reduce unnecessary healthcare utilization. To participate in the MSSP, healthcare providers form Accountable

Care Organizations, joint ventures created to improve care coordination among independent providers. Nearly any Medicare provider can start or participate in an ACO, including individual physicians, group practices, and large hospital systems. Medicare fee-for-service (FFS) beneficiaries are then assigned to ACOs by Medicare according to their primary care provider (PCP).

Under MSSP, providers who are members of an ACO are still reimbursed by Medicare according to the standard fee-for-service system. Hence, providers still receive the marginal payment for each service, and therefore, the FFS reimbursement is still proportional to the volume of services. The MSSP gives providers financial motivation to integrate care delivery by creating an incentive payment that depends on the ACO's performance. Each ACO is assigned a per capita spending benchmark, which should represent the counterfactual Medicare FFS spending on the ACO's assigned beneficiaries without the MSSP. At the end of the year, each ACO can be eligible to earn an additional bonus payment called shared savings if the average per capita spending of the ACO's providers is below the spending benchmark.

Quality Score A common concern is that ACOs might lower care quality (e.g., by curtailing services) to cut spending and earn MSSP bonuses. However, the regulations of the MSSP require Medicare to verify that any savings generated by an ACO are not due to quality reductions. Medicare closely monitors ACOs for risk selection and underuse of services, and conditions both participation and shared savings eligibility on meeting quality standards. Quality is summarized in a composite "quality score".[1] Failure to meet these standards or to comply with monitoring can jeopardize an ACO's participation in the MSSP. As a consequence, ACOs have neither the incentive nor the ability to use quality as a lever to generate shared savings payments. We therefore focus our analysis on the ACO's spending behavior.

Therefore, we assume throughout our analysis that quality of care is fixed, and that the ACO only decides on the effort to reduce spending without compromising quality (Aswani et al.). In other words, the model rules out quality-reduction as a way of generating savings. This assumption is consistent with CMS performance data: quality scores are near the maximum (median 0.9425) and have increased over time. However, for completeness of exposition, I will describe how the MSSP contract depends on the quality score.

[1] See Appendix A for details.

2.1 The Medicare Shared Savings Contract

Let y denote the average per capita FFS spending of the Medicare beneficiaries assigned to the ACO, and let $q \in [0,1]$ be the quality score. The shared savings payment obtained depends on the spending performance relative to the benchmark b and on the quality score q. The ACO's spending performance is evaluated in terms of the saving rate

$$s = \frac{b-y}{b}$$

ACOs earn a fraction $\psi q \in [0,1]$ of the spending reduction relative to the benchmark $(b-y)$ if the savings rate is above the minimum saving rate $\underline{s}$. Notice that the fraction of savings paid to the ACO depends on the shared savings rate $\psi = \frac{1}{2}$ and also on the quality score $q \in [0,1]$. This contract is called one-sided since the ACO does not incur any penalty or loss if spending is above the benchmark. The shared savings payments under the one-sided contract are given by the equation Equation 1

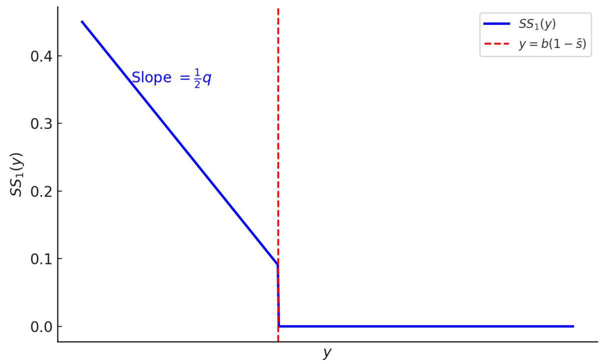
$$SS_1(y,q) = \begin{cases} \frac{1}{2}q\Big(b-y\Big) & \text{if } \frac{b-y}{b} > \underline{s} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The MSSP also gives ACOs the option to choose a two-sided contract that has both upside and downside risk. This contract has a higher shared savings rate ($\psi = 0.75$), but requires the ACO to pay a penalty if its spending is larger than the benchmark. The penalty is given by a fraction $(1-\psi)(1-q)$ of the excess spending relative to the benchmark if the savings rate is lower that $-\overline{s}$. The shared savings payments under the one-sided contract are given by the equation Equation 2.

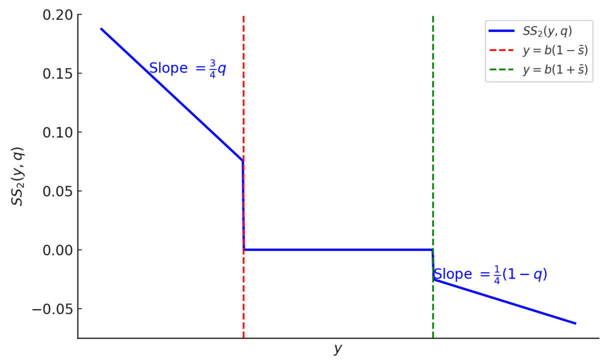
$$SS_2(y,q) = \begin{cases} \frac{3}{4}q\Big(b-y\Big) & \text{if } \frac{b-y}{b} > \underline{s} \\ \frac{1}{4}(1-q)\Big(b-y\Big) & \text{if } \frac{b-y}{b} < -\overline{s} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Panel (a) in Figure 1 shows the one-sided shared savings contract. The one-sided shared savings payments are a non-increasing function of spending. Indeed, the shared savings are zero if spending is above $b(1-\underline{s})$ and the slope of the shared savings function is $-0.5q$ when the shared savings payments are positive. Panel (b) in Figure 1 shows the two-sided shared savings contract. The two-sided shared savings payments is a non-increasing function of spending. Indeed, the shared savings payments are zero if spending is between $b(1-\underline{s})$ and $b(1+\overline{s})$, and the slope of this function is $-0.75q$ if spending is below $b(1-\underline{s})$ and $-0.25(1-q)$

if spending is above $b(1-\bar{s})$. Therefore, the two-sided contract implies stronger incentives to keep spending below the benchmark as each additional dollar increase in spending reduces the shared savings payment by $0.75q$ dollars under the two-sided contract, and by $0.5q$ dollars under the one-sided contract. Additionally, if $y > b(1+\bar{s})$, the penalty loss for each additional dollar increase in spending is $0.25q$ dollars under the two-sided contract, and zero under the one-sided contract.



(a) One-sided Contract



(b) Two-sided Contract

Figure 1: Shared Savings Payment

Notes: b denotes the benchmark, y is the ACO per capita spending, q is the quality score, and $\underline{s}$ and $\bar{s}$ are the minimum savings rate and minimum loss rate respectively. Panel (a) shows the shared savings payments under the one-sided contract (with shared savings rate equal to $\frac{1}{2}$) as given by equation Equation 1. Panel (b) shows the shared savings payments under the two-sided contract (with shared savings rate equal to $\frac{3}{4}$ and shared loss rate equal to $\frac{1}{4}$) as given by Equation 2.

2.2 Benchmark

The ACO's participation in the MSSP is divided into Agreement Periods of three years, and each year under the MSSP is called a Performance Year (PY). When an ACO joins MSSP, it enters a first Agreement Period (AP1) of three years with Medicare. The benchmark for AP1 is called the Historical Benchmark and is calculated based on the expenditure in the three Benchmark Years prior to joining MSSP. Two adjustments are applied to the ACOs' historical benchmark starting from the second Agreement Period. First, the ACO benchmark is rebased every three years based on the average spending of the previous three years. Secondly, a regional adjustment factor is applied to the benchmark in proportion to the difference between the ACO rebased benchmark and the average regional Medicare spending.

The ACO benchmark level and the benchmark updating rule are key design elements of the MSSP since the benchmark ultimately affects the amount of shared savings and the ACOs' participation decision. In this section, I explain in more detail the benchmark rebasement and regionalization, as well as how the benchmark is updated to account for changes in the ACOs' beneficiaries' health risk over time and variations of costs in the local healthcare market.

Historical Rebased Benchmark The historical benchmark is rebased at the start of each Agreement Period and is called the Rebased Historical Benchmark. This rebased benchmark is calculated as the average spending in the three Performance Years of the Previous Agreement Period. The Performance Years used for calculating the rebased benchmark are called Benchmark Years (BY). Hence, the Historical Rebased Benchmark of a given AP uses the Performance Years of the previous AP as Benchmark Years.

For instance, consider an ACO that joins the MSSP in 2015. The timeline of Agreement Periods, Performance Years and Benchmark Years are illustrated in Figure 2. Let $b^h_{AP_1}$ denote the historical benchmark in Agreement Period 1, and y_t the ACO per capita spending in year t. In this case, years 2012 to 2014 are the Benchmark Years for the first AP, and the historical benchmark for the first AP is given by

$$b^h_{AP_1} = 0.6y_{2014} + 0.3y_{2013} + 0.1y_{2012}$$

and years 2015 to 2017 are the performance years for the first Agreement Period (PY AP1) and also Benchmark Years for second AP. Similarly, the historical rebased benchmark for the second AP is given by

$$b^h_{AP_2} = \frac{1}{3}y_{2015} + \frac{1}{3}y_{2016} + \frac{1}{3}y_{2017}$$

and years 2018 to 2020 are the Performance Years of second AP.

Benchmark Regionalization Starting from the second Agreement Period, a regional adjustment factor is applied to the Rebased Historical Benchmark. Let y^R_t be Medicare's average per capita risk-adjusted expenditure in the ACO's regional service area. The risk adjustment is used to account for the difference in the average health risk between the ACO's beneficiaries and the overall Medicare population of the region where the ACO's providers operate. The regional adjustment factor is calculated as a fraction λ of the difference y^R and the ACO's expenditure y. The regionalized rebased historical benchmark b^r_t is given by the sum of the rebased historical benchmark b^h_t and the regional adjustment factor

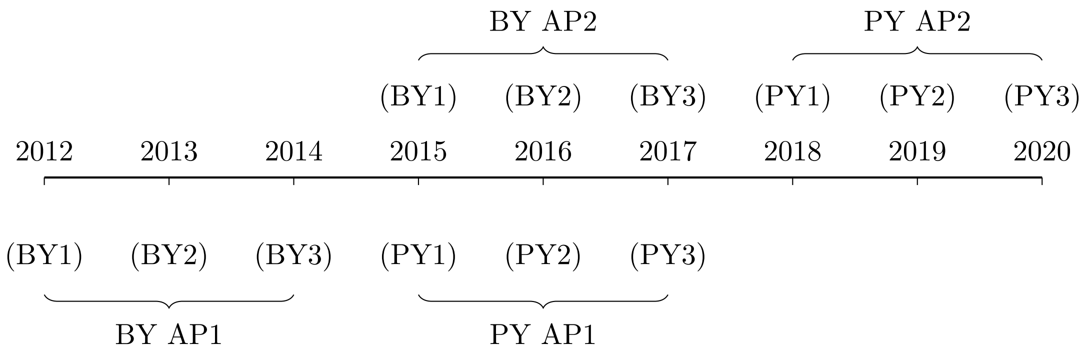


Figure 2: Timeline of MSSP Benchmark Rebasement

Notes: This Figure shows the timeline for an ACO that joins MSSP in 2015. AP denotes Agreement Period, PY denotes Performance Years and BY denotes Benchmark Years. Years from 2012 to 2014 are the BY for the first AP (AP1). Years from 2015 to 2017 are the PY of the first AP and also the BY of the second AP (AP2). Years from 2018 to 2020 are the PY of the second AP.

$$b_t^r = b_t^h + \underbrace{\lambda(y_t^R - b_t^h)}_{\substack{\text{regional} \\ \text{adjustment factor}}} = (1-\lambda)b_t^h + \lambda y_t^R \tag{3}$$

Therefore, the Regionalized Rebased Historical Benchmark is a weighted average of the ACO's Rebased Historical Benchmark and the Medicare's average regional expenditure. The regional weight λ increases across Agreement Periods is larger, and its value depends on whether the sign of $y_t^R - b_t^h$ is positive or negative. Appendix A explains the regional adjustment in detail.

Updated Benchmark At the end of each performance year, the historical regionalized benchmark is adjusted to account for variations in patient health risk and FFS prices in the local medical market between the Benchmark Years and the current Performance Year. The changes in the health status of the patient population are measured through the ratio of the average risk score in the current Performance Year and that of the most recent Benchmark Year. Similarly, variation in local medical market prices and patient utilization trends are measured using the FFS trend factors. I will denote the risk ratio with $\tilde{\text{rr}}_t$ and FFS trend factors with $\tilde{\text{tf}}_t$.[2]

[2] $\tilde{\text{rr}}_t$ is computed as the ratio of the risk score in the PY and that of the latest benchmark year. Similarly, for the trend factors $\tilde{\text{tf}}_t$

Therefore, the update factors are given by

$$\tilde{\mathrm{uf}}_t = \tilde{\mathrm{rr}}_t \cdot \tilde{\mathrm{tf}}_t \tag{4}$$

and the updated benchmark that is relevant for the calculation of the shared savings payments is given by

$$b_t^u = b_t^r \cdot \tilde{\mathrm{uf}}_t \tag{5}$$

Going back to the example of the ACO joining the MSSP in 2015, the updated benchmark for performance years in the first AP is obtained by applying the update factor to the most recent Benchmark Year, which in this case is 2014. Similarly, the updated benchmark for performance years in the second AP is obtained by applying the update factor to the most recent Benchmark Year, which in this case is 2017.

3 Data and reduced-form Evidence

The data used in this paper are from MSSP ACO Public Use Files (2013-2022), MSSP Participant Lists, MSSP ACO Performance Year Results, and Number of ACO. Assigned Beneficiaries by County Public Use Files. The data consists of ACO expenditures, benchmark expenditures, quality scores, contract choice, assigned beneficiary demographics, and various participant and provider statistics.

Little public information is available on the characteristics of specific ACO participants. I complement the ACOs data that by merging the ACOs participants list with other data sources:

(i) the Physician Compare Database, which contains detailed information on the providers' characteristics (specialty, experience, location, beneficiaries risk score, hospital affiliations, EHR usage).

(ii) the American Hospital Association (AHA) Survey Database which allows to have detailed information on hospital characteristics and the degree of integration between hospitals and physicians' organizations.

3.1 Descriptive Evidence

Figure 3 shows how entry and exit varied over time in the MSSP. The number of ACOs has increased significantly over time, and currently, there are more than 500 active ACOs in the MSSP. The number of entrants was larger in the early years of the program and has been declining over time. The low number of entrants in 2021 can be attributed to the COVID-19 pandemic. Exit increased steadily in the years leading up to the introduction of the regional adjustment in 2016 and has been steady after that.

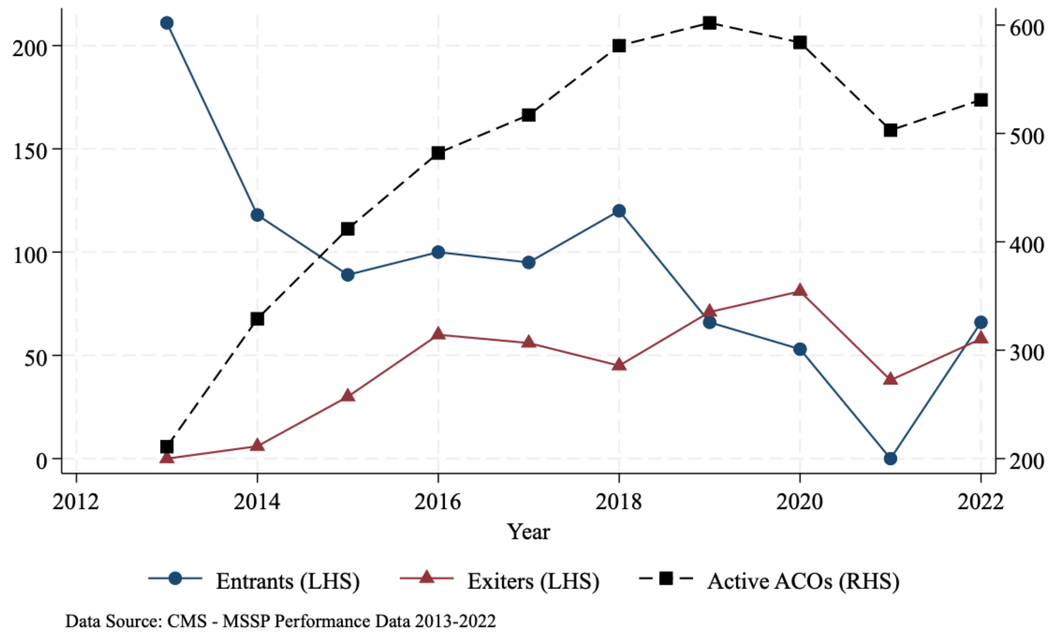


Figure 3: Entry, Exit and Active ACOs from 2013 to 2022

Table 6 shows some summary statistics on ACOs' characteristics and financial performance. In the early years of the program, only a third of the ACOs were eligible for shared savings, and the share of ACOs generating savings above the minimum savings rate is close to 50%. The savings rate has been modest in the early years. For example, in 2015, the total savings across all ACOs was approximately $430 million, which represents a 0.6% decrease in Medicare spending. This can be seen from the average savings rate, which is around 1%, but it has increased steadily over time. The savings rate has increased over time, but shows a large variation across ACOs.

ACOs tend to be very heterogeneous in terms of the number of providers, the number of assigned beneficiaries, and risk score. The average risk score of the ACOs' assigned beneficiaries is above 1, which indicates that the ACOs' beneficiaries tend to have a worse health status than the average Medicare beneficiary. The benchmark per capita is, on average, between 10 and 11 thousand dollars, which is close to the mean per capita expenditure of the overall Medicare population.

The vast majority of ACOs opted for the one-sided contract, but the share of ACOs in the two-sided contract has increased significantly over the last few years. This is mostly driven by the rule that requires ACOs to adopt the two-sided contract starting from the third agreement period. The average age of an ACO at exit is between 5 and 6 years. This shows that most ACOs leave the program after two agreement periods.

In the rest of this section, I will describe how the MSSP benchmarking rule affects ACOs' incentives to generate savings and participate in the program. In particular, I will provide reduced-form evidence that the benchmark rebasement is associated with decreased spending reduction, and the regional adjustment negatively affects ACOs' participation in the program.

3.2 Ratchet Effect

In this section, I present the empirical approach for identifying whether benchmark ratcheting gives rise to a ratchet effect. I take advantage of the presence of years that are not counted in the rebasement to test whether ACOs strategically delay cost-reduction efforts in order to preserve higher benchmarks over time. Our estimates indicate that target ratcheting has a substantial negative impact on ACO's savings, which I interpret as evidence of ratchet effect.

I exploit two policy-induced variations in the MSSP benchmarking rules that allowed ACOs to have their spending in some years not taken into account for the benchmark rebasement. The first is the deferral option. Between 2016 and 2018, ACOs had the option to defer the start of the next AP by one year. The fourth year option was intended to support ACOs that were preparing to transition into a two-sided risk model. If the ACO's request to renew into a two-sided model was approved, it could also request an extension of its existing one-sided contract by one additional year. The benchmark is rebased using only the last three years of these 4-years long AP. Thus, we have one year that is not counted for the rebasement.

The second variation is the introduction of five-year AP cycles. Before 2019, ACOs participated in Agreement Periods (APs) of three years. At the end of each AP, the benchmark was rebased using average spending in the three preceding years. With the "Pathways to Success" reform, Agreement Periods starting in 2019 or later last five years, and only the last three years are included to rebase the benchmark. This creates a two-year period where spending does not affect the benchmark of the next AP. The staggered rollout of the five-year AP structure across ACOs creates plausibly exogenous variation in the timing of exposure to non-rebasing years.

Table 1 shows the non-rebasing years induced by the deferral option and the five-year AP policy for each cohort of ACOs. An ACO is considered treated when it is in a non-rebasing year, and untreated when it is in a rebasing year. ACOs cycle in and out of rebasing-years depending on their position within the AP, and nearly all ACOs eventually experience both rebasing and non-rebasing years. As such, "treatment" status varies within units over time in a way that is mechanically determined by administrative rules, not chosen strategically. However, ACOs that entered in 2019 or after could potentially time their exposure to the non-rebasing years. For this reason, we will compare our analysis on the full sample with the analysis on the set of ACOs entered prior to 2019.

Table 1: Non-Rebasing Years by ACO Cohort

Cohort	**AP**	**Deferral**	**Non-Rebasing**	**ACOs-Years**
2013	3	6 months	2019–2020	145
2014	3	No	2020–2021	92
2014	3	2017	2021–2022	10
2015	3	No	2021–2022	73
2015	3	2018	2022–2023	2
2015	2	2018	2019–2020	2
2016	2	6 months	2019–2020	99
2017	2	No	2020–2021	117
2018	2	No	2021–2022	127
2018	2	2021	2022–2023	8
2019	1	No	2019–2020	91
2020	1	No	2020–2021	67
2021	1	No	2021–2022	106
2022	1	No	2022–2023	27

Notes: (i) This table shows the Non-Rebasing years for different cohorts of ACOs. The specific years might vary depending on whether the ACO adopted the deferral option (ii) The second-to-last column indicates the number of ACO-Years observations (iv) The deferral option was discontinued as part of the 2019 policy changes.

Thus, we use these non-rebasing years to test whether ACOs strategically respond to the presence or absence of benchmark ratcheting. We distinguish between the two types of non-rebasing years by defining two indicators. The deferral indicator that equals one when the first PY is not included in the rebasement because the ACO has adopted the deferral option and

$$\mathrm{DF}_{it} = \begin{cases} 1 & \text{if year } t \text{ is PY 1 of a 4-Years AP} \\ 0 & \text{otherwise} \end{cases}$$

and Non-Rebasing Years indicators that equals one when the ACO is in first or second PY of a five-year AP cycle

$$\text{Non-RY}_{it} = \begin{cases} 1 & \text{if year } t \text{ is in PY 1 or 2 of 5-Year AP} \\ 0 & \text{otherwise} \end{cases}$$

I control for ACO, year and AP fixed effects, and ACO characteristics. Thus, the impact of non-rebasing years is identified from within-ACO variation in treatment, netting out all time-invariant differences across ACOs and all common shocks across years.

Panel A of Table 2 shows the estimation results of a Two-Way Fixed Effect linear model with Savings Rate as dependent variable, while Panel B shows the results of Two-Way Fixed Effect Logistic model with the indicator of Savings Rate above the minimum savings rate as dependent variable.

The results in Panel A provide evidence consistent with the presence of a ratchet effect. Focusing on the columns that include ACO fixed effects (Columns 1 and 3), we find that ACOs exhibit significantly higher savings rates and greater reductions in spending during non-benchmark years. Specifically, being in a non-benchmark year is associated with a 0.94 percentage point increase in the CMS savings rate, which corresponds to approximately 40% of the average savings rate. The estimated impact of the non-rebasing years induced by the deferral option is even stronger, approximately a 1.8% point increase in the savings rate, which is about 80% of the average savings rate.

Importantly, these effects are only present when including ACO fixed effects, which absorb permanent differences in cost levels across ACOs and allow identification from within-ACO variation over time. When ACO fixed effects are omitted (Columns 2 and 4), the estimates for both *Non-Benchmark Year* and *Deferral* are smaller in magnitude and lose statistical significance, underscoring the importance of controlling for unobserved ACO heterogeneity. This implies that identification of the ratchet effect comes from within-ACO variation over time. Without ACO FE, the estimates are confounded by cross-sectional differences. This suggests that the ratchet effect is a within-ACO phenomenon: the same ACO changes behavior across benchmark and non-benchmark years.

The coefficients in Panel B are reported as odds ratios to aid interpretation. In the preferred specification with ACO fixed effects (Column 1), ACOs in non-benchmark years are over twice as likely to generate savings relative to when they are in benchmark years (OR = 2.17). Similarly, ACOs that chose to defer rebasing are nearly three times more likely to achieve savings above the threshold compared to those that did not defer (OR = 2.87).

In both Panel A and Panel B, we observe the same pattern of results in the full sample and in the sample of ACOs that entered prior to 2019. This indicates that ACOs are not timing their exposure to the non-benchmarking years, and the quasi-random assignment assumption of the non-rebasing years is satisfied. These findings suggest that ACOs respond to the benchmark ratcheting by timing their spending reduction efforts to maintain a favorable benchmark over time.

3.3 Adverse Selection

ACOs generate savings and obtain shared savings payments when they reduce their FFS spending below their benchmark. If the baseline FFS spending is lower than the benchmark, ACOs can obtain shared savings payments without reducing the FFS spending. In this case, Medicare is wasting resources by paying providers for achieving an FFS spending level that they would have achieved also without the MSSP incentives. Following Einav et al., 2022, we define adverse selection as the ACOs' choice to select in the MSSP to exploit the benchmarking rules to obtain shared savings payments from Medicare without reducing their spending relative to their rebased benchmark.

Adverse selection may occur when the regional adjustment is applied. As described in Section 1, when the ACO's spending is lower than the Medicare average regional spending, a positive regional adjustment factor is applied to the ACO's historical rebased benchmark. Conversely, when the ACO's spending is higher than the Medicare average regional spending, a negative regional adjustment factor is applied to the ACO's historical rebased benchmark. Hence, ACOs with a positive regional adjustment factor might be able to obtain shared savings without further reducing their spending.

I test for the presence of adverse selection by estimating the impact of a positive regional adjustment on the ACOs' likelihood of leaving the MSSP. Since the regional adjustment was introduced at different times for different cohorts of ACOs [3], I define a Regional Adjustment indicator

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

and, since the regional adjustment factor can be positive or negative depending on how the ACO's rebased benchmark compares with the regional spending, I define the Positive Adjustment indicator

$$\text{Positive Adj}_{it} = \begin{cases} 1 & \text{if } b^h_{it} < y^r_{it} \\ 0 & \text{otherwise} \end{cases}$$

[3]Regional adjustment was introduced from the 3rd AP for ACOs entered in 2013, and from the 2nd AP for all other ACOs.

Table 2: Ratchet Effect Results

Panel A: Two Way Fixed Effects Regressions

	Full Sample		Entry Year < 2019	
	ACO FE	No ACO FE	ACO FE	No ACO FE
Non-Benchmark Year	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)
Observations	4,519	4,519	4,133	4,133
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
ACO FE	Yes	No	Yes	No
ACO Age FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Two Way Fixed Effects Logistic Regressions

	Full Sample		Entry Year < 2019	
	ACO FE	No ACO FE	ACO FE	No ACO FE
Non-Benchmark Year	2.172***	1.004***	2.259***	0.958***
	(0.407)	(0.146)	(0.438)	(0.151)
Deferral	2.865***	1.509***	2.626***	1.306***
	(0.918)	(0.321)	(0.858)	(0.287)
Observations	3,180	4,602	3,017	4,213
McFadden R^2	0.624	0.128	0.612	0.137
Share of ACOs > MSR	0.510	0.457	0.465	0.444
ACO FE	Yes	No	Yes	No
AP FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: (i) Source: CMS Performance Year Financial and Quality Results. (ii) Top panel dependent variable: CMS savings rate. Bottom panel dependent variable: indicator for savings rate above minimum savings rate. (iii) Standard errors clustered by ACO.

I estimate the impact of the regional adjustment of the likelihood of exit using a logistic regression

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

where Λ is the logistic cdf. Table 3 shows the estimated impact of Regional-Adj and Positive-Adj on the odds ratio of exit after controlling for Year fixed effects and AP fixed effects. Thus, the parameters of interest are identified from the variation of Regional-Adj and Positive-Adj across ACOs.

Table 3: Adverse Selection Results

	(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
Standard errors clustered by ACO

The estimated odds ratio indicates that, after the regional adjustment is applied, ACOs are more then three times as likely to leave the MSSP. However, conditional on the regional adjustment being applied, ACOs that receive a positive regional adjustment are about 70% less likely to leave the MSSP compared to ACOs that receive a negative regional adjustment. This indicates the presence of adverse selection in the MSSP. ACOs whose rebased benchmark is lower than the regional spending are more likely to stay in the MSSP since they can generate savings without further reducing their spending.

4 Structural Model

4.1 The spending equation

Under FFS, the average per capita spending of ACO i in year t is denoted by y_{it}^{FFS}. The latter is persistent over time and varies over time for some factors that do not depend on the ACO's behavior. These include (i) the national and regional trend in FFS prices, (ii) the healthcare utilization trend of the ACO's population, and (iii) the health status of the ACO's population. The first two are accounted for by Medicare using the trend factors tf_{it}, and the second by the risk ratio rr_{it}.[4]

We assume that the FFS spending of ACO i varies over time according Equation 6

$$y_{it}^{FFS} = y_{it-1}^{FFS} \cdot \mathrm{tf}_{it} \cdot \mathrm{rr}_{it} + u_{it} \tag{6}$$

where $u_{it} = \epsilon_{it} - \epsilon_{it-1}$ with ϵ_{it} i.i.d. from $N(0, \sigma_{it}^2)$. This implies that year-t spending shock ϵ_{it} do not affect the FFS spending distribution in the following year. Thus, the FFS spending follows a normal distribution

$$y_{it}^{FFS} \sim N\left(\mu_{it}, 2\sigma_{it}^2\right) \quad \text{with} \quad \mu_{it} = y_{it-1}^{FFS} \cdot \mathrm{tf}_{it} \cdot \mathrm{rr}_{it}$$

Under MSSP, ACOs exert a non-negative effort e_{it} that reduces per capita spending relative to the FFS level. The observed ACOs' spending is given by Equation 7

$$y_{it} = y_{it}^{FFS} - e_{it} \tag{7}$$

Before joining the MSSP, ACOs is under FFS and the optimal effort level is zero since any positive effort would reduce the benchmark in the first AP. Therefore, we can observe the FFS spending in the pre-MSSP years.

ACOs are forward-looking agents and take into account the impact of current year spending on future benchmarks. Since the benchmark is rebased every three (or five) years, we assume ACOs keep track of the rolling average spending over the course of each AP. Let $\tilde{y}_{it}$ denote the rolling average spending in year t. The evolution of $\tilde{y}_{it}$ over time is given by

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

where uf_{it} denotes the update factors that are used to put year t spending in year $t+1$ terms. [5] The value of rolling average spending in the third PY of each AP is used to rebase the benchmark for the subsequent AP. The rolling average spending for a five-year AP is similar, but only takes into account the spending of the last three PYs.

[4]the risk ratio is computed as the ratio of the risk scores of two consecutive years.

[5]the update factors are given by $\mathrm{uf}_{it} = \mathrm{tf}_{it} \cdot \mathrm{rr}_{it}$.

The spending benchmark is rebased and updated over time via the following formula

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

where y_{it}^r is the observed regional average and λ_{it+1} is the regional blending parameter, varying across time and ACOs.[6] The term $\tilde{\mathrm{uf}}_{t+1}^j$ denotes the update factors that account for variation in the risk score and FFS trends between the latest benchmark year and the current PY j. [7] For five-year AP cycles, the formula includes two additional performance years ($\mathrm{PY}_{t+1} = 4$ and $\mathrm{PY}_{t+1} = 5$).

4.2 ACOs' Dynamic Problem

ACOs are groups of different healthcare providers, from hospitals to physician practices to nursing homes. The ACOs' participation and spending are the results of complex interaction between the ACOs' providers and the board of the ACO. Since the objective of this paper is to study how the benchmarking rules affect spending and participation, I will abstract from these complex interactions and model each ACO as a single agent. I will use a simple dynamic behavioral model to infer the ACOs' unobserved effort to reduce spending, and I will describe how the model primitives map into the key quantity of interest, ratchet effect, and adverse selection.

Each year t, the timing of the events is as follows: (i) ACOs choose whether to participate in the MSSP or remain under the standard fee-for-service (FFS), (ii) if they participate in the MSSP, they choose an effort level e_{it} to maximize their discounted flow of profits, (iii) the spending shock ϵ_{it} is realized, (iv) the MSSP spending y_{it}^M is observed, and the ACO obtains profits π_{it}.

For ease of exposition, in this section, we only consider the case where ACOs can choose between FFS and one type of MSSP contract. Let d_{it} denote the discrete participation choice between MSSP and FFS

$$d_{it} = \begin{cases} 1 & \text{if MSSP} \\ 0 & \text{if FFS} \end{cases}$$

ACOs' dynamic decisions depend on a set of state variables that include the rolling

[6] See Appendix A

[7] $\tilde{\mathrm{uf}}_t^j = \tilde{\mathrm{tf}}_{it} \cdot \tilde{\mathrm{rr}}_{it}$ where $\tilde{\mathrm{tf}}_{it}$ can be written as the ratio of the trend factors in year $t+j$ and the trend factors in year t. Similarly for the $\tilde{\mathrm{rr}}_{it}$.

average spending, the current period rebased benchmark, the regional spending, the risk ratio, and the FFS trend factors. I denote the set of state variables in year t as Ω_{it}.

The choice specific value function of participating in the MSSP given Ω_{it} is given by

$$v_{it}^M(\Omega_{it}) + \varepsilon_{it}^M = \max_{e_{it}} \left\{ \pi_{it}^M(e_{it}) + \delta \mathbb{E} V_{it+1}(\Omega_{it+1}) \right\} + \varepsilon_{it}^M$$

where ε_{it}^M and ε_{it}^F are idiosyncratic choice specific shocks. Under the assumption that these shocks have TIEV distribution, it can be shown that the continuation value function is given by

$$\mathbb{E} V_{it+1}(\Omega_{it}) = \ln \left[\exp(v_{it+1}^M(\Omega_{it+1})) + \exp(v_{it+1}^F(\Omega_{it+1}) \right],$$

where v_{it+1}^F is the value of leaving MSSP and going back to FFS.

The MSSP participation condition is given by

$$d_{it} = 1 \iff v_{it}^M(\Omega_{it}) + \varepsilon_{it}^M > v_{it}^F(\Omega_{it}) + \varepsilon_{it}^F$$

and the conditional choice probabilities

$$\Pr(d_{it} = 1 \mid \Omega_{it}) = \frac{1}{1 + \exp(v_{it}^F(\Omega_{it}) - v_{it}^M(\Omega_{it}))}.$$

During rebasing years, the optimal level of effort satisfies the first order condition

$$\frac{\partial \pi_{it}^M}{\partial e_{it}} = \delta \Pr(d_{it+1} = 1 \mid \Omega_{it}) \frac{\partial v_{it+1}^M}{\partial \tilde{y}_{it+1}} \frac{\partial \tilde{y}_{it+1}}{\partial y_{it}} \frac{\partial y_{it}}{\partial e_{it}}$$

whereas in non-rebasing years

$$\frac{\partial \pi_{it}^M}{\partial e_{it}} = 0$$

Using the Envelope Theorem, it can be shown that, for the rebasing years, the effort satisfies the Euler equation [8]

$$\frac{\partial \pi_{it}^M}{\partial e_{it}} = \delta \Pr(d_{it+1} = 1 \mid \Omega_{it}) \left[\frac{\partial \pi_{it+1}^M}{\partial e_{it+1}} \mathbb{1}(\mathrm{PY}_{it+1} \neq 1) + \frac{1}{3} \frac{\partial \pi_{it+1}^M}{\partial b_{it+1}} (1 - \lambda_{it+1}) \mathbb{1}(\mathrm{PY}_{it+1} = 1) \right] \tag{8}$$

This equation shows that increasing current effort leads to lower spending and increased profits (higher shared savings), but reduces the continuation value through lower future benchmark.

Since the right-hand side of the Euler equation is positive, the optimal level of effort under

[8] See Appendix C.

the benchmark rebasement is lower than the level of effort that would be optimal under a static benchmark. The Euler equation shows the factors that contribute to the ratchet effect: (i) the weight of current period spending on the rolling average (1/3 in our case), (ii) the contribution of current AP spending on the next AP benchmark which corresponds to one minus the regional blending factor ($1 - \lambda_{t+1}$), and (iii) how sensitive profits are to a change in benchmark which equals the shared savings rate ($\frac{\partial \pi^M_{t+1}}{\partial b_{t+1}}$).

4.3 Model Primitives

The profit $\pi^M_{it}(e_{it})$ of the ACO under MSSP is given by Equation 9

$$\pi^M_{it}(e_{it}) = \mathbb{E}\left[SS(e_{it})\right] - C(e_{it}) - F_i \tag{9}$$

where the $\mathbb{E}\left[SS(e_{it})\right]$ are the expected shared savings payments, $C(e_{it})$ are variable cost of effort and F_i are fixed costs. [9]

I assume that the cost of effort is quadratic and depends on an unknown ACO specific cost parameter γ_{it}

$$C(e_{it}) = \frac{1}{2}\gamma_{it}\frac{e^2_{it}}{\mu_{it}}$$

Since e_{it} is the effort in dollar terms, the expected FFS spending μ_{it} enters in the denominator to allow the cost of effort to be scale invariant. In other words, variable costs depend on dollar effort relative to the FFS spending.

We allow γ_{it} and F_i to depend on observables x_{it} and on a vector of persistent unobserved types ν_i:

$$\log \gamma_{it} \;=\; x'_{it}\beta_C \;+\; \nu'_i\alpha_C, \qquad \log F_i \;=\; x'_{it}\beta_F \;+\; \nu'_i\alpha_F,$$

with ν_i is a vector of indicator of unobserved types.[10] Reduced-form evidence in our data indicates that (i) even with rich controls and ACO and time fixed effects, a large share of the cross-sectional and within-ACO variation in savings remains unexplained (e.g., $R^2 \approx 0.18$ in Table 2); and (ii) participation (exit) decisions display substantial residual variation (McFadden $R^2 \approx 0.14$–0.16 in Table 3), consistent with persistent heterogeneity in both variable and fixed costs. Parallel evidence in related settings documents large heterogeneity in costs and FFS spending with observables explaining only a small fraction of that variation, reinforcing the need for unobserved types[11]. Allowing ν_i to load on both γ and F ties the intensive

[9] See Appendix C for the derivation of the expected shared savings payments.

[10] If ACO i is of type k, then ν_i will be a vector whose k-th entry equals one, and all the other entries are zero.

[11] See Einav et al.

(effort) and extensive (participation) margins and is critical for credible counterfactuals that quantify ratcheting and adverse selection.

I illustrate graphically in Figure 4 how the model primitives map into the two phenomena of interest—ratchet effect (RE) and adverse selection (AS). In order to express the ratchet effect and adverse selection in terms of the cost primitives γ_i and the policy parameters (ssr, λ), we make the following simplifying assumptions : (i) the benchmark is rebased every year according to the following rule

$$b_{it+1} = (1-\lambda)y_{it} + \lambda y_{it}^R$$

(ii) ACOs cannot exit the MSSP, (iii) $\delta = 1$, and (iv) there is no spending shock ϵ_{it}

Under these assumptions, the Euler equation in the dynamic case (non-rebasing year) reduces to

$$\frac{\partial \pi_{it}^M}{\partial e_{it}} = (1-\lambda)\frac{\partial \pi_{it}^M}{\partial b_{it+1}}$$

and we can solve to the optimal effort $e_{it}^D = \mu_{it}\frac{ssr}{\gamma_i}\lambda$ where ssr denote the shared savings rate. In the static case (non-rebasing years), the optimal effort is given by $e_{it}^S = \mu_{it}\frac{ssr}{\gamma_i}$. Therefore, the ratchet effect (RE) can be written as

$$RE(\gamma_i, \lambda) = e_{it}^S - e_{it}^D = \mu_{it}\frac{ssr}{\gamma_i}(1-\lambda)$$

Notice that if the benchmark is fully regionalized ($\lambda = 1$), the RE is zero since the dynamic effort is equal to the static effort, whereas when the benchmark is fully rebased ($\lambda = 0$), the dynamic effort is zero and the ratchet effect is its largest.

To capture adverse selection, consider the shared savings payment in year $t+1$ given b_{it+1} if the ACO makes zero effort in $t+1$

$$SS_{it+1} = \text{ssr}(b_{it+1} - y_{it+1}^{FFS})$$

where b_{it+1} depends on λ and y_{it}^R. As λ increases, $b_{i,t+1}$ approaches y_{it}^R. Thus, whenever regional spending exceeds the ACO's FFS level, $\left(b_{i,t+1} - y_{i,t+1}^{FFS}\right)_+$ grows and "free" savings rise. We therefore summarize the AS incentive as

$$AS_i(y_i^{FFS}, y_i^R, \lambda) \; = \; \text{ssr}\left(b_i - y_i^{FFS}\right)_+,$$

where b_i depends on λ and y_i^R. It is easy to observe that there is a trade-off between ratchet effect and adverse selection when setting λ. When effort is cheap (low γ_i) or the shared-savings rate is generous, ACOs would want to cut spending more. However, because past spending lowers future benchmarks, effort is reduced in years that feed into rebasing. This ratchet effect is stronger the more the benchmark depends on an ACO's own past spending (lower λ)). By contrast, adverse selection is mechanical: when the benchmark lies above an ACO's own FFS level, the ACO can earn shared-savings even with little or no effort. Increasing the regional weight reduces the ratchet (by making current effort hurt future benchmarks less), however, when the regional FFS level is more expensive than the ACO, it also raises the benchmark relative to FFS and thereby strengthens these mechanical selection incentives.

From the regulators' perspective, ACO i efficiently selects into MSSP if the total cost under the MSSP is lower the than the cost under FFS

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

When $b_i - y_i^{FFS} > 0$, this inequality is equivalent to

$$(1 - \text{ssr})\, e_i \ > \ \text{ssr} \left(\frac{b_i - y_i^{FFS}}{y_i^{FFS}}\right),$$

i.e., MSSP generates net savings only if the effort-driven savings that Medicare keeps, $(1-\text{ssr})e_i$, exceed the "free" shared-savings generated by a high benchmark, $\text{ssr}(b_i - y_i^{FFS})$. Substituting $e_i = e_{it}^D = \lambda\, \text{ssr}/\gamma_i$ delivers the threshold that separates *Efficient* from *Inefficient* selection:

$$\frac{b_i - y_i^{FFS}}{y_i^{FFS}} < \frac{\lambda(1-\text{ssr})}{\gamma_i} \tag{10}$$

Figure 4 plots this downward-sloping frontier as a function of the cost parameter γ_i. Selection is efficient whenever the behavioral savings that Medicare keeps under the MSSP exceed the "free" shared-savings created by a high benchmark. Raising the regional weight λ moves the efficient–inefficient frontier in two opposite ways. A higher λ weakens the ratchet and raises the effort that is actually exerted in rebasing years, so—holding $b_i - y_i^{FFS}$ fixed—the frontier shifts upward (it becomes easier for MSSP participation to be cost-reducing). A higher λ also pulls the benchmark toward regional spending. When the regional spending is above the ACO's FFS level, this increases $b_i - y_i^{FFS}$ and enlarges the free shared savings. The frontier effectively shifts downward, meaning that it becomes harder for participation to be cost-reducing. Hence, increasing λ simultaneously relaxes the efficiency condition through the effort/ratchet channel and tightens it through the benchmark/adverse selection channel. Which effect dominates depends on the ACO's position in the $(\gamma_i, b_i - y_i^{FFS})$ space. When regional spending is not above FFS, the selection channel is absent, and

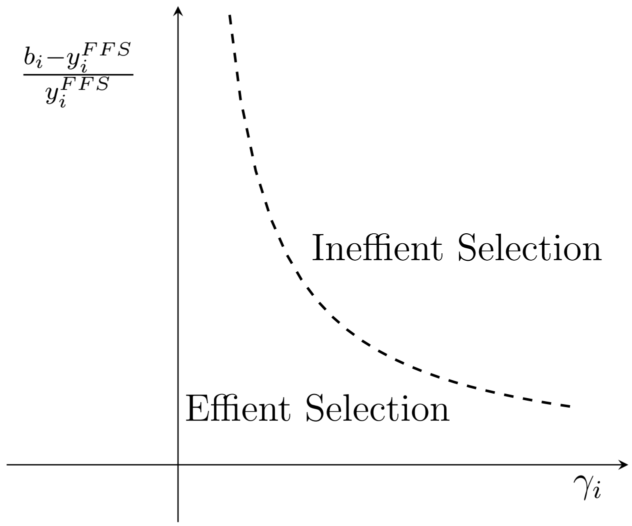


Figure 4: Selection frontier

a higher λ unambiguously makes efficient selection more likely.

This trade-off in setting λ suggests the need for an alternative benchmarking rule that better balances the trade-offs between rebasement and regionalization. In Section 6, I will introduce and evaluate the impact of an alternative benchmarking rule called Conditional Regionalization that uses benchmark regionalization to mitigate the ratchet effect while also addressing the issue of adverse selection.

5 Estimation and Results

5.1 FFS Spending

I estimate the mean FFS spending outside the model using the spending equation. Each ACO is observed since three years prior to the MSSP entry, and in those three years, we observe the ACO's FFS spending. I use the observed FFS spending before entry to estimate the expected FFS spending for the first PY. Let t_{i0} be the entry year. I estimate the mean FFS spending in t_{i0} as the mean FFS spending in the three years prior to entry plus the trend due to the FFS trend factors $\mathrm{tf}_{i,t_{i0}}$ and the risk ratio $rr_{i,t_{i0}}$

$$\mu_{i,t_{i0}} = \frac{1}{3}\left(y^{FFS}_{i,ti0-1} + \tilde{y}^{FFS}_{i,ti0-2} + \tilde{y}^{FFS}_{i,ti0-3}\right) \cdot \mathrm{tf}_{i,t_{i0}} \cdot \mathrm{rr}_{i,t_{i0}}$$

where $\tilde{y}^{FFS}_{i,t_{i0}-2}$ and $\tilde{y}^{FFS}_{i,t_{i0}-3}$ indicate that the FFS spending in $t_{i0}-2$ and $t_{i0}-3$ are expressed in $t_{i0}-1$ terms using the corresponding FFS trend factors and risk ratio.

From the spending equation, the mean log FFS spending in t is given by

$$\mu_{it} = \mu_{it-1} \cdot \mathrm{tf}_{it} \cdot \mathrm{rr}_{it}$$

The standard deviation of the spending shock is assumed to be proportional to the FFS spending $\sigma_{it} = \rho\mu_i t$ and ρ is estimated within the model.

5.2 Estimation

Let $\theta = (\beta_C, \beta_F, \alpha_C, \alpha_F, \rho)$ be the vector of parameters that define the model primitives. I estimate the model parameters with maximum likelihood. We observe the MSSP spending during its MSSP participation, whereas we do not observe spending after exit. Let T_i be the number of years ACO i participates in the MSSP. For each ACO i, we observe a sequence of length T_i of participation choices and spending $\{(d_{it}, y_{it})\}_{t=t_{i0}}^{t_{i0}+T_i}$ with $d_{it} = 1$ and $y_{it} = y_{it}^{FFS} - e_{it}$. Notice that $y_{it}^{FFS} = \mu_{it} + u_{it}$ is the unobserved realized FFS spending level. The effort e_{it} is obtained as a solution of the Euler equation. [12] In year $t_{i0} + T_i + 1$, I observe only the exit choice $d_{it} = 0$.

Let K be the number of unobserved types, and q_{ik} the probability that ACO i is of type k. We treat the unobserved type as an observed ACO characteristic, and write the likelihood function for ACO i as a finite mixture over the set of unobserved types:

$$L_i(\theta) = \sum_{k=1}^{K} q_{ik} \left[\prod_{t=t_{i0}}^{t_{i0}+T_i} \phi(y_{it}, \Omega_{it}, k; \theta) \Pr(d_{it} = 1 | \Omega_{it}, k; \theta) \right] \times \Pr(d_{i,t_{i0}+T_i+1} = 0 | \Omega_{i,t_{i0}+T_i+1}, k; \theta)$$

where

$$\phi(y_{it} | \Omega_{it}, k; \theta) = \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} \exp\left(-\frac{(y_{it} - \mu_{it} + e_{it})^2}{2\sigma_\epsilon^2} \right)$$

is the distribution of the observed spending under MSSP given μ_{it} and e_{it}, and

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

is the discrete choice probability.

I implement an Expectation-Maximization (EM) algorithm to estimate θ and the mixture type probabilities. The EM algorithm requires to iteratively update the mixture probabilities given the likelihood and find θ that maximizes the likelihood given the mixture probabilities. This two step process yields a solution to the log likelihood maximization problem upon

[12] See Appendix for details.

convergence.[13].

The likelihood in equation requires to compute the choice specific value functions. I estimate the latter as part of the EM algorithm using simulations. For each ACO i, year t and unobserved type k, I simulate S paths of discrete choices, effort, spending and profits for T periods. For each simulated paths, I compute the discounted sum of profit flows and compute its average the to estimate v_{it}^{M}.[14]

Standard errors are calculated using the bootstrap method. Specifically, I construct bootstrap samples by drawing the observed number of ACOs with replacement. I estimate the parameters of the model on each bootstrap sample and calculate the standard errors as the standard deviation of the bootstrap parameter estimates.

5.3 Identification

The likelihood ties observed spending to the model-implied effort. From the model assumptions $y_{it}|e_{it} \sim N\Big(\mu_{it} - e_{it}, 2\sigma_{\epsilon}^2\Big)$. The level of effort that maximize the likelihood is $\Delta y_{it} = \mu_{it} - y_{it}$. Replace $y_{it} = \mu_{it} - e_{it} + u_{it}$ to obtain

$$\Delta y_{it} = e_{it} - u_{it}$$

The model implied effort e_{it} solves the Euler equation $MB(\Omega_{it}) = \frac{\gamma(x_{it},\nu_i;\theta)}{\hat{y}_{it}^{FFS}} e_{it}$ where $MB(\Omega_{it})$ is the marginal benefit od effort given Ω_{it}. Hence, we have that

$$\Delta y_{it} = \mu_{it} \frac{MB(\Omega_{it})}{\gamma(x_{it}, \nu_i; \theta)} - u_{it}$$

Changes in the state Ω_{it} (benchmarks, phase/caps, risk–TF factors that enter the marginal benefit) shift $MB(\Omega_{it})$ while holding $\gamma(\cdot)$ fixed. Variation in the numerator change the level of Δy_{it} one-for-one via $\mu_{it} \cdot MB/\gamma$, anchoring the scale of Δy_{it} at a given γ. At the same state Ω, variation in observed characteristics x_{it} and types ν_i identify the shape of $\gamma(\cdot)$ governed by θ. In other words, the gaussian part of the likelihood ties variation in Ω_{it} and x_{it} to the observed Δy_{it} , which identifies (β_C, α_C).

5.4 Results

Variable and fixed cost estimates In the model, the intensive margin is governed by the variable–cost index γ_i, which scales the marginal cost of effort through $C(e_{it}, \mu_{it}) =$

[13]See Arcidiacono and Miller (2010) and Appendix D.2

[14]See Appendix D.3 for details

$\frac{1}{2}\gamma\, e_{it}^2/\mu_{it}$. A larger γ_i implies a steeper marginal cost schedule and, holding the incentive $MB(\Omega_{it})$ fixed, lower optimal effort. Table 9 in Appendix D reports the estimated coefficients in (β_C, α_C). Three patterns are robust across the number of unobserved types K. First, risk score coefficients are positive and statistically significant in every specification (≈ 0.44–0.54). Sicker populations are more costly to manage at the margin; increasing risk raises the dollar cost of achieving a 1% reduction, exactly the vertical shift predicted by the model (larger $\gamma \Rightarrow$ weaker intensive response). Secondly, hospital indicators load positively on γ (≈ 1.5–1.7) with good precision, consistent with higher opportunity costs of internal reorganization or weaker levers on utilization within hospital systems. Third, the beneficiaries' coefficient is negative with coarse heterogeneity ($K = 1$–2) (economies of scale). Once richer unobserved heterogeneity is allowed ($K \geq 3$), the effect attenuates or flips sign, indicating that composition across types absorbs part of the apparent scale effect.

Finally, type dummies are positive and significant when included, capturing persistent unobserved differences in variable costs (managerial quality, IT, local networks). Goodness-of-fit improves notably from $K = 1$ to $K = 3$, with a mild decrease at $K = 4$, suggesting that three mixture components absorb most cross-sectional heterogeneity without over-fitting.

Table 10 in Appendix D reports the estimated coefficients (β_F, α_F) that governs the extensive margin. Both Beneficiaries and Hospital load positively and significantly on fixed costs in every K. Larger organizations face higher participation overhead (reporting, analytics, contracting), and hospital systems have higher fixed operating costs. The magnitudes are economically meaningful: fixed costs rise with size even when variable costs display limited residual scale effects, which matters for the participation boundary. and a small number of unobserved types captures residual, persistent cost differences.

Selection frontier and adverse selection (Figure). Figure 5 is the empirical analogue of Figure 4 in Section 4. I partition the estimated cost index γ_i into twenty equal–mass bins and, for each bin, plot the midpoint of γ against the average ratio y_{it}^R/y_{it}^{FFS} separately for ACOs that *enter* MSSP and for those that remain in FFS. The dashed curve is a smoothed empirical frontier obtained from the threshold $(b_i - y_i^{FFS})/y_i^{FFS} = \lambda(1 - \text{ssr})/\gamma_i$ using the bin–specific average λ. The right axis shows the empirical density of γ.

Consistent with the model in Section 4.3, the frontier is downward sloping: higher y_{it}^R/y_{it}^{FFS} have to be compensated by smaller marginal effort costs (smaller γ) to make the regulator between MSSP and FFS. Moreover, Figure 5 confirms the empirical evidence that adverse selection is a primary concern since a significant number of ACOs are selecting MSSP or selecting FFS inefficiently. In particular, when the variable cost of effort is large (high γ), ACOs that select MSSP are associated with higher y_{it}^R/y_{it}^{FFS}, which implies higher positive regional adjustment. Instead, when the variable cost is low (low γ), the ratio y_{it}^R/y_{it}^{FFS} is similar across the two sets of ACOs. The different participation choice is explained by different fixed costs.

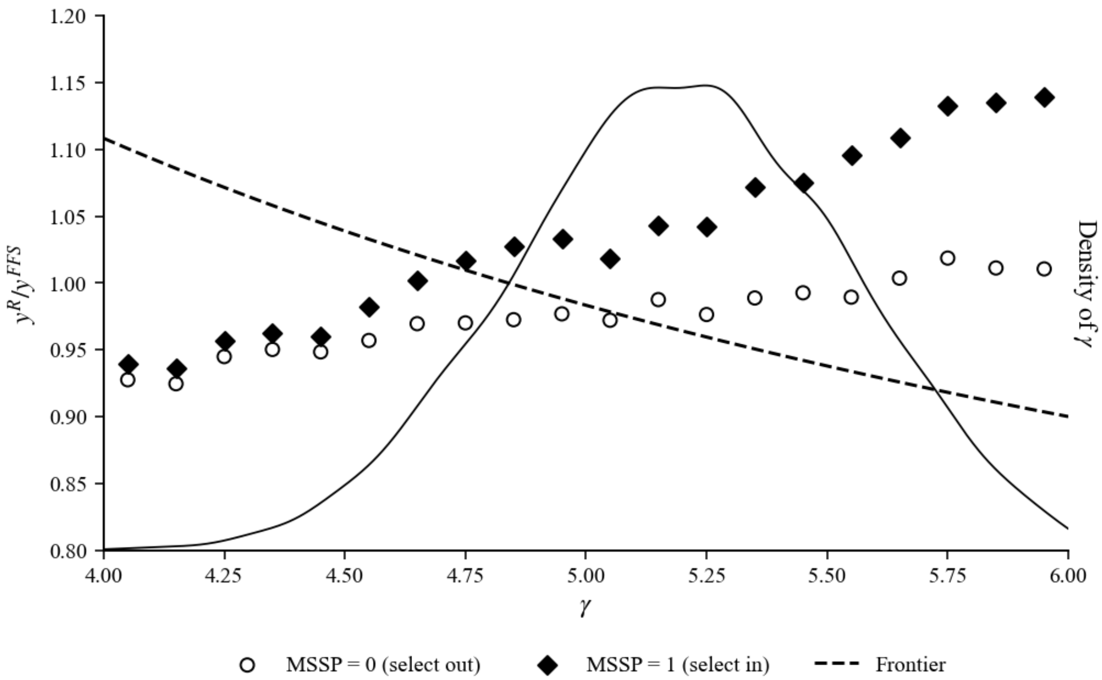


Figure 5: Selection into MSSP

Notes: The estimated cost parameter γ is plotted on the x-axis, and its empirical density is plotted on the right-hand side. The ratio between the Medicare average regional spending and the FFS spending y^R/y^{FFS} is plotted on the y-axis. (2) This figure shows the binned scatterplot of y^R/y^{FFS} and γ. Each dot represents the average value of y^R/y^{FFS} for each ventile (5% bin) of the γ distribution. The circle-shaped dots correspond to the value of the ACOs that select in the MSSP, while the black diamond-shaped dots correspond to the value for the ACOs that select out of the MSSP. The dashed line represents the empirical (smoothed) frontier computed using the average value of λ in each bin.

5.5 Potential ACOs

To study the impact of the MSSP benchmarking rules on the MSSP outcomes, I need to estimate how ACOs' participation changes under alternative MSSP benchmarking rules. Under different benchmarking rules, some ACOs may choose not to participate or exit the MSSP, while new ACOs may enter the program. However, the new potential ACOs that could join the MSSP under alternative rules are not observed in the data, as we can only see the ACOs that actually participated in the MSSP. Nevertheless, it is essential to construct these potential ACOs for the counterfactual analysis.

The construction proceeds in three steps using public administrative sources. First, I start from the AHRQ Compendium of U.S. Health Systems, which identifies groups of healthcare organizations (e.g., physician practices, hospitals, skilled nursing facilities) that are jointly owned or managed. Second, I link hospitals in each system to clinicians using the hospital–provider affiliation data from the Physician Compare database. This allows to delimit the pool of providers plausibly within the system's organizational boundary. Third, within each pool, I use the Physician Shared Patients Patterns data, which records the number of unique patients shared between each pair of providers. I use the latter to construct a measure of how closely providers are connected through their patient population.

From the Physician Shared Patients Patterns Data, I construct providers' networks, where nodes represent providers, and edges represent the number of shared patients and quantify collaboration intensity. I apply a community detection algorithm to this network. Specifically, we use the Louvain clustering method, which is a widely used algorithm for detecting strongly interconnected groups in large networks.

The Louvain method works by maximizing modularity, which measures how well a network is divided into communities compared to a random distribution of edges. The algorithm proceeds in two main steps: (1) local optimization, where each provider is initially assigned to its own group and then moved to neighboring groups if doing so increases modularity, and (2) hierarchical aggregation, where clusters formed in the first step are merged into larger nodes. The process is repeated iteratively until modularity is maximized.

To validate this approach, I compare the recovered communities with MSSP Participant Lists and find close agreement in membership overlap and size distributions, indicating that the method captures ACO-like organizational structures. Since the inferred networks closely match the actual ACOs, I conclude that the algorithm is effective at capturing ACO-like structures. This indicates that this algorithm can be applied to identify the networks of providers that resemble the actual ACOs. These potential ACOs are then used, together with the actual ACOs, in counterfactual analysis.

6 Counterfactuals

In this Section, I use the estimated model to perform a set of counterfactual exercises. First, I discuss how benchmark rebasement and regionalization affect participation into MSSP and Medicare savings. Secondly, I present and discuss the results of an alternative benchmarking policy that is designed to mitigate the ratchet effect while also preventing adverse selection. Finally, I evaluate the performance of the MSSP and the alternative policy compared to the counterfactual scenario where the MSSP does not exist, and all providers are under the standard FFS system.

I consider savings and participation obtained from simulating the model with the estimated parameters (Simulated MSSP) as the status quo. I use the results of counterfactual simulations to evaluate the impact of benchmark regionalization and benchmark rebasement on the ACOs' savings and participation. I assess their impact in terms of the total Medicare per capita spending, which is defined as the sum of the FFS spending per capita and the shared savings payments per capita. Let Y_j^M and Y_j^C denote the average total spending per capita under the status quo and under the counterfactual scenario, respectively. Y_j^M is given by the sum of the per capita spending y_j^M and the shared savings payments per capita ss_j^M

$$Y_j^M = y_j^M + ss_j^M$$

Similarly, Y_j^C is given by the sum of the per capita spending y_j^C and the shared savings payments per capita ss_j^C under the counterfactual scenario C

$$Y_j^C = y_j^C + ss_j^C$$

The key metric of interest is the percentage change in the total Medicare per capita spending between the counterfactual scenarios and the actual MSSP. The latter is denoted as ΔY_j and can be written as follows:

$$\underbrace{\frac{Y_j^C - Y_j^M}{Y_j^M}}_{\Delta Y_j} = \underbrace{\frac{y_j^C - y_j^M}{Y_j^M}}_{\Delta y_j} + \underbrace{\frac{ss_j^C - ss_j^M}{Y_j^M}}_{\Delta SS_j} \tag{11}$$

where Δy_j is the change in per capita spending relative to the total Medicare spending , and Δss_j is the change in shared savings payments as a share of the total Medicare spending.

Results of the counterfactual simulations are reported in Table 4. The weight assigned to each ACO is proportional to the number of ACOs assigned beneficiaries so that the statistics in Table 4 represent the overall impact of MSSP on Medicare spending. In both

Panel A and B, columns one to four show the following variables: (1) P is the average number of ACOs active after six years from the start of the start of the program, (2) Δy is the percentage change in the FFS spending, (3) ΔSS is the total percentage change in the shared savings payments, and (4) ΔY is total percentage change in net spending per capita. For each counterfactual scenario, I show the results under both voluntary participation and mandatory participation. Under this second scenario, all ACOs are required to participate in the MSSP and cannot exit the program. In Appendix E, I decompose Δy as the sum of the change in spending of the ACOs that select in the MSSP Δy^I and that of the ACOs that select out of the MSSP Δy^O.

Table 4: COUNTERFACTUALS
(Percentage change relative to status quo)

	Participation Rate in MSSP P	%Δ Spending Net of SS Δy	Shared Savings Payments Δss	%Δ Spending Gross of SS ΔY
Panel A: Voluntary MSSP				
Simulated MSSP	56.2	0.00	0.00	0.00
No Rebasement	65.5	-2.12	0.58	-1.54
No Regionalization	46.4	0.13	-0.71	-0.58
Conditional Regionalization	58.7	-2.86	0.73	-2.13
Panel B: Mandatory MSSP				
Simulated MSSP	100	-0.97	0.13	-0.85
No Rebasement	100	-2.42	0.69	-1.73
No Regionalization	100	-0.16	-0.55	-0.71
Conditional Regionalization	100	-3.18	0.81	-2.37

Notes: This table shows the percentage change in spending and shared savings payments between counterfactual scenarios and the simulated MSSP. I weight the ACO-level spending data by the number of assigned beneficiaries, so that the statistics are representative of the average value across ACOs. Panel A shows the results under the voluntary MSSP participation, while Panel B shows the results under the mandatory MSSP participation. In both Panel A and B, the columns are: (1) P is the average number of ACOs active after six years from the start of the start of the program, (2) Δy is the percentage change in the FFS spending (net of SS payments), (3) ΔSS is the total percentage change in the shared savings payments, and (4) ΔY is total percentage change in net spending per-capita (gross of SS payments). The simulated MSSP shows the results model simulations under status quo, and rows 2–4 report the percentage between the counterfactual scenario and the status quo: (i) No Rebasement, (ii) No Regionalization, and (iii) Conditional Regionalization (positive regional adjustment requires savings in the previous AP).

6.1 No-Rebasement Scenario

Benchmark rebasement influences both spending and participation. As discussed in Section 3, benchmark rebasement induces ACOs to delay spending reductions to prevent the benchmark from decreasing over time. Participation is also affected because ACOs have higher incentives to exit the MSSP as the benchmark declines over time. To estimate the impact of benchmark rebasement on net MSSP savings, I consider a counterfactual scenario where the benchmark is not rebased, while the regional adjustment factor is still applied. Specifically, the regionalized benchmark at the start of the second agreement period (AP) is given by

$$b^r_{it+1} = (1-\lambda)b^u_{it} + \lambda(y^R_{it} - \tilde{y}_{it})$$

where b^u_{it} is the (updated) historical benchmark based on the FFS spending prior to entry. Since $\tilde{y}_{it}$ enters negatively in the calculation of b^r_{it+1}, achieving a greater spending reduction during a given AP enables ACOs to secure a larger regional adjustment. This, in turn, results in a higher benchmark for the subsequent AP, mitigating the incentive to delay spending reductions.

The second row of Panel A in Table 4 reports the outcomes under this counterfactual scenario. Medicare net spending decreases by 1.54% relative to the status quo. The decomposition of ΔY shows that this is mainly due to the reduction in spending per capita. Shared savings payments also increase since the savings rate is higher. Moreover, the spending reductions are larger in the first AP and then level off in subsequent AP, which is the opposite of what we see in the Simulated MSSP. Under mandatory participation (Panel B), we observe a similar pattern, and net Medicare spending reduction only sees a modest increase of 0.19% points. This indicates that most of the gain from additional participation can be achieved by reducing the influence of ACOs' spending on their own future benchmark.

These results are largely consistent with the reduced-form evidence and confirm the presence of ratchet effect. In terms of per capita spending, the ratchet effect reduces net Medicare savings by 104$ per capita, which amounts to approximately 2.962 billion dollars. However, removing benchmark rebasement is not an ideal solution since spending reductions level off after the first AP, and it does not address the issue of adverse selection.

Figure 6 is analogous to Figure 5, and it illustrates selection into MSSP under this counterfactual scenario. Selection patterns are similar to those observed in the actual MSSP. This is not surprising since the adverse selection through the regional adjustment is still in place. Participation, however, increases significantly from 56.2% to 65.5%, driven by a lower exit rate. This can be attributed to the absence of rebasement, which enables ACOs to maintain higher benchmarks over time despite achieving a spending reduction. However,

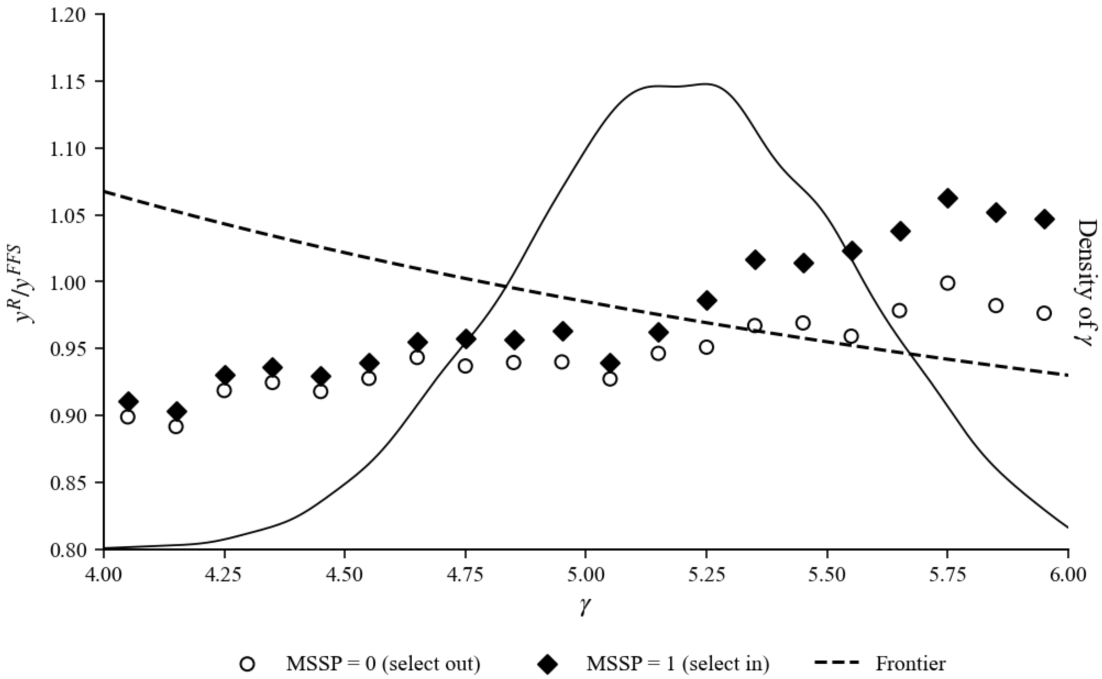


Figure 6: Selection under "No Rebasement"

Notes: The estimated cost parameter γ is plotted on the x-axis, and its empirical density is plotted on the right-hand side. The ratio between the Medicare average regional spending and the FFS spending y^R/y^{FFS} is plotted on the y-axis. (2) This figure shows the binned scatterplot of y^R/y^{FFS} and γ. Each dot represents the average value of y^R/y^{FFS} for each ventile (5% bin) of the γ distribution. The circle-shaped dots correspond to the value of the ACOs that select in the MSSP, while the black diamond-shaped dots correspond to the value for the ACOs that select out of the MSSP. The dashed line represents the empirical (smoothed) frontier computed using the average value of λ in each bin.

adverse selection is still present since the incentive to exploit the regional adjustment is still in place.

6.2 No Regionalization Scenario

The benchmark regionalization has two effects on MSSP net spending reduction. First, there is a direct effect through the regional adjustment factor. As we discussed in Sections 3 and 4, ACOs that have a positive regional adjustment can obtain shared savings payment without significantly reducing their spending relative to the FFS level. Second, there is an indirect effect through participation. As discussed in Section 3, ACOs that have negative regional adjustment are more likely to exit the MSSP.

Figure 7 illustrates selection under the counterfactual scenario where the benchmark is not rebased. We observe that the ratio y^R/y^{FFS} is similar between the set of ACOs that select MSSP and FFS. This reflects a shift in participation patterns: fewer ACOs with positive regional adjustment join, while those with negative regional adjustment are less likely to exit. These participation changes are what we expected to observe based on the results from Section 3. Without the regional adjustment factor, the ACO benchmark aligns more closely with counterfactual FFS spending, requiring ACOs to reduce spending below the FFS level to generate savings. As a result, adverse selection is less likely to occur in this counterfactual scenario. Furthermore, ACOs with spending above the regional average have a greater incentive to participate, as their benchmarks are no longer penalized by a negative regional adjustment factor.

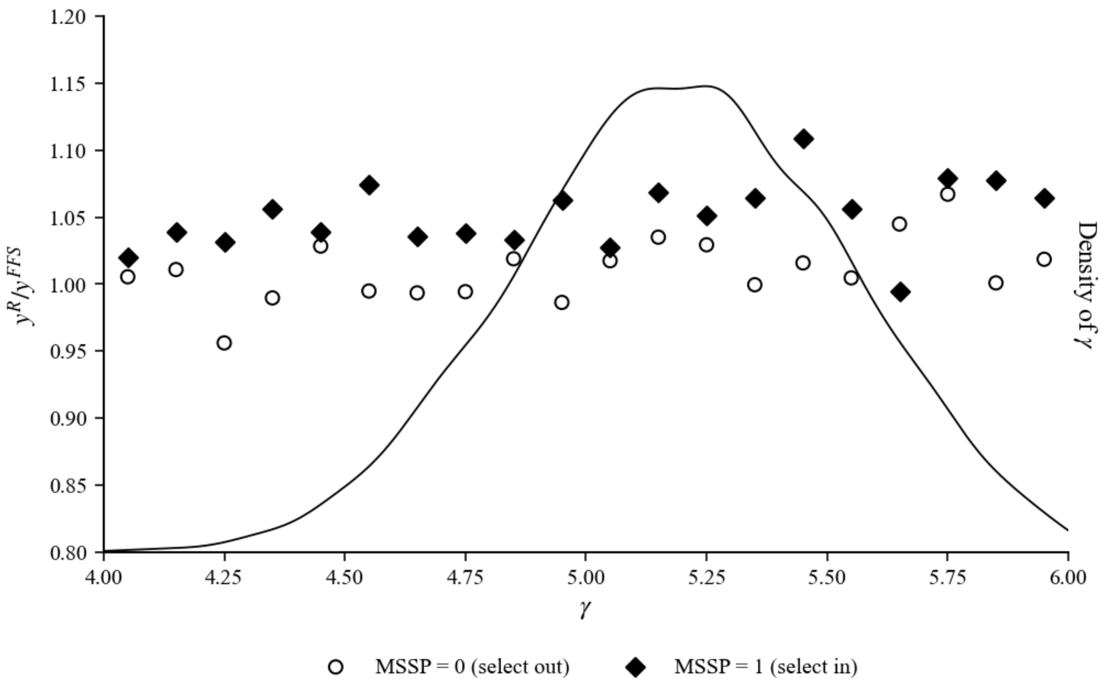


Figure 7: Selection under "No Regionalization"

Notes: The estimated cost parameter γ is plotted on the x-axis, and its empirical density is plotted on the right-hand side. The ratio between the Medicare average regional spending and the FFS spending y^R/y^{FFS} is plotted on the y-axis. (2) This figure shows the binned scatterplot of y^R/y^{FFS} and γ. Each dot represents the average value of y^R/y^{FFS} for each ventile (5% bin) of the γ distribution. The circle-shaped dots correspond to the value of the ACOs that select in the MSSP, while the black diamond-shaped dots correspond to the value for the ACOs that select out of the MSSP. The empirical (smoothed) frontier is not plotted since under No-Regionalization the definition of efficient and inefficient selection does not apply.

The third row of Panel A in Table 4 shows how the MSSP savings change when the benchmark regionalization is not applied. Net Medicare spending decreases by 0.58% relative to the status quo, with most of this reduction attributed to lower shared savings payments. The lower shared savings payments are due to two main factors. First, the different composition of the set of ACOs that participate in the MSSP. I observe more ACOs with FSS spending above the regional average and less ACOs with FFS spending below the regional average. Second, benchmarks are reduced since positive regional adjustments are less likely to be applied. Finally, FFS spending among participating ACOs shows only a modest increase compared to the status quo (0.13% points). This result can be explained by the fact that ratchet effect is even stronger in the absence of the regional adjustment.

These results match the reduced-form evidence and show that Medicare is rewarding ACOs that are not contributing to lowering the FFS spending. In terms of spending per capita, these excessive shared savings payment amount to 48$ per capita, which corresponds to 1.367 billion dollars. Making MSSP participation mandatory would only see a small improvement of 0.13% points relative to the voluntary scenario.

6.3 Conditional Regionalization

The reduced-form evidence and results of the counterfactual simulations indicate that the major disincentive to reduce spending is due to the benchmark ratcheting. Benchmark regionalization is not an ideal solution since it results in adverse selection, which costs Medicare additional payments to ACOs that do not reduce spending relative to the FFS level. I propose an alternative benchmarking rule called Conditional Regionalization, which seeks to balance the trade-offs between rebasement and regionalization. This approach leverages regionalization to mitigate the ratchet effect while also including additional conditions to prevent adverse selection.

Let $\tilde{b}^h_{it}$ denote the average benchmark of the first AP. An ACO is considered to have generated savings in a given AP if the three-year rolling average spending $\tilde{y}_{it}$ is less than $\tilde{b}^h_{it}$. Under the Conditional Regionalization policy, the rebased benchmark at the start of the second AP is determined as follows:

$$b^r_{it+1} = \begin{cases} (1-\lambda)\tilde{y}_{it} + \lambda(y^R_{it} - \tilde{y}_{it}) & \text{if} \quad \tilde{b}^h_{it} - \tilde{y}_{it} > 0 \quad \text{and} \quad y^R_{it} - \tilde{y}_{it} > 0 \\ b^h_{jt} & \text{if} \quad \tilde{b}^h_{it} - \tilde{y}_{it} \leq 0 \quad \text{and} \quad y^R_{it} - \tilde{y}_{it} > 0 \\ \tilde{y}_{it} & \text{if} \quad \tilde{b}^h_{it} - \tilde{y}_{it} > 0 \quad \text{and} \quad y^R_{it} - \tilde{y}_{it} \leq 0 \\ (1-\lambda)b^h_{it} + \lambda(y^R_{it} - \tilde{y}_{it}) & \text{if} \quad \tilde{b}^h_{it} - \tilde{y}_{it} \leq 0 \quad \text{and} \quad y^R_{it} - \tilde{y}_{it} \leq 0 \end{cases}$$

The first two conditions are designed to eliminate the participation incentives for "free shared-savings"-motivated ACOs while still mitigating the ratchet effect. The regional adjustment factor is calculated using the standard MSSP approach. However, to address adverse selection, the MSSP rule is modified to require ACOs to achieve savings in the previous AP in order to qualify for a positive regional adjustment. As a result, ACOs with a positive regional deviation that generates savings in the first AP are subject to the standard benchmarking rule. In contrast, ACOs with a positive regional deviation that fail to generate savings are assigned the same historical (updated) benchmark as in the first AP.

Furthermore, the third and fourth conditions are intended to encourage the participation of ACOs whose historical spending exceeds the regional average. The negative regional adjustment is waived for ACOs that achieve savings in the prior AP, and their benchmark is fully rebased. However, the incentive to delay spending reductions is offset by the motivation to obtain a positive regional adjustment in the subsequent agreement period. Instead, ACOs that fail to generate savings receive a negative regional adjustment as in the standard MSSP policy.

Figure 8 illustrates ACO selection under Conditional Regionalization. We observe that participation increases among ACOs with negative regional deviation and decreases among those with positive regional deviation. Hence, the condition to qualify for a positive regional adjustment is effective to mitigate the participation incentives of "free shared-savings" motivated ACOs. Moreover, this also shows that the negative regional adjustment discourages participation, leading many ACOs to exit the MSSP. Indeed, both under No-Regionalization and Conditional Regionalization, we observe a substantial increase in participation among ACOs with historical spending above the regional average.

The fourth row of Panel A in Table 4 summarizes the counterfactual results under the proposed benchmarking rule. Net Medicare spending decreases by 2.13% points relative to the status quo. The decomposition of ΔY reveals that FFS spending per capita is lower by 2.86% points, whereas shared savings payments increase by 0.73% points. The latter is explained by the significant increase in the savings rate, and the positive regional adjustment that is still applied to those ACOs that achieve savings as prescribed by the proposed policy.

Unlike the No-Rebasement scenario, I observe that the net spending reduction does not plateau and is slightly increasing over time. This can be explained by the sustained incentive to lower the FFS spending that is driven by the opportunity to maintain a positive regional adjustment. Table 11 in Appendix E shows that this additional spending reduction is driven by both existing ACOs and new entrants participating in the MSSP under this counterfactual scenario. This trend suggests that the additional conditions for applying the positive regional adjustment effectively mitigate the ratchet effect.

The alternative policy generates additional net Medicare savings of 156$ per capita compared to the status quo which amounts to approximately 4.225 billion dollars (about 1% of Traditional Medicare FFS total expenditure). As shown in Panel B, under mandatory participation, net Medicare savings relative to the status quo only increase by an additional 0.24% points compared to voluntary participation. This indicates that the ACOs that self-

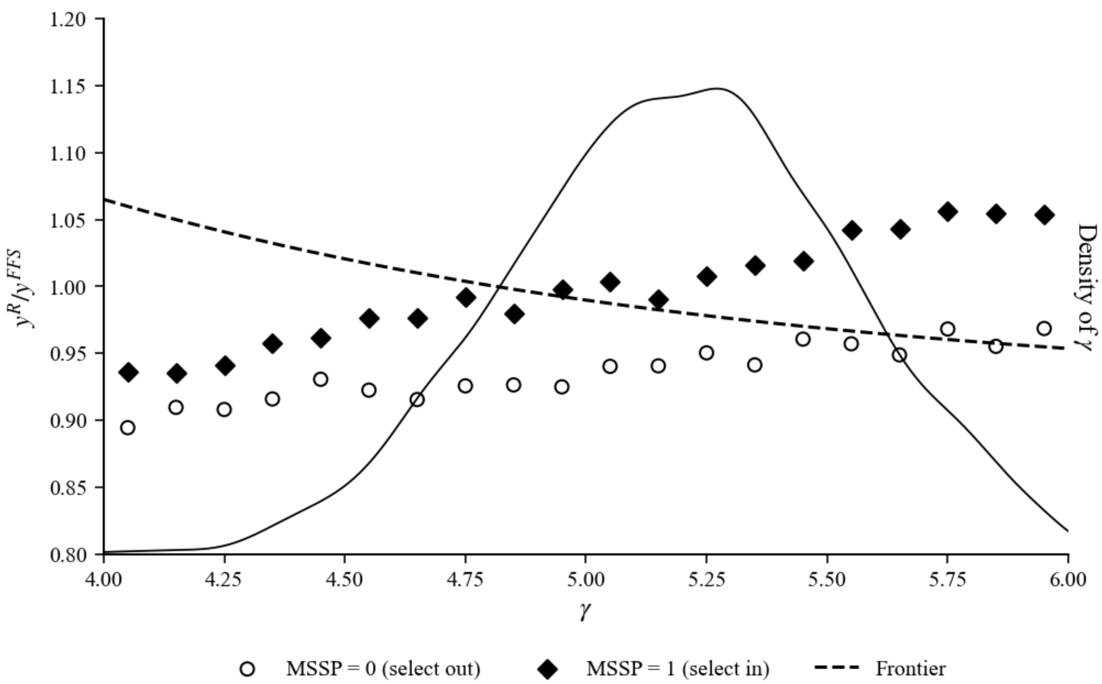


Figure 8: Selection under "Conditional Regionalization"

Notes: The estimated cost parameter γ is plotted on the x-axis, and its empirical density is plotted on the right-hand side. The ratio between the Medicare average regional spending and the FFS spending y^R/y^{FFS} is plotted on the y-axis. (2) This figure shows the binned scatterplot of y^R/y^{FFS} and γ. Each dot represents the average value of y^R/y^{FFS} for each ventile (5% bin) of the γ distribution. The circle-shaped dots correspond to the value of the ACOs that select in the MSSP, while the black diamond-shaped dots correspond to the value for the ACOs that select out of the MSSP. The dashed line represents the empirical (smoothed) frontier computed using the average value of λ in each bin.

select in the MSSP are able to generate almost the maximum possible savings under the proposed rule.

7 Conclusions

Incentive payment programs and pay-for-performance contracts are becoming increasingly popular as a form of Government regulation to improve cost-efficiency of healthcare delivery. The Medicare Shared Savings Program is a voluntary incentive payment contract designed to reduce FFS spending through improved care coordination among providers. Under this program, organizations of independent providers, known as Accountable Care Organizations (ACOs), are rewarded for keeping the average per capita spending below a benchmark.

This paper examines the impact of benchmarking rules on ACO participation and effort to reduce spending, and provides empirical and model-based evidence on how these rules influence program effectiveness and overall MSSP savings. Specifically, the findings emphasize two significant issues: the ratchet effect induced by benchmark rebasement and adverse selection stemming from benchmark regionalization.

The ratchet effect occurs because the MSSP's rebasement mechanism ties future benchmarks to past spending, incentivizing ACOs to moderate their initial cost-reduction efforts to secure more favorable benchmarks in subsequent periods. Empirical evidence reveals that this benchmark rebasement distorts incentives, leading to delayed savings and reduced participation in the MSSP. Counterfactual analysis shows that excluding ACOs' own spending from future benchmark calculations could mitigate these inefficiencies.

Benchmark regionalization, introduced to address the ratchet effect, results in adverse selection. Empirical evidence suggests that ACOs receiving positive regional adjustments are more likely to participate, while those with negative adjustments are more likely to exit the program. The resulting increase in shared savings payments for high-cost ACOs inflates Medicare spending without commensurate improvements in cost efficiency. The counterfactual analyses demonstrate that removing benchmark regionalization reduces per capita Medicare spending, primarily through lower shared savings payments.

To balance these conflicting necessities to mitigate the ratchet effect and prevent adverse selection, I propose an adjustment to the current MSSP design called Conditional Regionalization. This alternative benchmarking rule applies regional adjustments only to ACOs that generate savings relative to their FFS level. I estimate that this policy effectively addresses adverse selection while mitigating the ratchet effect, offering a pathway to increase the MSSP's net savings.

The findings underscore the importance of carefully aligning incentives in value-based payment models to balance participation and continued cost containment. While this study focuses on the MSSP, its insights have broader relevance to other Medicare initiatives, such as the Prospective Payment System and the Bundled Payments for Care Improvement Initiative. Future research could build on this work by incorporating interactions among providers within an ACO or exploring the implications of similar incentive structures in other health-care contexts.

References

Aswani, A., Shen, Z.-J. M., and Siddiq, A. (2019). Data-driven incentive design in the medicare shared savings program. *Operations Research*, 67(4):1002–1026.

Cebul, R. D., Rebitzer, J. B., Taylor, L. J., and Votruba, M. E. (2008). Organizational fragmentation and care quality in the us healthcare system. *Journal of Economic Perspectives*, 22(4):93–113.

Chatterji, P., Nguyen, T., and Yörük, B. K. (2022). The effects of medicare on healthcare utilization and spending among the elderly. *American Journal of Health Economics*, 8(2):151–180.

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

Cutler, D. M. (1993). The incidence of adverse medical outcomes under prospective payments.

Einav, L., Finkelstein, A., Ji, Y., and Mahoney, N. (2022). Voluntary regulation: Evidence from medicare payment reform. *The quarterly journal of economics*, 137(1):565–618.

Eliason, P. J., Grieco, P. L., McDevitt, R. C., and Roberts, J. W. (2018). Strategic patient discharge: The case of long-term care hospitals. *American Economic Review*, 108(11):3232–3265.

Frandsen, B. and Rebitzer, J. B. (2015). Structuring incentives within accountable care organizations. *The Journal of Law, Economics, and Organization*, 31(suppl_1):i77–i103.

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

Hackmann, M. B. (2019). Incentivizing better quality of care: The role of medicaid and competition in the nursing home industry. *American Economic Review*, 109(5):1684–1716.

Hendee, W. R., Becker, G. J., Borgstede, J. P., Bosma, J., Casarella, W. J., Erickson, B. A., Maynard, C. D., Thrall, J. H., and Wallner, P. E. (2010). Addressing overutilization in medical imaging. *Radiology*, 257(1):240–245.

Ho, K. and Pakes, A. (2014). Physician payment reform and hospital referrals. *American Economic Review*, 104(5):200–205.

Reddig, K. (2023). Designing physician incentives and the cost-quality tradeoff: Evidence from accountable care organizations.

Zhang, D. J., Gurvich, I., Van Mieghem, J. A., Park, E., Young, R. S., and Williams, M. V. (2016). Hospital readmissions reduction program: An economic and operational analysis. *Management Science*, 62(11):3351–3371.

Appendix A

A.1 Details on Benchmark Calculation

In this section, I will illustrate the details of the benchmark calculation. First, at the start of each agreement period, the ACO historical benchmark is rebased, and the regional adjustment factor is applied. Then, the update factors are used to account for changes in the population health risk and FFS prices between the benchmark years and the current performance year.

The population of ACO beneficiaries is divided into four segments: End Stage Renal Disease (ESRD), Disabled (DIS), Aged Dual (AGDU), Aged Non-Dual (AGND). Let $K = \{\text{ESRD, DIS, AGDU, AGND}\}$. For each population segment, we will compute the historical rebased benchmark hb_k, the regionalized benchmark rb_k, and the updated benchmark ub_k. Then, in each step, the overall benchmark is obtained as a weighted average over the population segments, where the weights are given by the share of each segment.

Historical Rebased Benchmark The ACO historical benchmark is rebased using the spending in each of the three historical benchmark years (BY) preceding the first performance year of the current AP. The three benchmark years are denoted as BY1, BY2, and BY3, where the latter is the most recent year. The first two benchmark years of historical expenditures are risk-adjusted and trended to put per capita expenditures on a BY3 basis. The risk adjusted and trended expenditure for segment k in benchmark years BY1 and BY2, denoted as $\tilde{\text{hb}}^k_{by1}$ and $\tilde{\text{hb}}^k_{by2}$ respectively, are given by

$$\tilde{\text{hb}}^k_{by1} = \text{hb}^k_{by1} \cdot \tilde{\text{rr}}^k_{by1} \cdot \tilde{\text{tf}}^k_{by1}$$
$$\tilde{\text{hb}}^k_{by2} = \text{hb}^k_{by2} \cdot \tilde{\text{rr}}^k_{by2} \cdot \tilde{\text{tf}}^k_{by2}$$

where $\tilde{\text{rr}}^k_{byj}$ is the risk ratio between the risk score in the benchmark year j and that of the benchmark year BY3. The trend factor $\tilde{\text{tf}}^k_{byj}$ is the growth rate in FFS prices and utilization between the benchmark year j and the benchmark year BY3.[15]

To obtain the rebased historical benchmark hb_{by3}, the three BYs are weighted together, and the population distribution in BY3 is used to create a composite rebased-historical

[15] The procedure to compute the trend factors is detailed in the next section.

benchmark[16]

$$
\begin{aligned}
\mathrm{hb}_{by3} &= \sum_{k \in K} \mathrm{hb}^k_{by3} \cdot \pi^k_{by3} \\
&= \sum_{k \in K} \left(\frac{1}{3} \tilde{\mathrm{hb}}^k_{by1} + \frac{1}{3} \tilde{\mathrm{hb}}^k_{by2} + \frac{1}{3} \mathrm{hb}^k_{by3} \right) \cdot \pi^k_{by3}
\end{aligned}
$$

where π^k_{by3} is the share of segment k in benchmark year BY3.

Benchmark Regionalization The second step is to calculate the regional adjustment to apply to this historical benchmark. This adjustment is made by comparing the BY3 risk-adjusted expenditures for the ACO and that for the ACO region. For each population segment, if the difference is positive (i.e., an ACO's rebased-historical expenditures during the benchmark period are lower than the region), a positive regional adjustment is applied. Similarly, if the difference is negative, a negative regional adjustment is applied. Specifically, the regionalized historical benchmark rb_{by3} is given by

$$
\begin{aligned}
\mathrm{rb}_{by3} &= \sum_{k \in K} \mathrm{rb}^k_{by3} \cdot \pi^k_{by3} \\
&= \sum_{k \in K} \left[\mathrm{hb}^k_{by3} + \alpha \left(y^k_{by3} - \mathrm{hb}^k_{by3} \right) \right] \cdot \pi^k_{by3}
\end{aligned}
$$

where π^k_t is the share of segment k in performance year t. The blending percentage α depends on various factors. As Figure 1 illustrates, it varies depending on: (i) how the historical rebased benchmark compares to the regional expenditure, (ii) the agreement period, and (iii) whether the adjustment is applied before or after the 2019 policy change becomes effective. In particular, for ACO cohorts that entered prior to 2019, the regional adjustment is applied from the second AP, whereas for ACO cohorts that entered in 2019 or later, the regional adjustment is applied from the first AP.[17]

Updated Benchmark Finally, the regionally adjusted historical benchmark of each population segment (rb^k_{by3}) are adjusted to be on the same basis as the performance year t using estimates of the national per capita trend and update factors (tf^k_t), and risk adjusted using the ACO's CMS-HCC risk ratios (rr^k_t). The overall updated benchmark (ub_t) is simply a

[16]For ACO cohorts starting prior to 2019, the weights used in the first AP are 0.1, 0.3, and 0.6 for BY1, BY2, and BY3, respectively. For the second AP and above, and ACO cohort starting in 2019 or later, benchmark years are equally weighted in each AP.

[17]One exception to this rule is represented by the ACOs entered in 2013. For this cohort, the regional adjustment is applied from the third AP.

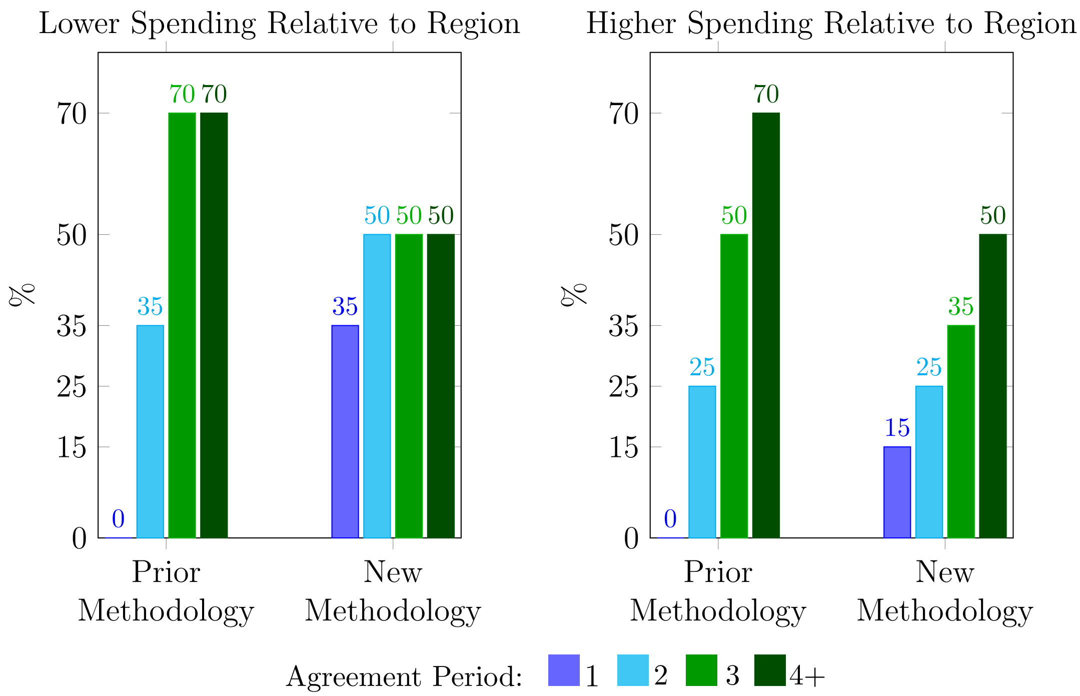


Figure 9: The figure shows the Regional Blending Percentages α before (Prior Methodology) and after the 2019 policy change (New Methodology), and over different agreement periods.

weighted average of the updated benchmarks of each segment of the population (ub_t^k).

$$\begin{aligned}\mathrm{ub}_t &= \sum_{k\in K} \mathrm{ub}^k \cdot s_t^k \\ &= \sum_{k\in K} \left(\mathrm{rb}_{by3}^k \cdot \mathrm{rr}_t^k \cdot \mathrm{tf}_t^k\right) s_t^k\end{aligned}$$

where s_t^k is the share of segment k in the performance year t.

The risk ratios rr_t^k are the ratio of the average risk score of the ACO's assigned PY beneficiaries (by population segment) to the ACO's assigned beneficiaries for BY 3. The trend factors tf_t^k The trend factor $\tilde{\mathrm{tf}}_{byj}^k$ is the growth rate in FFS prices and utilization between the benchmark year BY3 and the performance year t.[18]

Trend Factors Under current policy, CMS updates an ACO's historical benchmark from Base Year 3 (BY3) to the Performance Year (PY) by applying a blend of national and regional growth rate trends. Importantly, both the national and regional trends used are retrospective trends, meaning they reflect actual growth rates observed from BY3 to the PY. Additionally, the percentage weight applied to each trend component depends on an ACO's

[18]The procedure to compute the trend factors is detailed in the next section.

market share within their region – ACOs with higher regional market share receive a trend update factor that is more heavily weighted on national trends, and vice versa. The trend factors used to rebase and update the benchmark depend on the ACO entry year and vary over the course of the MSSP:

- **Historical Benchmark Rebasement:**
  (i) ACOs entering their first agreement in 2018 or earlier: *National* assignable FFS expenditure trend factors.
  (ii) ACOs entering a second agreement in 2017, 2018, or January 2019: *Regional* assignable FFS expenditure trend factors.
  (iii) ACOs entering an agreement on or after July 2019: *Blend of national and regional* assignable FFS expenditure trend factors.

- **Benchmark Updates:**
  (i) ACOs in a first agreement period in January 2019 or earlier, and ACOs entering a second agreement in 2016: the projected absolute growth in FFS *national* per capita FFS expenditures (Parts A and B).
  (ii) ACOs entering a second agreement in 2017, 2018, or 2019: *regional* FFS update factor.
  (iii) ACOs entering an agreement on or after July 2019: *blended national-regional* FFS update factor.

In the following paragraphs, I will illustrate the steps to compute the trend factors before and after the 2019 policy.

Regional Update Factor For ACOs entering a second agreement period in 2017, 2018, or January 1, 2019, CMS applied a regional update factor to the risk-adjusted historical benchmark expenditures in each performance year.

I will use the following notation:

- i denotes the ACO
- t denotes the performance year
- $c \in R_i$ denotes counties in ACO i's regional service area
- $\text{FFS}^k_{c,t}$: risk-adjusted county-level FFS expenditures for county c in year t, type k

- s_{ict}^k: share of ACO i's assigned beneficiaries of type k residing in county c
- hb_i^k: risk-adjusted historical benchmark for ACO i, type k
- $\pi_{i,t}^k$: share of ACO i's assigned beneficiaries in type k in year t

Step 1: Compute the regional growth factor for enrollment type k as the ratio of performance year to BY3 (benchmark year 3) expenditures:

$$\text{Regional Factor}_{i,t}^k = \frac{\sum_{c \in R_i} s_{ict}^k \cdot \text{FFS}_{c,t}^k}{\sum_{c \in R_i} s_{ict}^k \cdot \text{FFS}_{c,\text{BY3}}^k}$$

Step 2: Multiply historical benchmark by this update factor:

$$\text{ub}_{i,t}^k = \text{hb}_{i,t}^k \cdot \text{Regional Factor}_{i,t}^k$$

Step 3: Aggregate across enrollment types to compute the overall benchmark:

$$\text{ub}_{i,t} = \sum_{k \in K} \pi_{i,t}^k \cdot \text{ub}_{i,t}^k = \sum_{k \in K} \pi_{i,t}^k \cdot \text{hb}_{i,t}^k \cdot \text{Regional Factor}_{i,t}^k$$

Blended National-Regional Update Factor Under the policy change enacted in July 2019, for ACOs entering an agreement period beginning on or after July 1, 2019, CMS introduced a blended national-regional update factor to update the historical rebased benchmark.

Let us introduce this additional notation:

- NFFS_t^k: national risk-adjusted assignable FFS expenditures in year t, type k
- ab_{ict}^k: person-years of type k assigned to ACO i in county c in year t
- ab_{ct}^k: total assignable person-years of type k in county c in year t

Step 1: Compute national growth rate for enrollment type k:

$$\text{National Factor}_t^k = \frac{\text{NFFS}_t^k}{\text{NFFS}_{\text{BY3}}^k}$$

Step 2: Compute the regional growth rate as before:

$$\text{Regional Factor}_{i,t}^k = \frac{\sum_{c \in R_i} s_{ic} \cdot \text{FFS}_{c,t}^k}{\sum_{c \in R_i} s_{ic} \cdot \text{FFS}_{c,\text{BY3}}^k}$$

Step 3: The weight assigned to the national trend factor is given by:

$$\omega_{i,t}^{k} = \sum_{c \in R_i} \left(\frac{\text{ab}_{ict}^{k}}{\text{ab}_{ct}^{k}} \right) \cdot \left(\frac{\text{ab}_{ict}^{k}}{\sum_{c \in R_i} \text{ab}_{ict}^{k}} \right)$$

which is a weighted average of the ACO county-level market shares, where the weights are the distribution of the ACOs' assigned beneficiaries across counties in its regional service area. The weight $\omega_{i,t}^{k}$ is assigned to national trends in order to limit the ability of ACOs with a large regional market share to influence the regional growth rate. The weight given to the regional trends is the complement of the national weight.

Step 4: Compute blended update factor:

$$\text{Blended Factor}_{i,t}^{k} = \omega_{i,t}^{k} \cdot \text{National Factor}_{t}^{k} + (1 - \omega_{i,t}^{k}) \cdot \text{Regional Factor}_{i,t}^{k}$$

Step 5: Multiply historical benchmark:

$$\text{ub}_{i,t}^{k} = \text{ub}_{i,t}^{k} \cdot \text{Blended Factor}_{i,t}^{k}$$

Step 6: Aggregate across enrollment types:

$$\text{ub}_{i,t} = \sum_{k \in K} \pi_{i,t}^{k} \cdot \text{hb}_{i,t}^{k} \cdot \text{Blended Factor}_{i,t}^{k}$$

ACO Regional FFS Expenditure To compute the regional per capita FFS expenditure of a given ACO regional service area, CMS first determines the risk-adjusted FFS expenditures at the county level for each Medicare enrollment type (ESRD, disabled, aged/dual eligible, and aged/non-dual eligible). These county-level values are then aggregated into an ACO-specific regional average using weights that reflect the ACO's geographic footprint. Let $\text{FFS}_{c,t}^{k}$ be the risk-adjusted FFS per capita expenditure in county c in year t for enrollment type k. The weight applied to this county risk-adjusted spending is given by the share of ACO i's assigned beneficiaries of type k residing in county c, denoted as s_{ic}^{k}.

Hence, the ACO-specific regional per capita FFS expenditure is computed as follows

$$\text{rb}_{i,t}^{k} = \sum_{c \in R_i} s_{ic}^{k} \cdot \text{FFS}_{c,t}^{k}.$$

This is what CMS refers to as "ACO regional benchmark", and it is used to compute the regional FFS adjustment factor.

A.2 Deferral Option

Prior to the 2019 Pathways to Success reform, ACOs participated in the Medicare Shared Savings Program (MSSP) under agreement periods (APs) that typically lasted three years. However, beginning with the 2017 application cycle, CMS introduced an option for ACOs in Track 1 (the one-sided risk track) to request a fourth performance year (PY4) under their first AP. Although the original deferral option introduced in the 2016 final rule was limited to ACOs that began in 2014 or 2015, CMS later created a separate provision allowing ACOs that entered in 2018 to elect a fourth performance year (PY4), extending their agreement period through 2021.[19]

The fourth year option was intended to support ACOs that were preparing to transition into a two-sided risk model (Track 2 or Track 3). If the ACO's request to renew into a two-sided model was approved, it could also request an extension of its existing Track 1 agreement by one additional year. As a result:

- The ACO would operate under Track 1 for four years instead of three.
- Benchmark rebasing would be deferred for one year, meaning only the last three years (PY2–PY4) would be used to calculate the new benchmark for the next agreement period. Thus, PY1 was excluded from the rebasing window, and ACO spending in that year does not contribute to target ratcheting.
- For ACOs that did not opt for PY4, the benchmark for the second agreement period follows the standard three-year cycle rebasement.

Table 1 illustrates how the option to extend the first agreement period to a fourth performance year affected the benchmark rebasing schedule. For ACOs that entered in 2017 or 2018, the fourth PY option was available at entry, and they were likely aware that their spending in the first performance year was not used to rebase the benchmark for the subsequent agreement period. As a result, the first PY did not contribute to the benchmark ratcheting. Thus, these ACOs had little incentive to delay cost reductions in the initial years. In contrast, earlier cohorts did not anticipate the fourth PY option, and thus may have behaved strategically in anticipation of standard three-year rebasing.

Policy Discontinuation The 2019 MSSP overhaul eliminated Tracks 1–3 and replaced them with the Basic and Enhanced tracks. With this change, the policy allowing for a fourth performance year under Track 1 was discontinued. ACOs entering a new AP in 2019 or later

[19]See Federal Register: 425.200 Participation agreement with CMS

Table 5: Impact of Deferral Option on Rebasing Years by ACO Cohort

Cohort	AP	PY1–PY3	PY4	Rebasing Years Expected	Rebasing Years Actual	Ratcheting Affected	Number of ACOs
2013	2	2016–2018	2019	2016–2018	2017–2019	No	5
2014	1	2014–2016	2017	2014–2016	2015–2017	No	6
2014	2	2018–2020	2021	2019–2021	2019–2021	Yes	15
2015	1	2015–2017	2018	2015–2017	2016–2018	No	2
2015	2	2018–2020	2021	2019–2021	2019–2021	Yes	45
2016	1	2016–2018	2019	2016–2018	2017–2019	No	12
2018	1	2018–2020	2021	2019–2021	2019–2021	Yes	92

Notes: (i) This table shows how the option to extend the first or second agreement period (AP) for an additional performance year (PY4) affected the years used to compute the rebased benchmark for the subsequent AP. (ii) The second-to-last column indicates whether, at the time the AP began, ACOs were aware that the first PY would not be used in the benchmark rebasing. In such cases, it is reasonable to assume that, for those ACOs, the ratchet effect did not occur during that year. (iii) ACOs that entered in 2017 were not affected by the deferral option, as it applied only to APs beginning on or after January 2018. (iv) The deferral option was discontinued as part of the 2019 policy changes.

no longer had access to the PY4 deferral option, and the duration of each AP was extended to five years.

A.3 5-Year AP Cycles

7.1 Quality Score

The quality score is an index that is determined by the combination of 30-40 sub-measures of care quality. These sub-measures fall into the domains of Patient-Caregiver Experience, Care Coordination and Patient Safety, Preventative Health and Management of At-Risk Population. Patient/Caregiver Experience-related sub-measures are derived from survey responses and include the patient's doctor rating, access to specialists, and shared decision-making. "Care Coordination/Patient Safety" is a set of measures to evaluate (i) the ACO's effort at avoiding high-cost services like hospital unplanned admissions and readmissions, (ii) the ACO's utilization of tools to improve care coordination, like Electronic Health Records (EHR). The "Preventative Health" domain measures the use of immunization, vaccination, and the use of screening to assess health conditions. The "At-Risk Population" is a set of sub-measures to evaluate the ACOs' effort to monitor and keep track of the health status of patients with chronic conditions.

For each sub-measure, quality points are assigned based on the level of performance relative to a benchmark measured using FFS data. The total points earned for measures in each domain will be summed and divided by the total points available for that domain

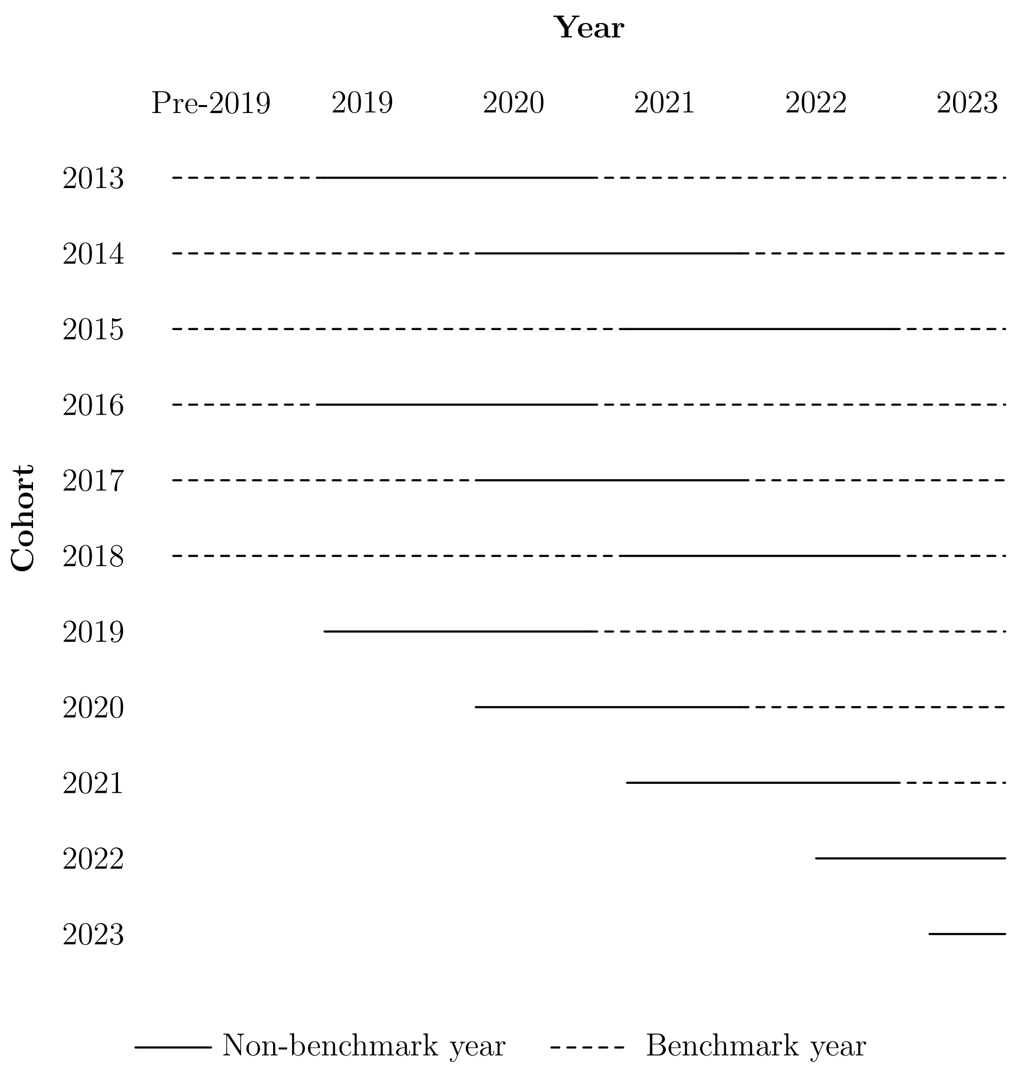


Figure 10: Illustration of MSSP policy change introducing two non-benchmark years in each 5-year agreement period. Each line corresponds to a cohort of ACO entry years. Red segments represent non-benchmark years; blue segments represent benchmark years.

to produce the overall quality score that will be used to determine the amount of shared savings (or shared losses).

Appendix B

B.1 Descriptive statistics

Table 6: Descriptive Statistics

	2013 - 2015	2016 - 2018	2019-2023	Total
sav rate	0.580	1.538	3.360	2.255
	(5.435)	(4.652)	(4.212)	(4.744)
sav above min	0.286	0.346	0.604	0.458
	(0.452)	(0.476)	(0.489)	(0.498)
qual score	0.956	0.973	0.966	0.964
	(0.131)	(0.072)	(0.076)	(0.089)
two-sided	1.014	1.107	1.410	1.239
	(0.116)	(0.309)	(0.492)	(0.426)
age at exit	4.694	5.061	5.669	5.099
	(2.338)	(2.177)	(2.371)	(2.313)
bench (1000)	10.537	11.020	11.865	11.345
	(2.543)	(2.417)	(2.665)	(2.621)
risk score	1.068	1.028	1.017	1.030
	(0.100)	(0.098)	(0.113)	(0.108)
benef (1000)	16.278	18.015	20.350	18.837
	(15.899)	(18.071)	(22.293)	(19.978)
prov (1000)	4.266	5.832	8.463	6.820
	(6.243)	(8.448)	(13.283)	(10.930)
hospitals	1.171	1.847	1.840	1.715
	(2.429)	(3.380)	(5.420)	(4.393)

mean coefficients; sd in parentheses

B.2 reduced-form Evidence

Table 8 and Table 8 show the full set of results of the TWFE regression in Section 3.2.

Table 7: Ratchet Effect: Two Way Fixed Effects Regressions

	Full Sample		Entry Year < 2019	
	ACO FE	No ACO FE	ACO FE	No ACO FE
Non-Benchmark Year	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
Lagged Spending	−0.0670***	−0.119***	−0.0716***	−0.124***
	0.0127	0.0121	0.0132	0.0131
Historical Benchmark	0.152***	0.161***	0.157***	0.167***
	0.0191	0.0168	0.0197	0.0183
Regional Spending	−0.196***	−0.0290**	−0.207***	−0.0397***
	0.0351	0.0135	0.0391	0.0143
Regional Adjsustment	0.331	0.722***	0.242	0.483*
	0.290	0.243	0.305	0.270
Risk Score	−0.107***	−0.0346*	−0.111***	−0.0292
	0.0331	0.0199	0.0349	0.0216
Risk Ratio	0.0197	0.0230	0.0126	0.00413
	0.0426	0.0309	0.0442	0.0330
Trend Factor	0.200***	0.120***	0.202***	0.113***
	0.0419	0.0356	0.0444	0.0392
Constant	0.288***	−0.0170	0.314***	0.00737
	0.0810	0.0242	0.0895	0.0265
Observations	4,519	4,519	4,133	4,133
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
ACO FE	Yes	No	Yes	No
ACO Age FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Source: CMS Performance Year Financial and Quality Results

Dependent Variable: CMS savings rate

Standard errors clustered by ACO

Notes: (i) All variables are in log terms except for Non-Benchmark Year and Deferral. The coefficients represents the change in the odds ratio for a one percentage change in the independent variable.

Table 8: Ratchet Effect: Two Way Fixed Effects Logistic Regressions

	Full Sample		Entry Year > 2019	
	ACO FE	No ACO FE	ACO FE	No ACO FE
Non-Benchmark Year	2.172***	1.004***	2.259***	0.958***
	0.407	0.146	0.438	0.151
Deferral	2.865***	1.509***	2.626***	1.306***
	0.918	0.321	0.858	0.287
Lagged Spending	0.951***	0.917***	0.945***	0.910***
	0.00808	0.00708	0.00847	0.00762
Historical Benchmark	1.103***	1.106***	1.110***	1.117***
	0.0134	0.0101	0.0140	0.0108
Regional Spending	0.851***	0.982***	0.850***	0.976***
	0.0198	0.00798	0.0206	0.00832
Regional Adjsustment	0.578***	0.717***	0.624***	0.628***
	0.198	0.163	0.206	0.179
Risk Score	0.941***	0.999***	0.941***	1.007***
	0.0181	0.0105	0.0187	0.0111
Risk Ratio	0.994***	0.998***	0.991***	0.984***
	0.0238	0.0178	0.0246	0.0183
Trend Factor	1.133***	1.084***	1.127***	1.088***
	0.0353	0.0260	0.0366	0.0283
Constant		0.455		1.884
		0.738		3.246
Observations	3,180	4,602	3,017	4,213
McFadden R^2	0.624	0.128	0.612	0.137
Share of ACOs > MSR	0.510	0.457	0.465	0.444
ACO FE	Yes	No	Yes	No
AP FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Source: CMS Performance Year Financial and Quality Results

Dependent Variable: Indicator for savings rate above minimum savings rate

Standard errors clustered by ACO

Standard errors clustered by ACO

Notes: (i) All variables are in log terms except for Non-Benchmark Year and Deferral. The coefficients represents the change in the odds ratio for a one percentage change in the independent variable.

Appendix C

C.1 Expected Shared Savings Revenue

The shared savings are given by

$$SS_t = \begin{cases} 0 & \dfrac{b_t - y_t^M}{b_t} < \underline{s}, \\ \text{ssr}\left(b_t - y_t^M\right) & \dfrac{b_t - y_t^M}{b_t} \geq \underline{s}, \end{cases}$$

where

$$y_t^M = y_t^F - e_t$$

The expected shared savings are given by

$$\begin{aligned} \mathbb{E}[SS_t \mid e_t] &= \text{ssr}\, \mathbb{E}\left[b_t - y_t^M \,\middle|\, \frac{b_t - y_t^M}{b_t} \geq \underline{s}\right] \Pr\left(\frac{b_t - y_t^M}{b_t} \geq \underline{s}\right) \\ &= \text{ssr}\, \mathbb{E}\big[b_t + e_t - y_t^F \,\big|\, y_t^F \leq e_t + b_t(1-\underline{s})\big] \Pr\big(y_t^F \leq e_t + b_t(1-\underline{s})\big) \\ &= \text{ssr}\Big[(b_t + e_t) \Pr(y_t^F \leq k) - \mathbb{E}\big(y_t^F \mid y_t^F \leq k\big) \Pr(y_t^F \leq k)\Big] \end{aligned}$$

where $k \equiv e_t + b_t(1-\underline{s})$. Using the distributional assumption on y_{it}^{FFS}, $\ln y_t^F \sim \mathcal{N}(\mu, \sigma^2)$

$$\Pr\big(y_t^F \leq e_t + b_t(1-\underline{s})\big) = \Phi\left(\frac{\ln k - \mu}{\sigma}\right)$$

$$\mathbb{E}\big[y_t^F \mid y_t^F \leq k\big] = \exp\left(\mu + \tfrac{1}{2}\sigma^2\right) \frac{\Phi\left(\dfrac{\ln k - \mu - \sigma^2}{\sigma}\right)}{\Phi\left(\dfrac{\ln k - \mu}{\sigma}\right)}$$

Hence,

$$\mathbb{E}[SS_t \mid e_t] = \text{ssr}\left[(b_t + e_t)\, \Phi\left(\frac{\ln k - \mu}{\sigma}\right) - \exp\left(\mu + \tfrac{1}{2}\sigma^2\right) \Phi\left(\frac{\ln k - \mu - \sigma^2}{\sigma}\right)\right]$$

Since $\exp\left(\mu + \tfrac{1}{2}\sigma^2\right) \approx y_t^F$

$$\mathbb{E}[SS_t \mid e_t] \approx \text{ssr}\left(b_t + e_t - y_t^{FFS}\right) \Phi\left(\frac{\ln k - \mu}{\sigma}\right)$$

Derivative w.r.t. e_t

$$\frac{\partial}{\partial e_t}\mathbb{E}[SS_t \mid e_t] \approx \text{ssr}\left[\Phi\left(\frac{\ln k - \mu}{\sigma}\right) + \frac{b_t + e_t - y_t^{FFS}}{b_t(1-\underline{s}) + e_t}\,\phi\left(\frac{\ln k - \mu}{\sigma}\right)\frac{1}{\sigma}\right]$$

C.2 Euler Equation

The optimal level of effort satisfies the first order condition

$$\frac{\partial \pi_t^M}{\partial e_t} + \delta\ \Pr\left(d_{t+1} = 1 \mid \tilde{y}_{t+1}, b_{t+1}\right)\frac{\partial v_{t+1}^M}{\partial \tilde{y}_{t+1}}\frac{\partial \tilde{y}_{t+1}}{\partial y_t}\frac{\partial y_t}{\partial e_t} = 0$$

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

$$\frac{\partial \tilde{y}_{t+1}}{\partial y_t} = \begin{cases} 1 & \text{if } \ \text{PY}_t = 1 \\ \frac{1}{2} & \text{if } \ \text{PY}_t = 2 \\ \frac{1}{3} & \text{if } \ \text{PY}_t = 3 \end{cases}$$

Let R_t denote $\frac{\partial \tilde{y}_{t+1}}{\partial y_t}$. The FOC can be written as follows

$$\frac{\partial \pi_t^M}{\partial e_t} = \delta R_t\ \Pr\left(d_{t+1} = 1 \mid \tilde{y}_{t+1}, b_{t+1}\right)\frac{\partial v_{t+1}^M}{\partial \tilde{y}_{t+1}}$$

Using the Envelope Theorem, it can be shown that

$$\frac{\partial \pi_t^M}{\partial \tilde{y}_t} = \frac{\partial \pi_t^M}{\partial b_t}\frac{\partial b_t}{\partial \tilde{y}_t}\mathbb{1}(\text{PY}_t = 1) + \delta R_t\ \Pr\left(d_{t+1} = 1 \mid \tilde{y}_{t+1}, b_{t+1}\right)\frac{\partial v_{t+1}^M}{\partial \tilde{y}_{t+1}}\frac{\partial \tilde{y}_{t+1}}{\partial \tilde{y}_t}$$

where $\frac{\partial b_t}{\partial \tilde{y}_t} = 1 - \lambda_t$ when $\text{PY}_t = 1$, and

$$\frac{\partial \tilde{y}_{t+1}}{\partial \tilde{y}_t} = \begin{cases} 0 & \text{if } \ \text{PY}_t = 1 \\ \frac{1}{2} & \text{if } \ \text{PY}_t = 2 \\ \frac{2}{3} & \text{if } \ \text{PY}_t = 3 \end{cases}$$

Let $\tilde{R}_t$ denote $\frac{\partial \tilde{y}_{t+1}}{\partial \tilde{y}_t}$. Multiply both sides of the FOC by $\tilde{R}_t$ and replace the second term on the right hand side of the expression obtained from the Envelope Theorem in the FOC

$$\tilde{R}_t\frac{\partial \pi_t^M}{\partial e_t} = \left[\frac{\partial v_t^M}{\partial \tilde{y}_t} - \frac{\partial \pi_t^M}{\partial b_t}(1-\lambda_t)\mathbb{1}(\text{PY}_t = 1)\right]R_t$$

and moving forward one period

$$\tilde{R}_{t+1}\frac{\partial \pi^M_{t+1}}{\partial e_{t+1}} = \left[\frac{\partial v^M_{t+1}}{\partial \tilde{y}_{t+1}} - \frac{\partial \pi^M_{t+1}}{\partial b_{t+1}}(1-\lambda_{t+1})\mathbb{1}(\text{PY}_{t+1}=1)\right] R_{t+1}$$

Isolating $\frac{\partial v^M_{t+1}}{\partial \tilde{y}_{t+1}}$ from the expression above and substituting it into the FOC we obtain the Euler equation

$$\frac{\partial \pi^M_t}{\partial e_t} = \delta R_t \ \Pr\left(d_{t+1}=1 \mid \tilde{y}_{t+1}, b_{t+1}\right)\left[\frac{\tilde{R}_{t+1}}{R_{t+1}}\frac{\partial \pi^M_{t+1}}{\partial e_{t+1}} + \frac{\partial \pi^M_{t+1}}{\partial b_{t+1}}(1-\lambda_{t+1})\mathbb{1}(\text{PY}_{t+1}=1)\right]$$

It can be easily shown that

$$\frac{\tilde{R}_{t+1}}{R_{t+1}} = \begin{cases} \frac{1}{3} & \text{if PY}_{t+1}=1 \\ 1 & \text{if PY}_{t+1}\neq 1 \end{cases}$$

Thus, we Euler equation becomes

$$\frac{\partial \pi^M_t}{\partial e_t} = \delta \ \Pr\left(d_{t+1}=1 \mid \tilde{y}_{t+1}, b_{t+1}\right)\left[\frac{\partial \pi^M_{t+1}}{\partial e_{t+1}}\mathbb{1}(\text{PY}_{t+1}\neq 1) + \frac{1}{3}\frac{\partial \pi^M_{t+1}}{\partial b_{t+1}}(1-\lambda_{t+1})\mathbb{1}(\text{PY}_{t+1}=1)\right]$$

8 Appendix D

8.1 D.1 Likelihood Function

$$
\begin{aligned}
&L(d_{i1},...,d_{iT},y_{it},...,y_{iT_i-1},\tilde{y}_{i1},...,\tilde{y}_{iT_i},b_{i1},...,b_{iT_i},\mathrm{uf}_{i1},...,\mathrm{uf}_{iT_i};\theta)=\\
&\left[\prod_{t=1}^{T_i-1} l(d_{it}=1,y_{it},\tilde{y}_{it},b_{it},\mathrm{uf}_{it}|z_{it-1},y_{it-1},\tilde{y}_{it-1},b_{it-1},\mathrm{uf}_{it-1};\theta)\right]\times l(d_{iT_i}=0,z_{iT_i-1},\tilde{y}_{iT_i},b_{iT_i};\theta)\\
&\left[\prod_{t=1}^{T_i-1}\phi(y_{it}|z_{it},\tilde{y}_{it},b_{it},\mathrm{uf}_{it})Pr(d_{it}=1|z_{it-1}\tilde{y}_{it},b_{it},\mathrm{uf}_{it};\theta)f(\tilde{y}_{it},b_{it},\mathrm{uf}_{it}|\tilde{y}_{it-1},b_{it-1},y_{it_i-1},\mathrm{uf}_{it-1},z_{it-1})\right]\\
&\times Pr(d_{iT_i}=0|z_{iT_i-1}\tilde{y}_{iT_i},b_{iT_i},\mathrm{uf}_{iT_i};\theta)f(\tilde{y}_{iT_i},b_{iT_i},\mathrm{uf}_{iT_i}|\tilde{y}_{iT_i-1},b_{iT_i-1},y_{iT_i-1}\mathrm{uf}_{iT_i-1},z_{iT_i-1})
\end{aligned}
$$

8.2 D.2 Expectation-Maximization Algorithm

$$
\begin{aligned}
L(\theta)&=\sum_i \ln\sum_k \omega_k L_{ik}(\theta;\hat{p})\\
&=\sum_i \ln\left[\sum_k \omega_k\left[\prod_{t=1}^{T_i-1} l(d_{it}=1,y_{it},\tilde{y}_{it},b_{it},\mathrm{uf}_{it}|\Omega_{it},k,\hat{p};\theta)\right]\times l(d_{iT_i}=0,\tilde{y}_{iT_i},b_{iT_i}|\Omega_{iT_i},k,\hat{p};\theta)\right]
\end{aligned}
$$

Maximizing the log likelihood of observed data now requires that one solves for both θ and ω. I allow the likelihood to depend on the CCP $\hat{p}$ to indicate that the CCP $\hat{p}$ are used to perform the forward simulation.

We obtain the solution to this maximization problem by implementing an Expectation Maximization (EM) algorithm based on Arcidiacono and Miller (2010). The algorithm begins by setting initial values for $\theta^{(1)}$, $\omega^{(1)}$ and $p^{(1)}$. The m-the iteration is given by the following two-step process:

- the Expectation Step is made of three parts:

  (i) Use Bayes' Rule to update the conditional probability that ACO i is of type k

  $$q_{ik}^{(m+1)}=\frac{\omega_k^{(m)}L_{ik}^{(m)}(\theta;p^{(m)})}{\sum_{k'=1}^{K}\omega_{k'}^{(m)}L_{ik'}^{(m)}(\theta;p^{(m)})}$$

  (ii) Update the population probability of type k (See AM (2010) Step 3A)

  $$\omega_k^{(m+1)}=\frac{\sum_i q_{ik}^{(m+1)}}{N}$$

(iii) Using $\theta^{(m)}$ and $p^{(m)}$, update the CCP $p_1^{(m+1)}(\Omega_{it}, k)$ using

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

where the dependence of v_{it}^M and v_{it}^F on $p^{(m)}$ indicates the CCP from iteration m are used to perform the forward simulation.

- Maximization Step: taking $q_{ik}^{(m+1)}$ and $p_1^{(m+1)}(\Omega_{it}, k)$ as given, obtain $\theta^{(m+1)}$ from

$$\theta^{(m+1)} = \arg\max_{\theta} \sum_{i=1}^{n} \sum_{t}^{Ti-1} \sum_{k=1}^{K} q_{ik}^{(m+1)} \Big[\ln l(d_{it} = 1, y_{it}, \tilde{y}_{it}, b_{it}, \mathrm{uf}_{it} | \Omega_{it}, k; p^{(m+1)}, \theta) + \ln l(d_{iT_i} = 0, \tilde{y}_{iT_i}, b_{iT_i} | \Omega_{iT_i}, k; p^{(m+1)}, \theta \Big]$$

8.3 D.3 Simulated Value Function

To evaluate v_t^j, we use **forward simulation** to simulate S paths of future participation and effort.

$$v_t^j \approx \frac{1}{S} \sum_{s=1}^{S} \sum_{h=0}^{H} \delta^h \pi_{t+h}^{(s)} \quad \text{for} \quad j \in \{M, F\}$$

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

- Simulated draws from CCP for d_{it}
- The Euler equation to compute e_{it}
- Use the spending equation to obtain y_{it}
- Rolling average and Benchmark transitions to update $\tilde{y}_{it}$ and b_{it}

The simulated v_t^j is used to compute the choice probability and hence form the likelihood.

8.4 D.4 Estimation Results

Table 9: Variable Costs Estimates

	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

Table 10: Fixed Costs Estimates

	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

Table 11: COUNTERFACTUALS
(Percentage change relative to status quo)

	Participation Rate in MSSP P	%Δ Spending Selected In Δy^I	%Δ Spending Selected Out Δy^O	%Δ Spending Gross SS Δy	Shared Savings Payments Δss	%Δ Spending Net of SS ΔY
Panel A: Voluntary MSSP						
Simulated MSSP	56.2	0.00	0.00	0.00	0.00	0.00
No Rebasement	65.5	-2.18	0.06	-2.12	0.58	-1.54
No Regionalization	46.4	0.24	-0.11	0.13	-0.71	-0.58
Conditional Regionalization	58.7	-2.65	-0.21	-2.86	0.73	-2.13
Panel B: Mandatory MSSP						
Simulated MSSP	100	0.00	-0.97	-0.97	0.13	-0.85
No Rebasement	100	-2.18	-0.24	-2.42	0.69	-1.73
No Regionalization	100	0.24	-0.40	-0.16	-0.55	-0.71
Conditional Regionalization	100	-2.65	-0.53	-3.18	0.81	-2.37

Notes: This table shows the percentage change in spending and shared savings payments between counterfactual scenarios and the simulated MSSP. I weight the ACO-level spending data by the number of assigned beneficiaries, so that the statistics are representative of the average value across ACOs. Panel A shows the results under the voluntary MSSP participation, while Panel B shows the results under the mandatory MSSP participation. In both Panel A and B, the columns are: (1) P is the average number of ACOs active after six years from the start of the start of the program, (2) Δy^I is the percentage change in the FFS spending (net of SS payments) among the ACOs that select MSSP, (3) Δy^O is the percentage change in the FFS spending (net of SS payments) among the ACOs that select MSSP, (4) Δy is the overall percentage change in the FFS spending (net of SS payments) (5) ΔSS is the total percentage change in the shared savings payments, and (6) ΔY is total percentage change in net spending per-capita (gross of SS payments). The simulated MSSP shows the results model simulations under status quo, and rows 2–4 report the percentage between the counterfactual scenario and the status quo: (i) No Rebasement, (ii) No Regionalization, and (iii) Conditional Regionalization (positive regional adjustment requires savings in the previous AP).