# Participation and Spending in the Medicare Shared Savings Program

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December 16, 2025

**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. I provide reduced-form and model-based evidence that the current benchmark design adversely affects ACOs' participation and performance in the MSSP. First, the benchmark rebasement, which updates the benchmark over time to reflect observed ACOs' spending, causes the ratchet effect: ACOs delay spending reductions to avoid lowering future benchmarks. Second, the region-specific adjustment applied to the rebased benchmark induces adverse selection: ACOs that are most likely to enroll are those with initial spending below the benchmark. Moreover, I propose a revised benchmarking methodology to address these inefficiencies. Counterfactual analyses demonstrate that this alternative policy mitigates adverse selection without introducing ratchet effect and significantly increases Medicare savings.

**Key Words:** Health Economics, Medicare, Pay-for-Performance, Accountable Care Organizations, Ratchet Effect, Adverse Selection.
**JEL:** L10, I18, L51.

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*I am sincerely grateful to my advisors, Michael Grubb, Richard Sweeney and Diana Bowser. Special thanks to Hanno Foerster, Arthur Lewbel, Edson Severnini, and Emma Kramer for numerous conversations. I also thank all seminar participants at Boston College for helpful comments. All errors are mine.

# 1 Introduction

The series of healthcare spending reforms introduced over the past decades has been motivated by the evidence suggesting that as much as 30% of U.S. health expenditures may be wasteful (Fisher et al., 2009; Cutler, 2018; Doyle et al., 2017; Curto et al., 2019). The inefficiencies in the U.S. healthcare system are largely due to the fragmented nature of healthcare delivery and misalignment of incentives between payers and healthcare providers (Cebul et al., 2008; Chernew,2025). In particular, Medicare's fee-for-service (FFS) system reimburses providers based on the cost and volume of services rendered. As a result, healthcare providers may find it profitable to deliver excessive services or use unnecessarily expensive procedures, even when doing so does not improve patient outcomes (Hendee et al., 2010; Chatterji et al., 2022).

Pay-for-performance programs are increasingly popular forms of government regulation that aim to correct the adverse incentives of the FFS system and improve the efficiency of healthcare delivery (Eijkenaar,2013; Mendelson et al., 2017; Norton, 2024; Gandjour, 2024). This paper focuses on the Medicare Shared Savings Program (MSSP), an incentive payment program administered by the Centers for Medicare and Medicaid Services (CMS) since 2012. The objective of the MSSP is to reduce Medicare spending relative to the level that would be observed under the standard FFS system. Large organization of independent Medicare providers -including hospitals, physician groups, primary care physicians, and post-acute care facilities - form a joint venture, known as an Accountable Care Organization (ACO). ACOs can voluntarily participate in the MSSP and are assigned a population of Medicare beneficiaries. Providers who are part of an ACO are still paid according to the standard FFS system. The ACO is rewarded with a bonus payment, known as shared savings, if the average per capita FFS spending of its beneficiaries falls below a predetermined benchmark. Therefore, under the MSSP, the reimbursement system is the same as that of FFS. The MSSP incentives are designed to induce providers to reduce the volume of services through improved care coordination between ACO providers.

I investigate how the MSSP rules for setting and updating the benchmark affect the ACOs' participation and spending (Congressional Budget Office,2024). Participation in the MSSP is divided into agreement periods (AP) of three years (before 2019) or five years (from 2019 onward). When an ACO enters the MSSP, the benchmark is calculated as the average per capita FFS spending of the Medicare beneficiaries assigned to the ACO. Starting from the second AP, two adjustments are applied to the benchmark. First, the rebased benchmark is calculated using the average spending of the previous AP. Second, the rebased benchmark is regionalized using a regional adjustment factor proportional to the difference between the rebased benchmark and average regional Medicare spending. Thus, the benchmark that an ACO actually faces is a weighted average of the rebased benchmark and the Medicare regional average spending.

I find reduced form and model-based evidence that when the benchmark places greater weight on an ACO's own past spending, ACOs have an incentive to delay spending reduction to maintain higher future benchmarks. Conversely, when the benchmark places greater weight on regional spending, ACOs with historical spending lower than the regional average are more likely to participate and receive bonus payments even with little or no spending reduction. This indicates the presence of a trade-off between benchmark rebasement and regional adjustment, and the optimal policy should aim to find a balance between them.

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 rebasement mechanism, ACOs may find it advantageous to limit spending reduction to secure more favorable benchmarks in subsequent periods. This behavior, known as the ratchet effect, leads to higher spending than what would be observed under a static benchmark (Chernew et al.,2022). I exploit variations in the MSSP benchmarking rules to provide reduced-form evidence of the ratchet effect. I find that years in which spending is not included in the benchmark rebasement calculation are associated with a 40% increase in the average savings rate.

In 2017, to reduce the influence of an ACO's past spending on its benchmarks, Medicare began adjusting the ACO's rebased benchmark with the average FFS spending of the region where the ACO operates. The regional adjustment resulted in an adverse selection of ACOs in the MSSP: ACOs with baseline FFS spending below the regional average are more likely to participate in the MSSP and obtain shared savings without reducing their spending relative to the FFS level (Lyu et al.,2023). I exploit the staggered introduction of the regional adjustment across ACO cohorts to show 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 how the benchmark design affects ACOs' participation and spending in the MSSP, I estimated 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 estimated model is then used to perform a series of counterfactual analyses. The MSSP, under its current configuration, reduces spending relative to the FFS level by approximately 1.51 percentage points ($6.795 billions). First, to assess the impact of benchmark rebasement, I simulated a counterfactual scenario where the ACOs' spending is used to compute the regional adjustment, but does not directly influence future benchmarks. Under this scenario, Medicare per capita spending decreases by an additional 0.62 percentage points relative to the status quo. This confirms the reduced-form evidence that benchmark rebasement induces ACOs to delay cost-containment efforts.

Secondly, I find that removing the benchmark regionalization reduces Medicare spending by 0.37 percentage points ($1.665 billions) relative to the status quo, and most 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.

Motivated by the need to find a better balance between the ratchet effect and adverse selection, 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 rebased 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 relative to their rebased benchmark.

Counterfactual results indicate that this approach effectively leverages benchmark regionalization to mitigate the ratchet effect while simultaneously addressing the problem of adverse selection. Medicare spending decreases by 1.13 percentage points ($5.085 billions) relative to the status quo. 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 large 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 hospitals 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) studies 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 that free-riding incentives 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 have data before the regional adjustment becomes effective, they do not analyze adverse selection into MSSP, and their single-period framework abstracts from dynamic benchmark rebasement and its implications for participation and 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 the benchmark rebasement and the adverse selection arising from the regional adjustment. Finally, it proposes an alternative benchmarking rule that can mitigate the ratchet effect and contain 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 regional adjustment work. Section 3 describes the data sources and presents reduced-form evidence of the 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 the ratchet effect and adverse selection. In Section 5, I present my estimation strategy and discuss the identification of the model primitives. Section 6 shows 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 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 overall per-capita spending. Each ACO is assigned a per capita spending benchmark, which is used to evaluate its spending performance. At the end of the year, each ACO earns 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.

Therefore, I assume throughout our analysis that ACOs have neither the incentive nor the ability to use quality as a lever to generate shared savings payments (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.

## 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 relative to the benchmark $b$, the quality score $q$, and the contract chosen by the ACO. The MSSP gives ACOs a choice of one-sided or two-sided contract.

Under the one-sided contract (Equation 2.1), the shared savings rate is a fraction $0.5q \in [0, 1]$ of the spending reduction relative to the benchmark $(b - y)$. The ACO is eligible to receive the shared savings bonus if the spending is lower than the benchmark by at least the

[1] See Appendix A for details.

minimum savings rate $\underline{s}\%$. This contract is called one-sided since the ACO does not incur any penalty or loss if spending is above the benchmark.

$$SS_1(y,q) = \begin{cases} 0.5q(b-y) & \text{if } y < (1-\underline{s})b \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

Under the two-sided contract (Equation 2.2), the shared savings rate ($0.75q \in [0,1]$) is higher than under the one-sided contract, but ACOs incur a downside risk. If spending is above the benchmark by more than the maximum loss rate $\overline{s}\%$, ACOs are required to pay a penalty equal to a fraction $0.25(1-q)$ of the excess spending relative to the benchmark.

$$SS_2(y,q) = \begin{cases} 0.75q(b-y) & \text{if } y < (1-\underline{s})b \\ 0.25(1-q)(b-y) & \text{if } y > (1+\overline{s})b \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

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. 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. 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 $b(1-\overline{s})$. 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, while the reduction is $0.5q$ dollars under the one-sided contract. Additionally, if $y > b(1+\overline{s})$, 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.

## 2.2 Benchmark

The ACO benchmark level and the benchmark updating rule are key design elements of the MSSP since the benchmark ultimately determines the amount of shared savings earned by the ACOs. These rules change over the course of the ACOs' participation in the MSSP and have been subject to multiple revisions by CMS. In this section, I will present a simplified version of the MSSP benchmarking rule and describe it in full detail in Appendix A.

The ACO's participation in the MSSP is divided into Agreement Periods (AP), and each

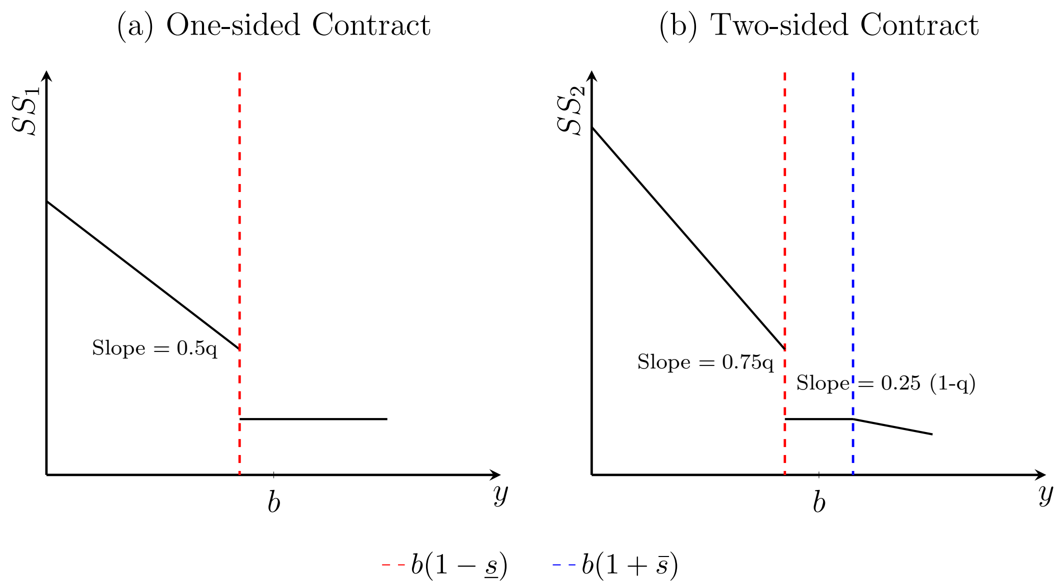


Figure 1: Shared Savings Payments

*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 maximum loss rate respectively. Panel (a) shows the shared savings payments under the one-sided contract as given by equation Equation 2.1. Panel (b) shows the shared savings payments under the two-sided contract as given by Equation 2.2.

year under the MSSP is called a Performance Year (PY). The length of each AP started prior to 2019 was three years, while that of APs started in 2019 or later was five years. The benchmark for the first AP is called the Historical Benchmark and is calculated as a weighted average of the FFS spending in the three years prior to joining MSSP. As the ACO progresses in the MSSP, two adjustments are applied to the ACOs' historical benchmark. First, at the start of each new AP, CMS performs the benchmark rebasement which consists in calculating the Historical Rebased Benchmark as the ACO's average per-capita spending of the latest 3 years of the previous AP.[2] Thus, if a new AP starts in year $t$, the Historical Rebased Benchmark $b_t^h$ is given by Equation 2.3

$$b_t^h = \frac{1}{3}y_{t-1} + \frac{1}{3}y_{t-2} + \frac{1}{3}y_{t-3} \tag{2.3}$$

The second adjustment applied to the ACO benchmark is the regional adjustment factor. CMS introduced this adjustment in 2017, and the benchmark that results from this adjustment is referred to as Regionalized Benchmark. When ACOs enter their second or subsequent AP, the Historical Rebased Benchmark is adjusted to account for the ACO's spending efficiency relative to that of the region where the ACO operates. The regional

[2]For AP of 3 years, all years are used for the rebasement, whereas for AP of 5 years, only the latest 3 years are used

adjustment factor is proportional to the difference between the Medicare's FFS average regional spending $y_t^r$ and the ACO's Historical Rebased Benchmark $b_t^h$. I will refer to this constant of proportionality $\lambda_t$ as the regional weight. The Regionalized Benchmark is given by Equation 2.4

$$b_t^r = b_t^h + \lambda_t(y_t^r - b_t^h) = (1 - \lambda_t)b_t^h + \lambda_t y_t^r \tag{2.4}$$

Thus, the benchmark that ACOs actually face from the second AP is a weighted average between the Historical Rebased Benchmark and the Medicare's FFS average regional spending. [3] The regional weight factor has a time subscript because the regional adjustment has been introduced at different times for different cohorts of ACOs, and its value changes across AP. The regional adjustment was from the third AP for ACOs entered in 2013, from the second AP for all other ACOs, and from the first AP for ACOs entered after 2018. This staggered introduction will be important to find empirical evidence of the adverse selection induced by the regional adjustment.

At the end of each PY, the historical regionalized benchmark is updated to account for variations in patient health risk and FFS prices between the previous AP and the current PY. The changes in the health status of the patient population are measured through the risk ratio, which is given by the ratio of the average risk score in the current PY and that of the latest year of the previous AP. Similarly, the variations in local medical market prices and patient utilization trends are measured using the FFS trend factors. I will denote the risk ratio with $\mathrm{rr}_t^h$ and FFS trend factors with $\mathrm{tf}_t^h$.[4] The update factors that are used to update the regionalized benchmark are given by the product of the risk ratio and trend factors, $\mathrm{uf}_t^h = \mathrm{rr}_t^h \cdot \mathrm{tf}_t^h$. Thus, the updated benchmark that is relevant for the calculation of the shared savings payments is given by

$$b_t^u = b_t^r \cdot \mathrm{uf}_t^h = \left[(1 - \lambda)b_t^h + \lambda y_t^R\right] \cdot \mathrm{uf}_t^h \tag{2.5}$$

From Equation 2.3, it can be noticed how the spending in a given AP $(y_{t-1}, y_{t-2}, y_{t-3})$, affects the benchmark of the subsequent AP. This rebasement mechanism is what gives rise to the ratchet effect. CMS introduced the regional adjustment factor to reduce the influence of ACOs' spending on their own future benchmark. However, this adjustment favored those ACOs with a $b_t^h$ lower than $y_t^r$. Equation 2.4 shows how the Regionalized Benchmark is higher than the Historical Rebased Benchmark when $y_t^r > b_t^h$, and lower when $y_t^r < b_t^h$. This resulted in an adverse selection in the MSSP of those ACOs with little incentive to reduce

[3] The regional weight $\lambda$ depends on the sign of $y_t^R - b_t^h$. See Appendix A for details

[4] $\mathrm{rr}_t^h$ is computed as the ratio of the risk score in the PY and that of the last year of the previous AP. Similarly, for the trend factors $\mathrm{tf}_t^h$

their spending relative to $b_t^h$. In the next Section, I will present reduced-form evidence of the ratchet effect driven by the benchmark rebasement, and of the adverse selection induced by the regional adjustment.

# 3 Data and reduced-form Evidence

The data used in this paper are publicly available datasets collected by CMS since the start of the program in 2013. I will use data from 2013 to 2022, which is the latest available year. These datasets consists of (i) the Performance Year Financial and Quality Results, (ii) the List of ACO Participants, (iii) County-level Aggregate Expenditure and Risk Score Data on Assignable Beneficiaries, and (iv) the Number of ACO Assigned Beneficiaries by County.[5] These data include the ACO expenditures, benchmark, quality scores, contract choice, agreement period, performance year, Medicare regional average spending, various assigned beneficiaries' demographic characteristics, and the list of providers that is member of each ACO.

To obtain the characteristics of specific ACO participants, I merge the ACOs' Participants List with two additional data sources. First, the Physician Compare Database contains detailed information on the providers' characteristics, including specialty, experience, location, beneficiaries' average risk score, hospital affiliations, and EHR usage. Second, the American Hospital Association (AHA) Survey Database contains detailed information on hospital characteristics and the degree of integration between hospitals and physicians' organizations.

## 3.1 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 I 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

[5]See the MSSP data on the CMS webpage

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, I 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.

## 3.2 Descriptive Statistics

Figure 2 shows MSSP entry and exit over time. The number of ACOs has increased significantly since the program, and there are now more than 500 active ACOs. 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 and has been steady after that.

Table 6 in Appendix B 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, but since 2019, the fraction is closer to two thirds. The savings rate, which represents the spending reduction relative to the benchmark, has been modest

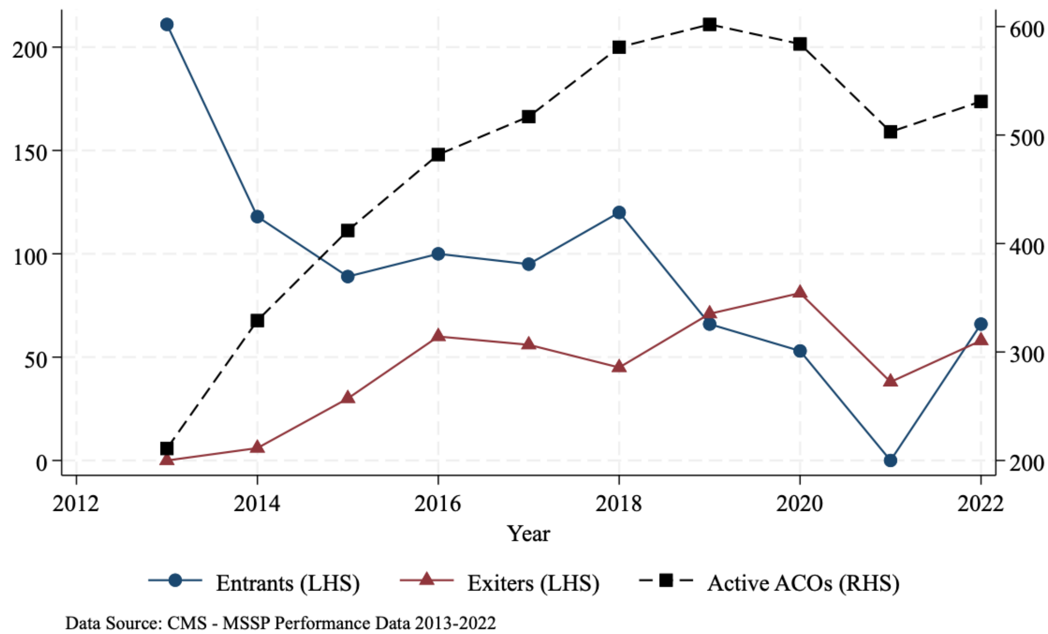


Figure 2: Entry, Exit and Active ACOs from 2013 to 2022

in the early years. For example, in the first three years of the program, the average savings rate was approximately 0.58%. The savings rate has increased over time, but shows a large variation across ACOs. For example, in the latest three years of the program, the average savings rate was 3.36% with a standard deviation of 4.21.

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.

### 3.3 Ratchet Effect

In this section, I present the empirical approach for identifying whether benchmark rebasement gives rise to a ratchet effect (Weitzman, 1980, Cardella and Depew, 2016, Coyne et al., 2022). 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. My estimates indicate that benchmark rebasement has a substantial negative impact on ACO's savings, which I interpret as evidence of the 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 and extend their existing one-sided contract by one additional year. The fourth-year option was intended to support ACOs that were preparing to transition into a two-sided risk model. Under this 4-year-long AP, the benchmark is rebased using only the last three years. Thus, the first year is not counted for the rebasement. However, only ACOs whose first PY of their first or second AP occurred between 2016 and 2018 knew in advance that the spending in that year would not be counted for the rebasement. For all the other ACOs, the deferral option did not have any impact on the actual rebasing years.

The second variation is the introduction of a five-year AP. With the "Pathways to Success" reform, Agreement Periods starting in 2019 or later last five years, and only the last three years are included in the benchmark rebasement. This creates a two-year period where spending does not affect the benchmark of the next AP. Since ACOs start their five-year AP cycle in different years depending on the entry year and on whether they opted for the deferral. This staggered rollout of the five-year AP structure across ACOs creates plausibly exogenous variation in the timing of exposure to non-rebasing years. Clearly, in this case, ACOs know in advance that the spending in the first two years would not be counted for the rebasement.

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, I 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 | Yes | 2019–2020 | 145 |
| 2014 | 3 | No | 2020–2021 | 92 |
| 2014 | 3 | Yes | 2021–2022 | 10 |
| 2015 | 3 | No | 2021–2022 | 73 |
| 2015 | 2 | Yes | 2019–2020 | 4 |
| 2016 | 2 | Yes | 2019–2020 | 99 |
| 2017 | 2 | No | 2020–2021 | 117 |
| 2018 | 2 | No | 2021–2022 | 127 |
| 2018 | 2 | Yes | 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, I use these non-rebasing years to test whether ACOs strategically respond to the presence or absence of benchmark rebasement. I 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 the Two-Way Fixed Effect linear model in Equation 3.1

$$\text{Savings Rate}_{it} = \alpha_i + \lambda_t + \beta_1 \cdot \text{Non-RY}_{it} + \beta_2 \cdot \text{DF}_{it} + X_{it}'\delta + \varepsilon_{it} \tag{3.1}$$

with Savings Rate as dependent variable, while Panel B shows the results of the Two-Way Fixed Effect Logistic model in Equation 3.2

$$\Pr\Big(\text{Savings Rate}_{it} > \text{MSR}_i\Big) = \Lambda\Big(\alpha_i + \lambda_t + \beta_1 \cdot \text{Non-RY}_{it} + \beta_2 \cdot \text{DF}_{it} + X_{it}'\delta\Big) \tag{3.2}$$

with the indicator of Savings Rate above the minimum savings rate (MSR) as dependent variable.[6]

Table 2: Ratchet Effect Results

| | OLS | | Logit | |
|---|---|---|---|---|
| | Full sample | Entry year < 2019 | Full sample | Entry year < 2019 |
| Non-Benchmark Year | 0.943*** | 0.907*** | 2.172*** | 2.259*** |
| | (0.210) | (0.227) | (0.407) | (0.438) |
| Deferral | 1.792*** | 1.798*** | 2.865*** | 2.626*** |
| | (0.472) | (0.497) | (0.918) | (0.858) |
| Observations | 4,519 | 4,133 | 3,180 | 3,017 |
| R-squared | 0.180 | 0.186 | 0.624 | 0.612 |
| Mean | 2.324 | 2.235 | 0.512 | 0.465 |
| SD | 4.173 | 4.207 | 0.249 | 0.248 |
| ACO FE | Yes | Yes | Yes | Yes |
| AP FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

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

The results in Table 2 provide evidence consistent with the presence of a ratchet effect. I 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

[6] $\Lambda$ is the logistic cdf.

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. These estimates are obtained including ACO fixed effects, which implies that the effect of non-rebasing years is identified from within-ACO variation over time. This suggests that the ratchet effect is a within-ACO phenomenon: the same ACO changes behavior across benchmark and non-benchmark years.

The coefficients of the logistic regression (Equation 3.2) are reported as odds ratios to aid interpretation. 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 the OLS and logistic models, I 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.

## 3.4 Adverse Selection

ACOs earn shared savings payments when their FFS spending is below their Regionalized Historical Rebased Benchamark as given by Equation 2.5. As it can be observed from Equation 2.4, ACOs whose Historical Rebased Benchmark is substantially lower than the Medicare's regional spending, obtain a positive regional adjustment. These ACOs can obtain shared savings payments without further reducing their spending. In particular, this happens when ACOs whose spending prior to joining the MSSP is more efficient than that of the region. In this case, Medicare is wasting resources by paying providers for achieving an FFS spending level that they would have achieved without the MSSP incentives. Following Einav et al., 2022, I 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, 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 Regional Adjustment indicator

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

I use the logistic model in equation Equation 3.3 to estimate the impact of the regional adjustment on the likelihood of ACOs' exit from the MSSP.

$$\Pr(\text{Exit}_{it} = 1) = \Lambda\Big(\lambda_t + \beta_1 \cdot \text{Regional Adj}_{it} + \beta_2 \cdot \text{Positive Adj}_{it} + X'_{it}\delta\Big) \tag{3.3}$$

where $\Lambda$ 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.

The estimated odds ratio indicates that, after the regional adjustment is applied, ACOs are more than 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.

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

# 4 Structural Model

## 4.1 The spending equation

Let $y_{it}^{FFS}$ denote the average per capita FFS spending of ACO $i$ in year $t$ that would be observed I the ACO did not participate in the MSSP. Following CMS approach, I assume that $y_{it}^{FFS}$ depends on factors that are exogenous to 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 CMS using the trend factors $\text{tf}_{it}$, and the third by the risk ratio $\text{rr}_{it}$.[7]

Since FFS spending is strongly correlated over time, I assume that it can be written as the sum of a persistent component $\mu_{it}$ and a transitory shock $\epsilon_{it}$. The persistent component represents the mean FFS spending and its evolution over time is driven by the trend factors $\text{tf}_{it}$ and the risk ratio $\text{rr}_{it}$ as given by Equation 4.1

$$\mu_{it} = \mu_{i,t-1} + \ln \text{uf}_{it}, \tag{4.1}$$

where $\ln \text{uf}_{it} = \ln \left(\text{tf}_{it} \cdot \text{rr}_{it}\right)$. The observed FFS spending is given by

$$\ln y_{it}^{FFS} = \mu_{it} + \epsilon_{it} \tag{4.2}$$

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

$\ln \epsilon_{it}$ are i.i.d. from $N(0, \sigma_{it}^2)$ Thus, the FFS spending follows a lognormal distribution

$$\ln y_{it}^{FFS} \sim N\left(\mu_{it}, \sigma_{it}^2\right)$$

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 4.3

$$y_{it} = y_{it}^{FFS} - e_{it} \tag{4.3}$$

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, I 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. Hence, I assume that 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

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

where $\text{uf}_{it}$ denotes the update factors that are used to put year $t$ spending in year $t+1$ terms. Using the rolling average spending is useful for two reasons. First, it allows to avoid to keep track of the past spending $(y_{it-1}, y_{it-2}, y_{it-3})$ that is used to computed $b_{it}^h$. Second, the evolution of the updated benchmark (Equation 2.5) can be written in terms the currect updated benchmark $b_{it}^u$, the next-period rolling average spending $\tilde{y}_{it+1}$, the current average regional spending $y_{it}^r$, the regional weight factor $\lambda_{it+1}$ and the update factors. Thus, for AP of three years, the evolution of the updated benchmark can be written as follows

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

whereas for AP of five years, the formula includes two additional performance years

$$b_{it+1}^u = \begin{cases} b_{it}^u \cdot \text{uf}_{4,t+1}^h & \text{if } \text{PY}_{t+1} = 4 \\ b_{it}^u \cdot \text{uf}_{5,t+1}^h & \text{if } \text{PY}_{t+1} = 5 \end{cases}$$

The subscript $j \in \{1,2,3,4,5\}$ in $\mathrm{uf}^h_{j,t+1}$ denotes that the update factors account for variation in the risk score and FFS trends between the latest year used for the rebasement and the current PY.

## 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 $\epsilon_{it}$ is realized, (iv) the MSSP spending $y^M_{it}$ is observed, and the ACO obtains profits $\pi_{it}$.

For ease of exposition, in this section, I 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 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 $\Omega_{it}$.

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

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

where $\varepsilon^M_{it}$ and $\varepsilon^F_{it}$ are idiosyncratic choice specific shocks. Under the assumption that these shocks have a TIEV distribution, it can be shown that the continuation value function is given by

$$\mathbb{E} V_{it+1}(\Omega_{it}) = \ln \left[ \exp(v^M_{it+1}(\Omega_{it+1})) + \exp(v^F_{it+1}(\Omega_{it+1}) \right],$$

where $v^F_{it+1}$ 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 by

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

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

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

whereas in non-rebasing years it is

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

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

$$\frac{\partial \pi_{it}^M}{\partial e_{it}} = \delta \, \Pr\left(d_{it+1} = 1 \mid \Omega_{it}\right) \left[\frac{\partial \pi_{it+1}^M}{\partial e_{it+1}} \mathbb{1}(\mathrm{PY}_{it+1} \neq 1) + \frac{1}{3} \frac{\partial \pi_{it+1}^M}{\partial b_{it+1}} (1 - \lambda_{it+1}) \mathbb{1}(\mathrm{PY}_{it+1} = 1)\right] \tag{4.4}$$

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

Since the right-hand side of the Euler equation is positive, the optimal level of effort under 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 weight $(1 - \lambda_{t+1})$, and (iii) how sensitive profits are to a change in benchmark which equals the shared savings rate $(\frac{\partial \pi_{t+1}^M}{\partial b_{t+1}})$.

## 4.3 Model Primitives

The profit $\pi_{it}^M(e_{it})$ of the ACO under MSSP is given by Equation 4.5

$$\pi_{it}^M(e_{it}) = \mathbb{E}\left[SS(e_{it})\right] - C(e_{it}) - F_i \tag{4.5}$$

[8]See Appendix C for the derivation of the Euler equation

where the $\mathbb{E}[SS(e_{it})]$ 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 $\gamma_{it}$

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

Since $e_{it}$ is the effort in dollar terms, the expected FFS spending $\mu_{it}$ enters in the denominator to allow the marginal cost of effort to be scale invariant. In other words, the marginal costs of effort do not depend on the absolute dollar amount of spending reduction, but on the spending reduction relative to the expected FFS level.

I allow $\gamma_{it}$ and $F_i$ to depend on observables $x_{it}$ and on a vector of persistent unobserved types $\nu_i$:

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

with $\nu_i$ is a vector of indicator of unobserved types. If ACO $i$ is of type $k$, then $\nu_i$ will be a vector whose k-th entry equals one, and all the other entries are zero. 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. Allowing $\nu_i$ to load on both $\gamma$ and $F$ ties the intensive (effort) and extensive (participation) margins and is critical for credible counterfactuals that quantify ratcheting and adverse selection.

## 4.4 Illustrative Model

I consider a simplified version of the model to describe how the model primitives and policy parameters map into the two phenomena of interest—ratchet effect (RE) and adverse selection (AS). I also illustrate how they determine whether the ACO's participation in the MSSP reduces spending relative to the FFS level.

I make several simplifying assumptions: (i) there is only the two-sided contract with shared savings rate $s$, (ii) the minimum savings rate and the maximum loss rate are zero, (iii) the regional spending and the regional weight are constant, (iv) the fixed costs are zero, (v) there are no spending shocks, (vi) the update factors are constant and equal to one, and

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

(vii) the discount factor is one. Since there are no spending shocks, the FFS spending is also constant. Moreover, I simplify the benchmark rebasement and regionalization formulas. I assume that the benchmark is rebased and regionalized every PY rather than every three or five PY. Thus, the benchmark evolves over time according to the formula

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

where $y_{it}$ is the ACO's spending in year $t$. To compute the benchmark for the first PY, I use the ACO's spending under FFS, $y_i^{FFS}$, and obtain $b_{i1} = (1-\lambda)y_i^{FFS} + \lambda y_i^R$.

These assumptions allow us to express the ratchet effect and adverse selection in terms of the ACOs' primitives $(\gamma_i, y_i^{FFS}, y_i^R)$ and the policy parameters $(s, \lambda)$. The Euler equation reduces to $\frac{\partial \pi_{it}^M}{\partial e_{it}} = (1-\lambda)\frac{\partial \pi_{it}^M}{\partial b_{it+1}}$ and the optimal effort $e_{it} = \frac{s}{\gamma_i}\lambda y_i^{FFS}$. Without benchmark rebasement, the optimal effort would be $e_{it}^{NR} = \frac{s}{\gamma_i} y_i^{FFS}$. Therefore, the ratchet effect (RE) can be written as follows

$$RE(\gamma_i, y_i^{FFS}, \lambda, s) = e_{it}^{NR} - e_{it} = y_i^{FFS}\frac{s}{\gamma_i}(1-\lambda) \tag{4.6}$$

If the benchmark is fully regionalized ($\lambda = 1$), the RE is zero since the dynamic effort is equal to the static effort, whereas if the benchmark is fully rebased ($\lambda = 0$), the dynamic effort is zero and the ratchet effect is its largest. Thus, the regional weight $\lambda$ controls the magnitude of the ratchet effect.

I derive the adverse selection (AS) incentive as the amount of profits that an ACO would obtain without exerting effort. Under zero effort, variable costs are zero, and profits equal shared savings payments $\pi_{it} = s(b_{it} - y_i^{FFS})$. Substituting $b_{it}$ for $t = 1$, I can express the ACOs' adverse selection incentives as follows

$$AS_i(y_i^{FFS}, y_i^R, \lambda, s, F) = s\big[\ \lambda(y_i^R - y_i^{FFS})\big] \tag{4.7}$$

As $\lambda$ increases, $b_{it}$ approaches $y^R$. Thus, when the regional spending exceeds the FFS level, a higher $\lambda$ makes the adverse selection incentive stronger. When, instead, the regional spending is below the FFS level, higher $\lambda$ diminishes the incentive to select in.

The ACOs' primitives $(y_i^{FFS}, y_i^R, \gamma_i)$ and the policy parameters $(\lambda, s)$ also impact whether MSSP allows Medicare to reduce spending relative to the FFS system. From Medicares' perspective, ACO $i$ generates savings if the condition in Equation 4.8 holds.

$$\underbrace{\left(y_i^{FFS} - e_{it}\right)}_{\text{MSSP spending}} + \underbrace{s \cdot \left(b_{it} - (y_i^{FFS} - e_{it})\right)}_{\text{shared savings payments}} \quad < \quad y_i^{FFS} \tag{4.8}$$

This condition implies that total spending under the MSSP must be lower than spending under FFS. Substituting the benchmark for the first PY, I obtain

$$(1-s)e_{it} > s\big[\ \lambda(y_i^R - y_i^{FFS})\big] \tag{4.9}$$

where $e_{it}$ depends on $\lambda$. The left-hand side is the effort-driven savings that Medicare keeps, while the right-hand side is the shared savings that the ACO earns without exerting effort. I will refer to the right hand side of Equation 4.9 as "free" shared savings.

Equation 4.9 can be written in terms of the effort-cost efficiency $\tilde{\gamma}_i = \frac{1}{\gamma_i}$ and the FFS spending efficiency relative to region $\Delta y_i^{FFS} = \left(\frac{y_i^R - y_i^{FFS}}{y_i^{FFS}}\right)$. Panel (a) of Figure 3 illustrates this threshold $\tilde{\gamma}_i^*$ as a function of $\Delta y_i^{FFS}$. On the x-axis, I plot the ACO's FFS spending efficiency relative to the region ($\Delta y_i^{FFS}$), and on the y-axis, I plot the ACO's effort cost efficiency $\tilde{\gamma}_i$. For a given level of $\Delta y_i^{FFS}$, there is some threshold value $\tilde{\gamma}_i^*$ above which ACOs' participation allows MSSP to generate savings relative to FFS. The threshold $\tilde{\gamma}_i^*$ is upward sloping because higher FFS spending efficiency (larger $\Delta y_i^{FFS}$) requires higher effort cost efficiency (higher $\tilde{\gamma}_i$) to generate enough effort-driven savings to outweigh the "free" shared-savings.

Similarly, imposing that profits from MSSP participation must be positive, I derive the threshold that separates the set of ACOs that select in MSSP from the set of ACOs that stay under FFS. This ACO's threshold is illustrated in panel (b) of Figure 3. Above this threshold, ACOs *Select In* MSSP, whereas below it ACOs *Select Out* of MSSP and stay under the standard FFS system. The ACOs' threshold is downward sloping because ACOs that are less efficient than the region ($\Delta y_i^{FFS} < 0$) need to be more effort-cost efficient (larger $\tilde{\gamma}_i$) to select into MSSP. Instead, ACOs that are more spending efficient than the region ($\Delta y_i^{FFS} > 0$) always participate because they can profit from MSSP even with zero effort.

Panel (c) of Figure 3 plots the three regions obtained by overlapping panels (a) and (b). First, the ACOs that select in MSSP and generate savings relative to FFS (Efficiently Select In). Second, the ACOs that select in MSSP but have a total spending (spending plus shared savings payments) higher than under FFS (Inefficiently Select In). Third, the ACOs stay in the FFS system, but could generate savings if they joined MSSP (Inefficiently Select Out).

Panel (d) illustrates the trade-off in setting the regional weight parameter. I consider an increase in $\lambda$ and its impact on the three regions depicted in panel (c). From Equation 4.6, higher $\lambda$ reduces the ratchet effect and, therefore, induces ACOs to cut spending more. However, from Equation 4.7, when $\Delta y_i^{FFS} > 0$, increasing the regional weight strengthens the adverse selection because these ACOs can earn shared-savings even with no effort. Thus, the effect of higher $\lambda$ on the Medicare threshold is ambiguous. Panel (d) shows the case where the adverse selection effect is stronger than the reduction in the ratchet effect, and the threshold rotates inward. The light grey area represents the lost *Efficiently Select In* area from the increase in $\lambda$.

The Medicare threshold rotates inward because, for those ACOs with $\Delta y_i^{FFS} < 0$, a higher lambda implies a larger negative regional adjustment and thus a lower benchmark. These ACOs need to be more effort efficient (higher $\tilde{\gamma}_i$) to participate profitably in the MSSP. Thus, the effort efficiency threshold increases, and the *Inefficiently Select In* becomes larger (dark grey area).

This suggests the need for a benchmarking rule that balances the trade-off between the ratchet effect and adverse selection. 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.

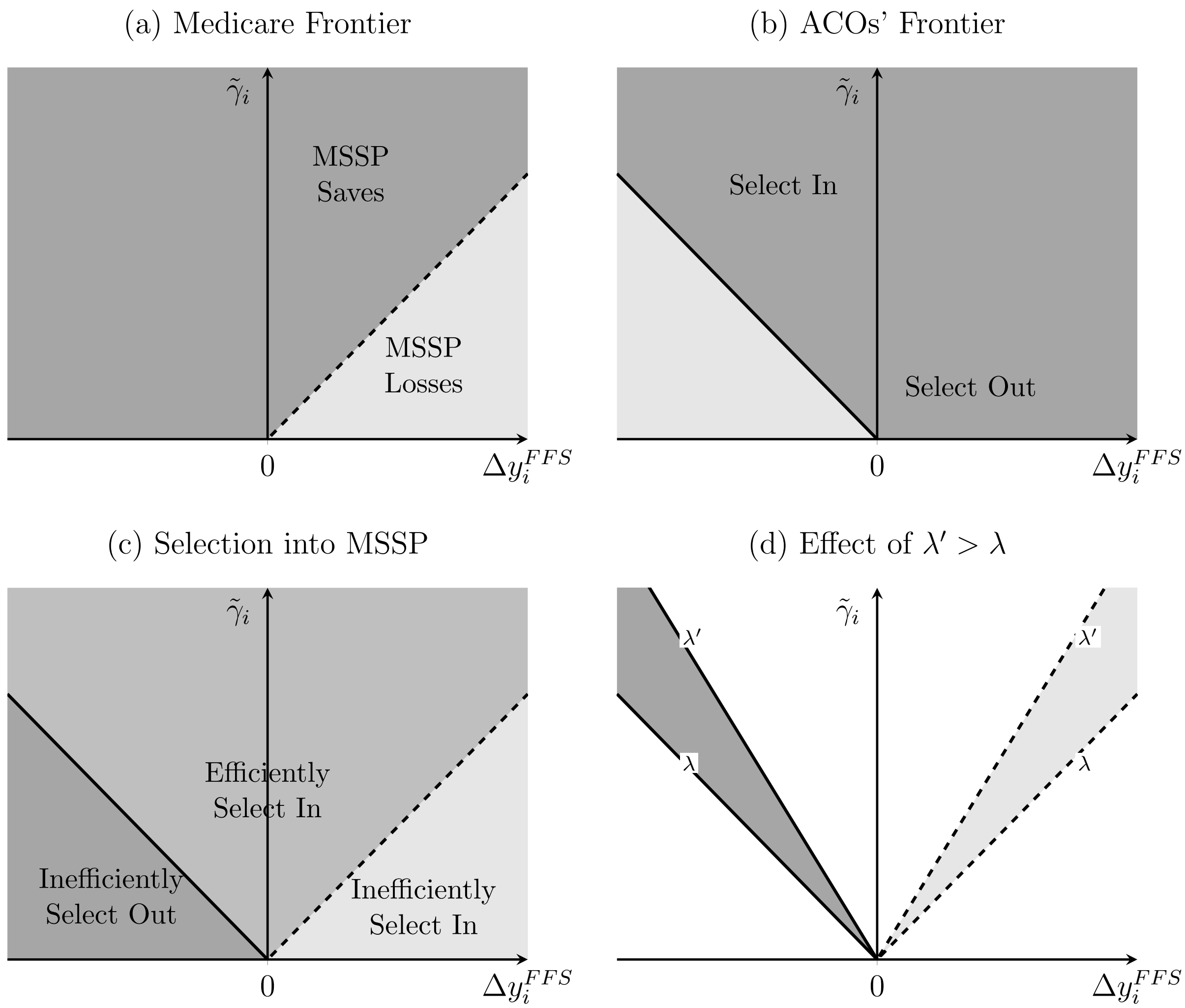


Figure 3: Selection into MSSP

*Notes*: $\Delta y_i^{FFS}$ denotes $(y_i^R - y_i^{FFS})/y_i^{FFS}$ and $\tilde{\gamma}_i$ denotes the inverse of the effort cost parameter $1/\gamma_i$. Panel (a) shows the ACOs' selection threshold and Panel (b) shows Medicare's selection threshold of ACOs. Panel (c) shows the three regions created by overlapping panel (a) and panel (b): the *Efficiently Select In* region represents the ACOs that select in MSSP and generate savings relative to FFS, the *Inefficiently Select In* region represents the ACOs that select in MSSP but have a total spending (spending plus shared savings payments) higher than under FFS , and the *Inefficiently Select Out* region represents the ACOs stay in the FFS system, but could generate savings if they joined MSSP. Panel (d) shows the effect of an increase in the regional weight $\lambda$ on the thee regions depicted in panle (c). The light area increase in the *Efficiently Select In* region and the dark grey area is the increase in the *Inefficiently Select Out* region.

# 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 from three years prior to the MSSP entry, and in those three years, I 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 $\text{tf}_{i,t_{i0}}$ and the risk ratio $rr_{i,t_{i0}}$

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

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

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

The standard deviation of the spending shock is assumed to be proportional to the FFS spending $\sigma_{it} = \rho\mu_i t$ and $\rho$ 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. I observe the MSSP spending during its MSSP participation, whereas I do not observe spending after exit. Let $T_i$ be the number of years ACO $i$ participates in the MSSP. For each ACO $i$, I 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 $y_{it} = y^{FFS}_{it} - e_{it}$. Notice that $y^{FFS}_{it} = \mu_{it} + u_{it}$ is the unobserved realized FFS spending level. The effort $e_{it}$ is obtained as a solution of the Euler equation. [10] 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 $k$. I treat the unobserved type as an observed ACO characteristic, and write the likelihood

[10]See Appendix for details.

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 $\mu_{it}$ 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 $\theta$ and the mixture type probabilities. The EM algorithm requires to iteratively update the mixture probabilities given the likelihood and find $\theta$ that maximizes the likelihood given the mixture probabilities. This two-step process yields a solution to the log likelihood maximization problem upon convergence.[11].

The likelihood function requires the computation of 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 path, I compute the discounted sum of profit flows and compute its average to estimate $v_{it}^M$.[12]

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 $y_{it}|e_{it} \sim N\left(\mu_{it} - e_{it}, 2\sigma_\epsilon^2\right)$. 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

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

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

[12] See Appendix D.3 for details

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 $\Omega_{it}$. Hence, I have that

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

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

## 5.4 Results

**Variable and fixed cost estimates** In the model, the intensive margin is governed by the variable–cost index $\gamma_i$, which scales the marginal cost of effort through $C(e_{it}, \mu_{it}) = \frac{1}{2}\gamma\, e_{it}^2/\mu_{it}$. A larger $\gamma_i$ 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 $(\beta_C, \alpha_C)$. Three patterns are robust across the number of unobserved types $K$. First, risk score coefficients are positive and statistically significant in every specification ($\approx 0.44$–$0.54$). 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 $\gamma$ ($\approx 1.5$–$1.7$) 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 $(\beta_F, \alpha_F)$ 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.

From Section 4, we know that the adverse selection incentive depends on the difference between the regional spending and the FFS spending. To make this difference comparable across ACOs, I consider the relative difference $(y^R - y^{FFS})/y^{FFS}$, and I will refer to this as regional deviation. I use the estimated model to conduct a test for the presence of adverse selection across different levels of effort cost efficiency. In Figure 4, for each decile of the distribution of $\gamma$, I plot the mean percentage difference (and its 95% confidence interval) of the regional deviation between ACOs that select in the MSSP and ACOs that select out. In the absence of adverse selection, we should observe that the mean is not statistically different from zero. Instead, we observe that the regional deviation is approximately 10% to 20% higher among ACOs that select in the MSSP. This difference is statistically significant and holds across different levels of effort cost efficiency $\gamma$. In the next Section, I will use counterfactual simulations to estimate the actual cost of adverse selection in terms of the dollar value of the wasteful shared savings payment due to the regional adjustment.

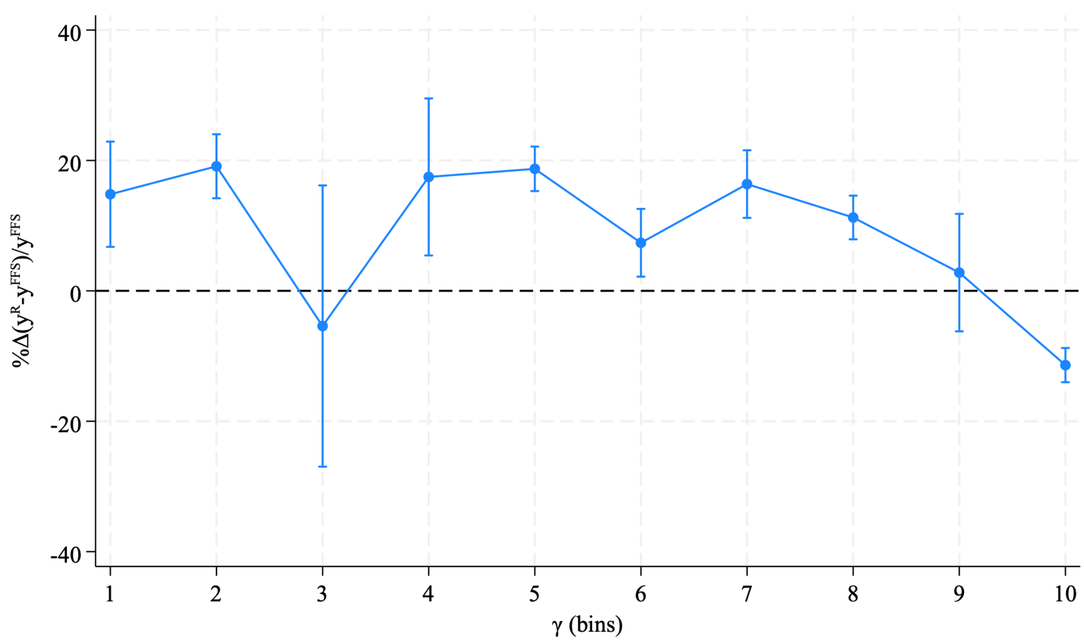


Figure 4: Adverse Selection under MSSP

*Notes*: This figure shows the test for the adverse selection across different levels of effort cost efficiency. The x-axis plots the deciles of the distribution of the estimated cost parameter $\gamma$. This y-axis plots the mean percentage difference (and its 95% confidence interval) of the regional deviation, $(y^R - y^{FFS})/y^{FFS}$, between ACOs that select in the MSSP and ACOs that select out. The mean difference is statistically significant when then confidence interval does not contain zero.

# 6 Counterfactuals

In this Section, I use the estimated model to perform a set of counterfactual exercises. First, I simulate a scenario where the benchmark is regionalized but not rebased. Secondly, I simulate a scenario where the benchmark is rebased but not regionalized. I use the results from these simulations to estimate the impact of the ratchet effect and adverse selection on participation and MSSP savings. Third, I present and discuss the results of an alternative benchmarking policy that is designed to mitigate the ratchet effect while also preventing adverse selection. ACOs' spending and participation in these counterfactual scenarios are compared to those of the simulated model under the actual MSSP benchmarking rules. I will refer to the latter as "status quo". Finally, I compare Medicare spending under the status quo and the alternative policy to the counterfactual scenario where the MSSP does not exist, and all ACOs are under the standard FFS system.

Under the status quo, Medicare's total per-capita spending on ACO $i$, $Y_i^M$, is the sum of the per-capita FFS spending, $y_i^M$, and the per-capita shared savings payments, $ss_i^M$. Similarly, in a counterfactual scenario, Medicare's total per-capita spending on ACO $i$, $Y_i^C$, is the sum of the per-capita FFS spending, $y_i^C$, and the per-capita shared savings payments, $ss_i^C$.

I evaluate the impact of a change in the benchmarking rule in terms of the percentage change in the total Medicare per capita spending relative to the status quo. The latter is denoted by $\Delta Y_i^C$ and can be decomposed as the sum of the change in the FFS spending, $\Delta y_i^C$, and the change in the shared savings, $\Delta ss_i^C$.

$$\underbrace{\frac{Y_i^C - Y_i^M}{Y_i^M}}_{\Delta Y_i^C} = \underbrace{\frac{y_i^C - y_i^M}{Y_i^M}}_{\Delta y_i^C} + \underbrace{\frac{ss_i^C - ss_i^M}{Y_i^M}}_{\Delta ss_i^C} \tag{6.1}$$

For each calendar year and ACO, I perform the decomposition of Equation 6.1 and take a weighted sum over all ACOs. The weight assigned to each ACO is proportional to the number of ACOs assigned beneficiaries. Let $\Delta Y^C$ denote the overall percentage change in total spending, and let $\Delta y^C$ and $\Delta ss^C$ denote the decomposition of $\Delta Y^C$ in terms of FFS spending and shared savings, respectively.

Results of the counterfactual simulations are reported in Table 4. In panel A, ACOs voluntarily participate in the MSSP, whereas in panel B, all ACOs are required to participate in the MSSP and cannot exit the program. In both panels, 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 program, (2) $\Delta y^C$ is the percentage change in the net spending, (3) $\Delta ss^C$ is the total percentage change in the shared savings payments, and (4) $\Delta Y^C$ is percentage change in total spending per capita.

I also investigate the adverse selection under the counterfactual scenarios. Following the same approach of Section 5, across each decile of the distribution of $\gamma$, I plot the mean percentage difference of the regional deviation, $(y^R - y^{FFS})/y^{FFS}$, between the ACOs that select in the MSSP and those that select out. Figure 6, 7 and 8 serve as a test for the presence of adverse selection across different levels of effort cost efficiency. I expect that adverse selection is stronger when the benchmark is not rebased, whereas it should vanish when the regional adjustment is not applied.

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

| | Participation Rate in MSSP $P$ | %$\Delta$ Spending Net of SS $\Delta y^C$ | Shared Savings Payments $\Delta ss^C$ | %$\Delta$ Spending Gross of SS $\Delta Y^C$ |
|---|---|---|---|---|
| *Panel A: Voluntary MSSP* | | | | |
| Simulated MSSP | 56.2 | 0.00 | 0.00 | 0.00 |
| No Rebasement | 65.5 | -1.12 | 0.58 | -0.62 |
| No Regionalization | 46.4 | 0.13 | -0.51 | -0.37 |
| Conditional Regionalization | 58.7 | -1.86 | 0.73 | -1.13 |
| *Panel B: Mandatory MSSP* | | | | |
| Simulated MSSP | 100 | -0.52 | 0.25 | -0.27 |
| No Rebasement | 100 | -1.36 | 0.65 | -0.71 |
| No Regionalization | 100 | -0.16 | -0.43 | -0.59 |
| Conditional Regionalization | 100 | -2.18 | 0.91 | -1.27 |

*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) $\Delta y^C$ is the percentage change in the FFS spending (net of SS payments), (3) $\Delta ss^C$ is the total percentage change in the shared savings payments, and (4) $\Delta Y^C$ 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

In Section 3, I presented empirical evidence that the benchmark rebasement significantly impacts ACOs' savings rate relative to their benchmark. To estimate the impact of benchmark rebasement, I compare the total MSSP spending under the status quo to that of the counterfactual scenario where the benchmark is not rebased. From Equation 2.3 we know that the current period spending affects future benchmarks through the historical rebased benchmark $b^h_{it}$. To prevent the ratchet effect while maintaining the regional adjustment, I perform one change to the regionalized benchmark formula of Equation 2.4. I replace $b^h_{it}$ with the ACO's average FFS spending in the three years prior to joining the MSSP, $\bar{y}^h_{it+1}$. Since the latter does not depend on the ACO's spending during the MSSP, a reduction in spending does not cause the benchmark to decrease over time. I still use the historical rebased benchmark to compute the regional adjustment, $\lambda(y^R_{it} - b^h_{it})$. Therefore, a lower historical rebased benchmark increases $b^r_{it+1}$ through a larger regional adjustment. This benchmark formulation eliminates the ratchet effect and preserves the incentives driven by the regional adjustment. Therefore, the formula used to compute the regionalized benchmark is given by Equation 6.2.

$$b^r_{it+1} = \left[(1-\lambda)\bar{y}^h_{it+1} + \lambda(y^R_{it} - b^h_{it})\right] \tag{6.2}$$

The second row of Panel A in Table 4 reports the outcomes under this counterfactual scenario. Medicare total spending decreases by 0.62 percentage points relative to the status quo ($2.792 billion). The decomposition of $\Delta Y^C$ shows that this reduction is mainly due to the reduction in spending per capita. Thus, I estimate that in terms of per capita spending, the ratchet effect reduces net Medicare savings by 104$ per capita ($5.041 billion). Shared savings increase by about $39 per-capita. This increase can be explained by two main factors. First, lower spending leads to larger shared savings paid to ACOs. Second, benchmarks are higher since spending reduction does not lead to a lower benchmark over time.

Participation in MSSP increases substantially from 56.2% to 65.5%, and this increase is driven mainly by a lower exit rate. This suggests that benchmark rebasement has a significant impact on MSSP participation. Therefore, removing rebasement enables ACOs to maintain higher benchmarks over time despite achieving a spending reduction and incentivizes ACOs to stay in the program. Indeed, under mandatory participation (Panel B), total Medicare spending only sees a modest additional decrease of 0.19 percentage points relative to the voluntary participation setting. 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 the ratchet effect. However, removing benchmark rebasement is not an ideal solution since adverse selection becomes stronger. Moreover, the fact that lower spending does not reduce the benchmark over time, but allows to achieve a positive regional adjustment, reinforces the adverse selection incentive. This can be observed in Figure 5. The mean difference in the regional deviation between the ACOs that select in the MSSP and those that select out is around 20% and statistically significant. This suggests that there could be a significant amount of shared savings paid to ACOs that do not reduce their spending relative to their FFS level. In the next subsection, I will use the results from the counterfactual simulation where the regional adjustment is not applied to quantify the dollar value of these excessive shared savings payments.

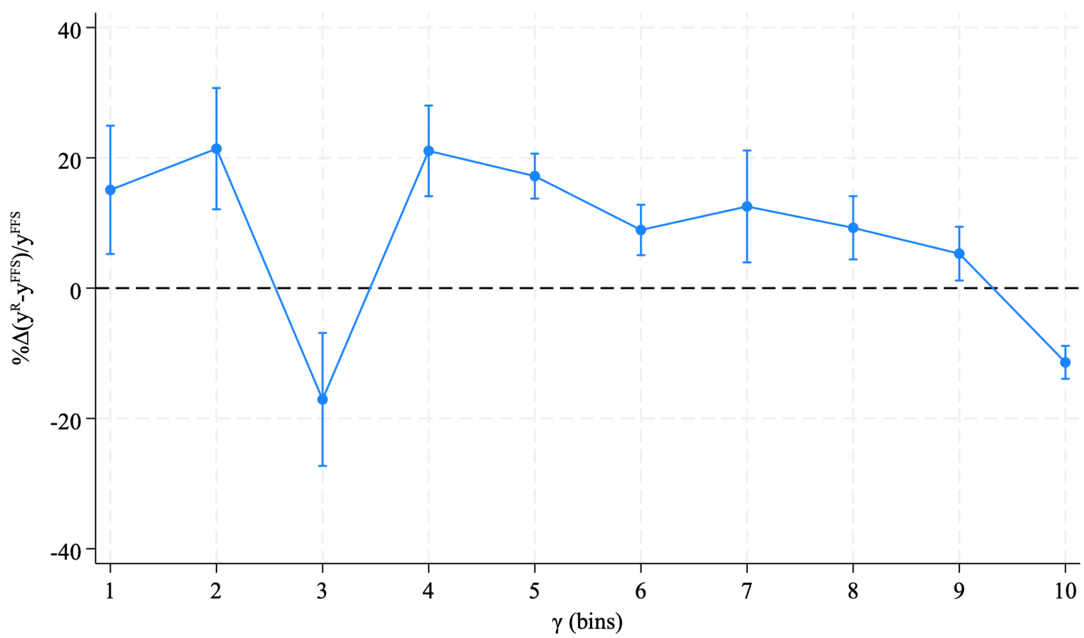


Figure 5: Adverse Selection under "No Rebasement"

*Notes*: This figure shows the test for the adverse selection across different levels of effort cost efficiency. The ACOs' participation choices are obtained under the counterfactual scenario where the benchmark is not rebased and the regionalized benchmark is given by Equation 6.2. The x-axis plots the deciles of the distribution of the estimated cost parameter $\gamma$. This y-axis plots the mean percentage difference (and its 95% confidence interval) of the regional deviation, $(y^R - y^{FFS})/y^{FFS}$, between ACOs that select in the MSSP and ACOs that select out. The mean difference is statistically significant when then confidence interval does not contain zero.

## 6.2 No-Regionalization Scenario

In Section 3 I discussed that ACOs that obtain a positive regional adjustment might be able to earn shared savings without reducing their spending relative to their FFS level. I showed evidence that these ACOs are less likely to exit the MSSP, whereas ACOs that have negative regional adjustment are more likely to exit the MSSP. Therefore, the regional adjustment causes an adverse selection of ACOs in the MSSP, and this, in turn, leads Medicare to wasteful shared savings payments.

To estimate the impact of the regional adjustment on MSSP savings, I compare the ACOs' spending and shared savings under the status quo to those of a counterfactual scenario where the regional adjustment is not applied. The benchmark formula for the scenario is obtained from Equation 2.4 by setting the regional weight to zero. The benchmark is fully rebased, and the regional benchmark $b_{it}^r$ coincides with the rebased benchmark $b_{it}^h$. Therefore, under this scenario, the adverse selection does not occur since ACOs need to reduce their spending below the historical benchmark to earn shared savings.

Removing the regional adjustment significantly reduces the amount of shared savings that Medicare pays to the ACOs. The third row of Panel A in Table 4 shows that, under voluntary participation, the reduction in spending driven by the elimination of "free" shared savings is 0.51 percentage points relative to the status quo. Under mandatory participation (third row of Panel B), instead, the decrease is 0.43 percentage points because the ACOs that are forced to participate generates positive savings. In terms of spending per capita, the net reduction in spending amounts to \$48 (\$1.665 billion) and \$57 (\$1.845 billion) per capita, respectively.

These lower shared savings payments are due to two main factors. First, the different composition of the set of ACOs that participate in the MSSP. From Figure 6, I observe that the mean difference in the regional deviation between the ACOs that select in the MSSP and those that select out is not statistically different from zero. This suggests that participation in the MSSP involves a larger number of ACOs with FSS spending above the regional average and a lower number of ACOs with FFS spending below the regional average. Second, among ACOs whose spending is lower than the regional average, benchmarks are reduced because positive regional adjustments are no longer applied.

The ratchet effect is even stronger in the absence of the regional adjustment. Since the benchmark is fully rebased, each dollar of spending reduction leads to an equivalent dollar reduction in the rebased benchmark. This diminishes the incentives to reduce spending over time and leads many ACOs to leave the program. Indeed, under voluntary participation, the participation rate decreases significantly from 56.2% to 46.4%, and spending among participating ACOs increases slightly compared to the status quo (0.13 percentage points).

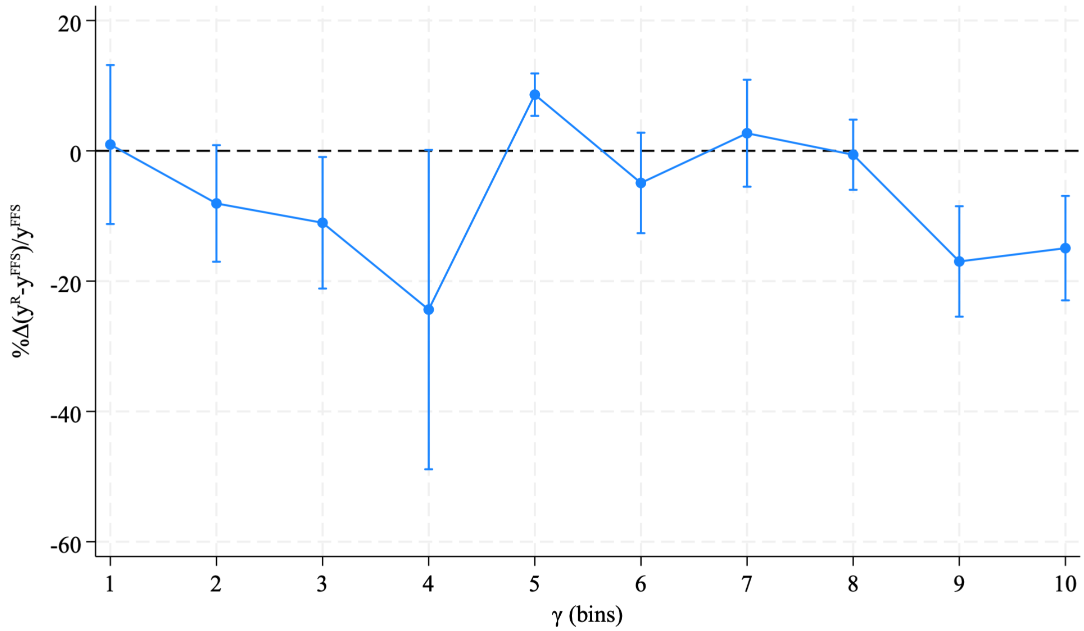


Figure 6: Adverse Selection under "No Regionalization"

*Notes*: This figure shows the test for the adverse selection across different levels of effort cost efficiency. The ACOs' participation choices are obtained under the counterfactual scenario where the regional adjustment is not applied and the benchmark is fully rebased. The x-axis plots the deciles of the distribution of the estimated cost parameter $\gamma$. This y-axis plots the mean percentage difference (and its 95% confidence interval) of the regional deviation, $(y^R - y^{FFS})/y^{FFS}$, between ACOs that select in the MSSP and ACOs that select out. The mean difference is statistically significant when the confidence interval does not contain zero.

## 6.3 Conditional Regionalization

In Section 4, I discussed that there is a trade-off between the ratchet effect and adverse selection. The results of the counterfactual simulations are consistent with the presence of this trade-off. When the benchmark is not rebased, the ratchet effect does not occur, but the adverse selection becomes stronger. Conversely, when the benchmark is fully rebased, adverse selection does not occur, but the ratchet effect is more intense.

I propose an alternative benchmarking rule called Conditional Regionalization, which aims to balance the trade-offs between the ratchet effect and adverse selection. This approach leverages the regional adjustment to mitigate the ratchet effect while also including additional conditions to prevent adverse selection. The Conditional Regionalization modifies the rule for setting the regionalized benchmark $b^h_{it+1}$ and is illustrated in Figure 7.

Panel a of Figure 7 considers the ACOs that are more spending efficient than the region and, therefore, would be eligible for a positive regional adjustment under the status quo. Under Conditional Regionalization, to qualify for the positive regional adjustment, ACO's spending should be lower than the rebased benchmark. In other words, if these ACOs generate savings in year $t$ ($y_t < (1 + \underline{s}) \cdot b_t^h$), the positive regional adjustment is applied. If, instead, these ACOs do not generate savings in year $t$ ($y_t > (1 + \underline{s}) \cdot b_t^h$), the regional adjustment is not applied and the benchmark is fully rebased. Thus, ACOs that are more spending efficient than the region need to keep generating savings to maintain the positive regional adjustment. This condition mitigates adverse selection by reducing the participation incentives of "free" shared-savings motivated ACOs.

Panel b of Figure 7 considers the ACOs that are less spending efficient than the region and, therefore, would be penalized with a negative regional adjustment under the status quo. Under Conditional Regionalization, these ACOs are exempted from the negative regional adjustment if their spending is lower than their rebased benchmark. In other words, if these ACOs generate savings in year $t$ ($y_t < (1 + \underline{s}) \cdot b_t^h$), the negative regional adjustment is not applied and the benchmark is fully rebased. If, instead, these ACOs do not generate savings in year $t$ ($y_t > (1+\underline{s}) \cdot b_t^h$), the negative regional adjustment is applied. Thus, ACOs that are less spending efficient than the region need to keep generating savings to avoid the negative regional adjustment, and have higher incentives to stay in the MSSP.

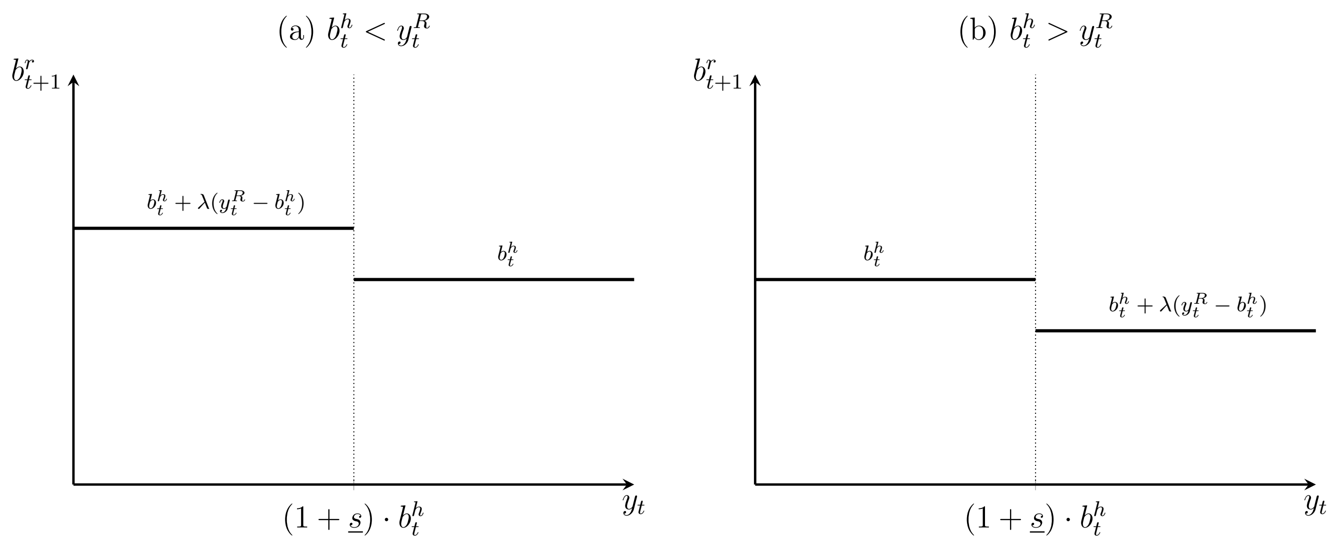


Figure 7: Conditional Regionalization

*Notes*: Let $b_{t+1}^r$, $b_t^h$, $y_t^R$, $y_t$ and $\underline{s}$ denote the regionalized benchmark, the rebased benchmark, the average regional spending, the year $t$ spending and the minimum savings rate respectively. Panel (a) shows that the positive regional adjustment $\lambda(b_t^h - y_t)$ is applied when $y_t < (1+\underline{s}) \cdot b_t^h$. Panel (b) shows that the negative regional adjustment $\lambda(b_t^h - y_t)$ is waived when $y_t < (1+\underline{s}) \cdot b_t^h$.

Table 4 shows the outcomes of this alternative benchmark rule. Under voluntary participation, total Medicare spending decreases by 1.13 percentage points relative to the status quo, whereas under mandatory participation, total Medicare spending decreases by 1.27 percentage points relative to the status quo. The decomposition of $\Delta Y^C$ reveals that, under voluntary participation, net spending per capita is lower by 1.86 percentage points, and shared savings payments increase by 0.73 percentage points. Under mandatory participation, net spending per capita is lower by 2.18 percentage points, and shared savings payments increase by 0.91 percentage points. In terms of per-capita spending, the alternative policy generates additional reductions in total Medicare spending by 156$ per-capita ($5.085 billion) under voluntary participation, and by 173$ per-capita ($5.276 billion) under mandatory participation.

The increase in shared savings payments is due mainly to the significant reduction in net spending. Under the alternative policy, adverse selection could still play a role in the amount of shared savings paid to ACOs. ACOs that, prior to joining the MSSP, have FFS spending below the regional average can obtain a positive regional adjustment. The latter clearly inflates the amount of shared savings, but, unlike the status quo rule, the alternative policy requires ACOs to reduce spending below the rebased benchmark. In other words, these inflated shared savings are only rewards to ACOs that keep reducing their spending over time.

The participation rate (57.8%) is only slightly higher than under the status quo, and the exit rate is significantly lower. However, the composition of ACOs that select in the MSSP differs substantially in terms of regional deviation. From Figure 6, I observe that the mean difference in the regional deviation between the ACOs that select in the MSSP and those that select out is not statistically different from zero. Therefore, participation in the MSSP involves a larger number of ACOs with FSS spending above the regional average and a lower number of ACOs with FFS spending below the regional average. This suggests that the additional conditions to obtain the positive regional adjustment are effective at diminishing the adverse selection.

Finally, I also observe that the exit rate is significantly lower and the spending reduction is slightly increasing over time, although most ACOs reach a plateau. This can be explained by the incentive to maintain a positive regional adjustment. This indicates that the ratchet effect is less intense than under the status quo.

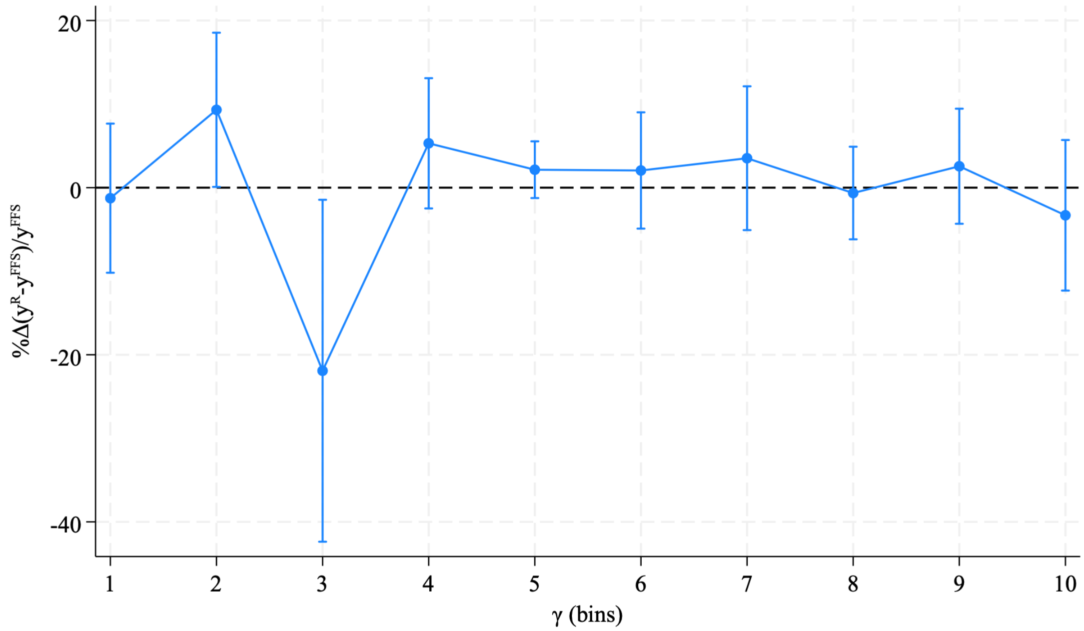


Figure 8: Adverse Selection under "Conditional Regionalization"

*Notes*:This figure shows the test for the adverse selection across different levels of effort cost efficiency. The ACOs' participation choices are obtained under the counterfactual scenario where the regionalized benchmark is illustrated in Figure 7. The x-axis plots the deciles of the distribution of the estimated cost parameter $\gamma$. This y-axis plots the mean percentage difference (and its 95% confidence interval) of the regional deviation, $(y^R - y^{FFS})/y^{FFS}$, between ACOs that select in the MSSP and ACOs that select out. The mean difference is statistically significant when the confidence interval does not contain zero.

# 7 Conclusions

The Medicare Fee-for-Service (FFS) system incentivizes inefficient health care spending. The Medicare Shared Savings Program (MSSP) is a government initiative designed to reduce providers' spending relative to the FFS level. Large organizations of independent providers, known as Accountable Care Organizations (ACOs), can voluntarily participate in the MSSP. Under this program, each provider is still paid according to the FFS system, but the ACO as a whole is rewarded for keeping the average per capita spending below a benchmark. The reward, known as shared savings, is a fraction of the spending reduction achieved by the ACO.

This paper examines the impact of benchmarking rules on ACO participation and efforts to reduce spending. The benchmark faced by an ACO is the sum of two components: the rebased benchmark that depends on the ACO's own past average spending, and the regional adjustment that reflects the difference between regional average Medicare spending and the ACO's rebased benchmark. I provide empirical and model-based evidence that these two components generate two major problems: a ratchet effect and adverse selection.

First, the ratchet effect arises because the rebasement rule ties future benchmarks to past spending. This gives ACOs an incentive to avoid or delay spending reductions today in order to keep high benchmarks in the future. I show that in years when spending does not count toward future rebasement, ACOs' savings relative to their benchmark are about 40% higher than in years when spending does count. Counterfactual analysis further shows that excluding an ACO's own spending from future benchmark calculations substantially increases MSSP savings. Under the current design, MSSP reduces Medicare spending by roughly 2% relative to FFS. I estimate that eliminating the ratchet effect would lower Medicare spending by an additional 1.54% relative to the status quo.

Secondly, the regional adjustment results in adverse selection: ACOs that are ex-ante more efficient than the regional average can exploit the positive regional adjustment and earn shared savings payments without actually reducing their own spending relative to FFS. I find that ACOs receiving positive regional adjustments are about 70% less likely to exit the program. This increases shared-savings payments to ACOs that are not delivering meaningful cost reductions, inflating Medicare spending without comparable efficiency gains. Counterfactual analysis shows that a significant amount of shared savings is paid to ACOs that adversely select in the MSSP. I estimate that removing the regional adjustment would reduce Medicare spending by 0.58%, primarily by eliminating these wasteful shared-savings payments.

The counterfactual results also highlight the presence of a trade-off between the ratchet effect and adverse selection. A larger weight assigned to the regional adjustment diminishes the ratchet effect, but worsens the adverse selection. I propose an adjustment to the current MSSP design, called Conditional Regionalization, to mitigate the ratchet effect and prevent adverse selection. This rule makes two key changes to the current MSSP benchmark formula. First, a positive regional adjustment is awarded only to ACOs that reduce their spending below their rebased benchmark. Second, ACOs that are less efficient than the regional average are exempted from the negative regional adjustment if they reduce their spending below their rebased benchmark. The role of these two additional conditions is to prevent adverse selection. The ratchet effect is also mitigated since ACOs are incentivized to reduce spending over time to reach or keep a positive regional adjustment. I estimate that the Conditional Regionalization policy reduces Medicare spending by approximately 2.13% relative to the status quo. Shared savings are higher compared to the status quo, but are paid to ACOs that actually lower their spending relative to their FFS level.

These findings highlight that voluntary government programs should carefully align incentives for participation and continued spending containment. While this paper focuses on the MSSP, its insights have broader relevance to other Pay-for-Performance Programs, 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 healthcare 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.

Cardella, E. and Depew, B. (2016). Testing for the ratchet effect: Evidence from a real-effort work task. IZA Discussion Paper 9981, IZA Institute of Labor Economics.

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.

Chernew, M. E. (2025). Fee-for-service, accountable care organizations, and medicare advantage: Why? *Health Affairs (Millwood)*, 44(8):920–924.

Chernew, M. E., Heath, J., and McWilliams, J. M. (2022). The merits of administrative benchmarks for population-based payment programs. *The American Journal of Managed Care*, 28(7):e239–e243.

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

Congressional Budget Office (2024). Medicare accountable care organizations: Past performance and future directions. Report 59879, Congressional Budget Office.

Coyne, C. J., Hall, A. R., and Owens, M. (2022). The ratchet effect. GMU Working Paper in Economics 22-34, George Mason University, Department of Economics.

Curto, V., Einav, L., Finkelstein, A., Levin, J., and Bhattacharya, J. (2019). Health care spending and utilization in public and private medicare. *American Economic Journal: Applied Economics*, 11(2):302–332.

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

Cutler, D. M. (2018). What is the us health spending problem? *Health Affairs*, 37(3):493–497.

Doyle, Joseph J., J., Graves, J. A., and Gruber, J. (2017). Uncovering waste in us healthcare: Evidence from ambulance referral patterns. *Journal of Health Economics*, 54:25–39.

Eijkenaar, F. (2013). Key issues in the design of pay for performance programs. *The European Journal of Health Economics*, 14(1):117–131.

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.

Fisher, E. S., Bynum, J. P., and Skinner, J. S. (2009). Slowing the growth of health care costs—lessons from regional variation. *The New England Journal of Medicine*, 360(9):849–852.

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.

Gandjour, A. (2024). Modelling the cost-effectiveness and budget impact of pay-for-performance programs in health care. *BMC Health Services Research*, 24:1484.

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.

Lyu, P. F., Chernew, M. E., and McWilliams, J. M. (2023). Benchmarking changes and selective participation in the medicare shared savings program. *Health Affairs (Millwood)*, 42(5):622–631.

Mendelson, A., Kondo, K., Damberg, C., Low, A., Motúapuaka, M., Freeman, M., O'Neil, M., Relevo, R., and Kansagara, D. (2017). The effects of pay-for-performance programs on health, health care use, and processes of care: A systematic review. *Annals of Internal Medicine*, 166(5):341–353.

Norton, E. C. (2024). Economic incentives in pay-for-performance programs. *The Reporter*, (1):13–15.

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

Weitzman, M. L. (1980). The "ratchet principle" and performance incentives. *The Bell Journal of Economics*, 11(1):302–308.

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, I will compute the historical rebased benchmark $\text{hb}_k$, the regionalized benchmark $\text{rb}_k$, and the updated benchmark $\text{ub}_k$. 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.[13]

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

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

benchmark[14]

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

where $\pi^k_{by3}$ 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 $\mathrm{rb}_{by3}$ 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 $\pi^k_t$ is the share of segment $k$ in performance year $t$. The blending percentage $\alpha$ 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.[15]

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

[14] 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.

[15] 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.

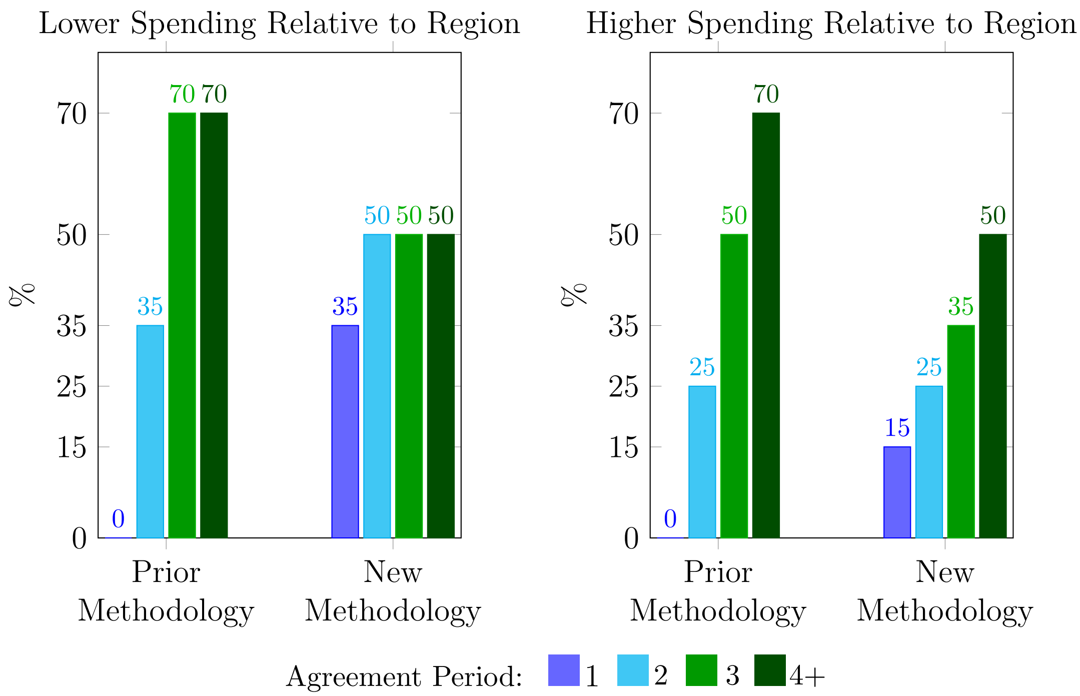


Figure 9: The figure shows the Regional Blending Percentages $\alpha$ before (Prior Methodology) and after the 2019 policy change (New Methodology), and over different agreement periods.

weighted average of the updated benchmarks of each segment of the population ($\text{ub}_t^k$).

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

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

The risk ratios $\text{rr}_t^k$ 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 $\text{tf}_t^k$ The trend factor $\tilde{\text{tf}}_{byj}^k$ is the growth rate in FFS prices and utilization between the benchmark year BY3 and the performance year $t$.[16]

**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

[16]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 $c$
- $\text{hb}_i^k$: 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:

- $\text{NFFS}_t^k$: national risk-adjusted assignable FFS expenditures in year $t$, type $k$
- $\text{ab}_{ict}^k$: person-years of type $k$ assigned to ACO $i$ in county $c$ in year $t$
- $\text{ab}_{ct}^k$: 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.[17]

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

[17] 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 Historical Rebased Benchmark Example

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 10. 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.

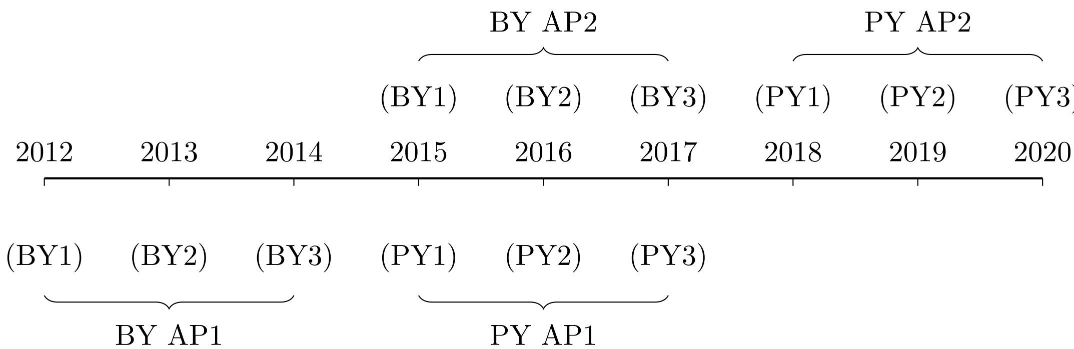


Figure 10: Timeline of MSSP Benchmark Rebasement

*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.

## A.4 5-Year AP Cycles

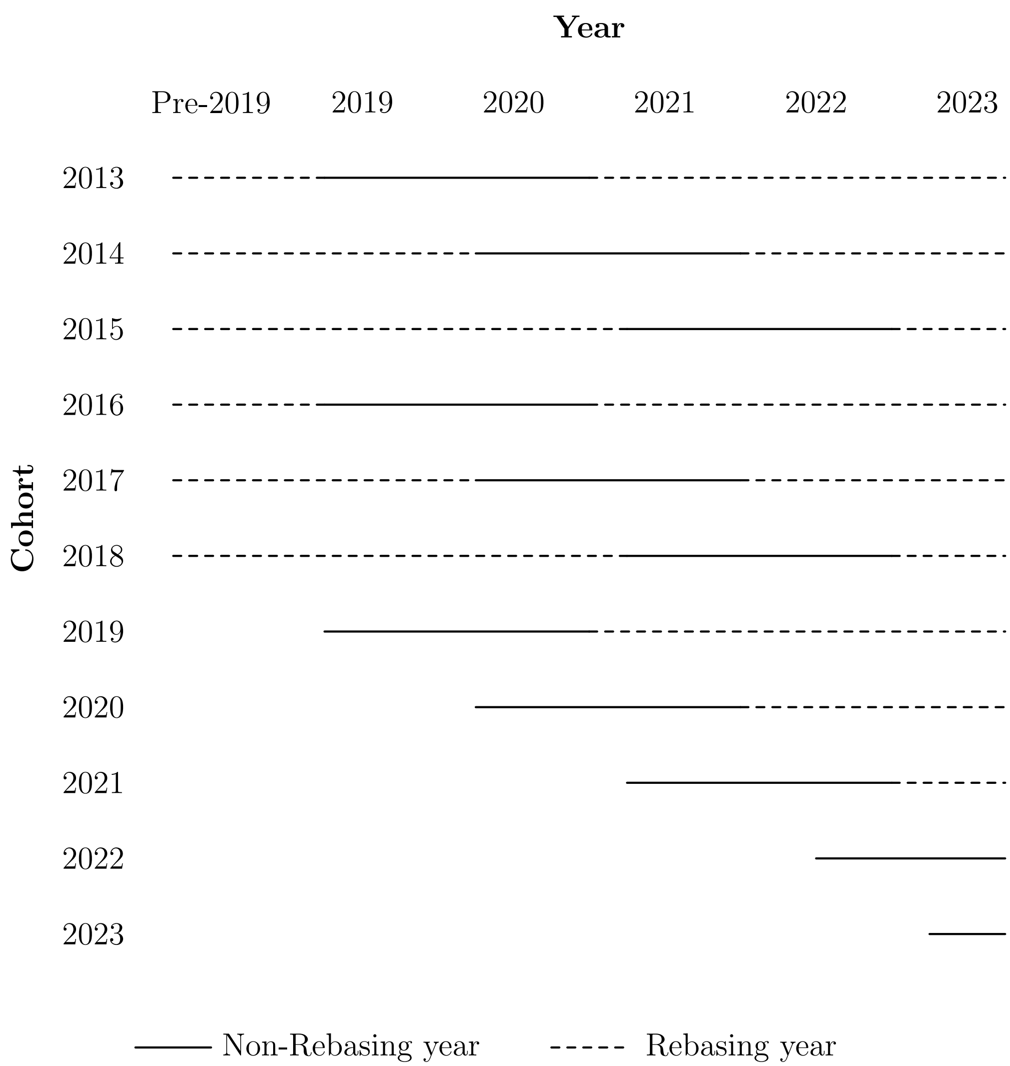


Figure 11: Illustration of MSSP policy change introducing two non-benchmark years in each 5-year agreement period. Each line corresponds to a cohort of ACO entry years. Red segments represent non-benchmark years; blue segments represent benchmark years.

## 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 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

In this section, I show the derivation of the expected shared savings under the distributional assumptions in Section 4. Let $SS^1$ and $SS^2$ denote the shared savings payed to the ACO under the one-sided and two-sided contracts respectively. For ease of exposition, I removed the ACO subscripts $i$. The shared savings under a one-sided contract are given by

$$SS_t^1 = \begin{cases} 0 & \frac{b_t - y_t^M}{b_t} \leq \underline{s}, \\ \text{ssr}_1 \left(b_t - y_t^M\right) & \frac{b_t - y_t^M}{b_t} > \underline{s}, \end{cases}$$

where

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

The expected shared savings are given by

$$\begin{aligned} \mathbb{E}[SS_t^1 \mid e_t] &= \text{ssr}_1 \, \mathbb{E}\left[b_t - y_t^M \,\middle|\, \frac{b_t - y_t^M}{b_t} \geq \underline{s}\right] \Pr\left(\frac{b_t - y_t^M}{b_t} \geq \underline{s}\right) \\ &= \text{ssr}_1 \, \mathbb{E}\big[b_t + e_t - y_t^F \,\big|\, y_t^F \leq e_t + b_t(1-\underline{s})\big] \Pr\big(y_t^F \leq e_t + b_t(1-\underline{s})\big) \\ &= \text{ssr}_1 \Big[(b_t + e_t) \Pr(y_t^F \leq k) - \mathbb{E}\big(y_t^F \mid y_t^F \leq k\big) \Pr(y_t^F \leq k)\Big] \end{aligned}$$

where $k \equiv e_t + b_t(1-\underline{s})$.

Using the distributional assumption on $y_{it}^{FFS}$, $y_t^F \sim \mathcal{N}(\mu_t, \sigma_t^2)$

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

Using the properties of the of the conditional normal distribution, it can be showed that the expected shared savings are given by

$$\mathbb{E}[SS_t^1 \mid e_t] = \text{ssr}_1 \cdot (b_t + e_t - \mu_t) \cdot \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right) + \text{ssr}_1 \cdot \sigma_t \cdot \phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right)$$

The derivative with respect to $e_t$ is given by

$$\frac{\partial}{\partial e_t}\mathbb{E}[SS_t^1 \mid e_t] = \text{ssr}_1 \cdot \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma}\right) + \frac{\text{ssr}_1}{\sigma_t} \cdot \underline{s} b_t \cdot \phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right)$$

Similarly, under the two-sided contract

$$SS_t^2 = \begin{cases} (1-\text{ssr}_2)\big(b_t - y_t^M\big) & \text{if} \quad \dfrac{b_t - y_t^M}{b_t} < -\underline{s} \\ 0 & \text{if} \quad -\underline{s} \leq \dfrac{b_t - y_t^M}{b_t} \leq \underline{s}, \\ \text{ssr}_2\left(b_t - y_t^M\right) & \text{if} \quad \dfrac{b_t - y_t^M}{b_t} \geq \underline{s}, \end{cases}$$

The expected shared savings are

$$\begin{aligned}\mathbb{E}[SS_t^2 \mid e_t] =& \text{ssr}_2 \cdot (b_t + e_t - \mu_t) \cdot \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right) + \text{ssr}_2 \cdot \sigma_t \cdot \phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right) + \\ & (1-\text{ssr}_2) \cdot (b_t + e_t - \mu_t) \cdot \left[1 - \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right)\right] - \\ & (1-\text{ssr}_2)\sigma_t\phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right)\end{aligned}$$

and the derivative with respect to $e_t$ is

$$\begin{aligned}\frac{\partial}{\partial e_t}\mathbb{E}[SS_t^2 \mid e_t] = & \text{ssr}_2 \cdot \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma}\right) + \frac{\text{ssr}_2}{\sigma_t} \cdot \underline{s}b_t \cdot \phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma}\right) \\ & (1-\text{ssr}_2) \cdot \left[1 - \Phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma_t}\right)\right] + \frac{(1-\text{ssr}_2)}{\sigma_t} \cdot \underline{s}b_t \cdot \phi\left(\frac{e_t + (1-\underline{s})b_t - \mu_t}{\sigma}\right)\end{aligned}$$

## 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

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

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

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

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

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

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

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

and moving forward one period

$$\tilde{R}_{t+1}\frac{\partial \pi_{t+1}^M}{\partial e_{t+1}} = \left[\frac{\partial v_{t+1}^M}{\partial \tilde{y}_{t+1}} - \frac{\partial \pi_{t+1}^M}{\partial b_{t+1}}(1-\lambda_{t+1})\mathbb{1}(\mathrm{PY}_{t+1} = 1)\right] R_{t+1}$$

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

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

It can be easily shown that

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

Thus, I Euler equation becomes

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

# 8 Appendix D

## 8.1 D.1 Likelihood Function

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

## 8.2 D.2 Expectation-Maximization Algorithm

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

Maximizing the log likelihood of observed data now requires that one solves for both $\theta$ and $\omega$. 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.

I 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 $v_t^j$, I 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 $\theta$, 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 $P$ | %$\Delta$ Spending Selected In $\Delta y^I$ | %$\Delta$ Spending Selected Out $\Delta y^O$ | %$\Delta$ Spending Gross SS $\Delta y$ | Shared Savings Payments $\Delta ss$ | %$\Delta$ Spending Net of SS $\Delta Y$ |
|---|---|---|---|---|---|---|
| *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) $\Delta y^I$ is the percentage change in the FFS spending (net of SS payments) among the ACOs that select MSSP, (3) $\Delta y^O$ is the percentage change in the FFS spending (net of SS payments) among the ACOs that select MSSP, (4) $\Delta y$ is the overall percentage change in the FFS spending (net of SS payments) (5) $\Delta SS$ is the total percentage change in the shared savings payments, and (6) $\Delta Y$ 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).