Reallocating Bonus Payments Through Competition to Improve Medicare Advantage Plan Quality: A Dynamic Game Approach

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Abstract

This paper explores how competition among firms can be used to improve the quality of plan offerings in a managed care setting like Medicare Advantage through changes in the reimbursement policy. In a managed market, private firms provide government sponsored services at regulated prices and compete for subsidies. Our paper studies how firms offering Medicare Advantage plans compete in terms of quality and evaluates how the markets would evolve under a competitive bonus payment system rewarding them based on their relative quality performance in a local market. We introduce a dynamic discrete game model of firm quality investment choice and use it to estimate the cost of quality improvements. The estimated model is used to predict the market outcomes in terms of average plan quality under the alternative payment system by calculating the counterfactual equilibria and simulating the markets forward. Our results show that 65% of the counties improve under the new payment rule compared to their observed outcomes in the data, with underperforming counties improving more.

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1 Introduction

Medicare is a national health insurance program in the United States that provides government sponsored insurance coverage to eligible beneficiaries, mostly comprised of citizens above the age of 65. The traditional Medicare works on a fee-for-service basis where the government pays for a portion of a beneficiary's costs of any covered medical service. A potential drawback of such government operated healthcare services is the inefficiency that stems from the lack of incentives to improve and innovate due to the absence of competition. Managed competition in healthcare lets private entities deliver these public health insurance services aiming to reduce the cost of such provisions. Competition among profit-maximizing firms is believed to provide the incentives to improve efficiency which can be exploited in a properly designed market. Such private delivery of public health insurance has been a growing phenomenon in the United States in recent times (Gruber, 2017) primarily based on this rationale.

The Medicare Advantage (MA) program allows private insurers to provide traditional Medicare services to eligible beneficiaries and subsidies are paid by the government to the insurers for every beneficiary they enroll. Beneficiaries can choose from a set of available plans in a local market and forgo traditional Medicare services. Private insurers compete with each other as in a normal insurance market for beneficiary enrollment and generate revenue primarily through government reimbursements. However, designing such a managed healthcare market is challenging and comes with a lot of unanswered issues that are being debated by economists and policymakers. One such pressing concern is monitoring the quality of service provided by private insurers. Competition in health insurance markets may fail to improve health outcomes if consumers are not able to identify high-quality plans (Abaluck et al, 2020) and thus may require interventions.

This paper explores how firms in a managed care setting like Medicare Advantage compete in terms of quality and how it can be improved by generating more competition at the local market level. We introduce a model of dynamic discrete game where firms choose the quality of their offered insurance plans in each period with a costly investment. Our model captures and quantifies the strategic interaction among firms while choosing plan quality. It also captures the intertemporal nature of the game where investment in quality in one period affects the outcomes and payoffs for the next period.

We use the Centers for Medicare and Medicaid Services (CMS henceforth) assigned star ratings as an objective measure of plan quality for our purpose. The plan star ratings are publicly available and provide the beneficiaries with information regarding quality. CMS also pays bonus subsidies to plans with higher star ratings. We provide the details regarding their calculations in Section 2. Thus, under the condition that the consumers value quality, a firm's payoff is dependent on both its own plan quality and also the quality of competing plans through the market share. However, the current quality bonus payments are based only on the absolute value of a plan's quality rating and are independent of the quality of its competitors. There exists some empirical evidences casting doubt on the ability of the current financial incentives to improve quality (Layton and Ryan, 2015).

The aim of this paper is to predict if the quality of Medicare Advantage plans can be improved by inducing quality competition among firms through changes in the reimbursement policy. We do this by introducing a new quality bonus payment system where firms are paid based on their relative performance compared to their peers in a local market area. In other words, firms earn bonuses if their plan quality is better than other plans in the market. We consider bonus payments in the form of transfers from low-performing to high-performing plans. This payment policy change can generate more competition among firms and we evaluate its effects in terms of quality outcomes.

It is important to understand the nature of the strategic interaction among firms in terms of quality to assess the effects of this proposed payment policy change. We introduce a framework where beneficiaries choose plans based on their characteristics, plan specific heterogeneity, and quality ratings and multiproduct firms choose equilibrium prices, and whether to invest in quality improvement in each period. Profit maximizing firms take into account the strategies of their competitors when investing in quality. We estimate the cost of such quality improvement initiatives in the context of Medicare Advantage using our dynamic discrete game model. The study of quality investment choice in a managed healthcare market under strategic interactions is an important contribution of this paper.

Implementing a dynamic game model in the context of managed healthcare markets is challenging. The payoff relevant state space for the firms are large as they take into consideration characteristics of their own, their competitors, and also market characteristics. Some of these variables are continuous which provides computational challenges while solving for the value function. Moreover, their relationship with the payoffs is not straightforward. We deal with this problem of a dense state space by assuming a linear parametric approximation of the value function (Sweeting, 2013) which reduces the computational burden of our estimation procedure. Given the estimates of our structural parameters, we simulate the Medicare Advantage markets forward by calculating the equilibrium policy function of the firms under the new bonus payment rule and predict how each market would evolve in terms of offered plan quality.

Our counterfactual analysis has important policy implications. The current bonus payment system in Medicare Advantage rewards plans if their quality ratings are above a national threshold. This can generate regional differences in government spending as shown in Figure 2 with three example markets. Under this payment system, government expenditure on quality bonuses is skewed towards Market 3 where all the plans have a quality rating above the threshold whereas Market 1 receives none. However, this difference in quality ratings across markets can be driven by local factors. For example, Market 1 might have an unhealthier population making it difficult for the plans there to improve their ratings and these differences are not taken into account by the current payment system. Also, the incentives to improve may vary across markets. Plans which are closer to the national threshold have more incentives to improve as a smaller investment takes them to bonus status. Thus markets with more marginal firms may see more quality investments and consequently more reimbursements from the government.

The counterfactual bonus payment rule we implement is based on the Medicare Payment Advisory Council (MedPAC) report to Congress in 2019 which addresses this issue. As illustrated in Figure 3, under the counterfactual payment rule, some plans in every market get access to quality bonus payments. Also, this payment system distorts the incentives of the firms to invest in quality. In contrast to the threshold based payment rule, a small improvement in quality for low performing plans can earn bonus payments if it makes them better than other plans in the market. This can potentially generate more quality competition in every market regardless of their initial conditions as the firms will try to outperform each other in terms of quality. In the context of our empirical analysis of Medicare Advantage, this is a relevant problem as there exists regional disparity in terms of average plan quality across counties as shown in Figure 5. We explore if the quality of care in the underperforming Medicare Advantage markets can be improved under the new payment policy.

The results predict that under the new bonus payment system 65% of the studied counties perform better when compared to the observed data under the status quo payment policy and that more counties will have a quality rating greater than 4 stars. This improvement is mostly seen in historically underperforming markets that are observed to have lower average ratings in the data. The results are indicative of the fact that the quality of care can be improved by introducing payment rules that induce more competition among firms. We also observe less variation in average plan quality across counties in our counterfactual, with most markets having an average quality rating between 4 and 4.25 stars reducing the heterogeneity in access to quality across regions. Though our estimates are specific to the Medicare Advantage markets, these results provide key insights regarding the proper use of financial incentives to improve the quality of care that may apply to other similar markets.

Related Literature. We contribute to the existing literature regarding managed healthcare markets and Medicare Advantage. Gruber (2017) studies the changing nature of public health insurance in the United States and the extensive use of "managed competition" approach employed by the government to deliver health insurance. We share similar motivations to explore how these markets work though differ methodologically. Previous papers have studied the nature of competition and issues of subsidy design in these markets. Miller et al. (2019) address the issue that the market benchmarks based on which CMS pays subsidies to individual plans are sub-optimally set and find the optimal benchmarks to maximize consumer surplus. Curto et al. (2019) study how market competition works in the managed competition setting of Medicare Advantage and the surplus generated by the competitive bidding process. Decarolis, Plyakova, and Ryan (2020) look at the interaction between strategic insurers and the subsidy mechanism in Medicare Prescription Drug plans. Though the aforementioned papers are similar to our work in exploring issues related to competition and subsidy design in a managed care setting, they study the implications of these factors on consumer surplus without explicitly considering the quality of care. Our paper focuses more on the problems regarding quality offerings in a similar market and explores the scope of improving the same through competition generated by subsidy incentives.

Previous papers have studied market structure, competition, and quality in other different market structures. Hoxby (2000) studies how competition among public schools affects education quality. Fan (2013) studies the quality of content in newspaper markets and how the quality offerings are affected by mergers under a static framework. We introduce a dynamic model for understanding the relationship between competition and product quality which captures the time lag between investment and outcome.

Our paper contributes to the existing literature regarding quality ratings in Medicare Advantage. Reid et al (2013) study how star ratings affect plan choice in Medicare Advantage by the beneficiaries. Similar work regarding information and publicly available performance reports and their effect on choice in healthcare and insurance markets have been done by Farley et al (2002), Scanlon et al. (2002), Wedig et al. (2002), Dafny and Dranove (2008), Darden and McCarthy (2015), and Handel and Kolstad (2015). Fioretti and Wang (2021) show how the current quality bonus payment system can widen the inequality in accessing social services by private insurers selecting healthier enrollees. However, we look at the supply side problems in the Medicare Advantage markets associated with plan quality offerings.

Some previous papers explore the supply-side implications of the star ratings and quality bonuses in Medicare Advantage. Adrion (2019) finds that contracts operating in more concentrated MA markets receive higher star ratings and relates how market competition affects star ratings through negotiations between private insurers and providers while forming provider networks. Sen et al. (2021) explore in more detail how narrow networks in Medicare Advantage translate into higher star ratings. We differ in our methodology from these papers and provide a structural framework for analyzing the effect of competition on quality offerings by firms. The introduction of a dynamic game to analyze this problem is a novel contribution of our paper.

This paper is methodologically indebted to the extensive existing literature on the estimation of dynamic games. We follow Ericson and Pakes (1995) to assume that firms use stationary Markov Perfect Nash Equilibrium in strategies. Our model and solution procedure for the value function by linear parametric functional approximation is based on Sweeting (2013), and Benitez-Silva et al. (2000). Our estimation procedure closely follows Pakes, Ostrovsky, and Berry (2007) We implement a nested pseudo-likelihood approach for estimating the dynamic game based on Aguirregabiria and Mira (2007, 2010). Our model of dynamic game also borrows from Aguirregabiria and Ho (2012), Aguirregabiria (2012), and Blevins (2014).

We organize the rest of the paper as follows. We discuss details regarding the Medicare Advantage and star ratings in Section 2. In Section 3 we give the details regarding the CMS data we use for our analysis. We introduce our model in Section 4 and proceed to estimation of the parameters in Section 5. In Section 6, we describe how we simulate the counterfactual market outcomes and discuss the results.

2 Empirical Setting and Data

In this section we provide a detailed discussion regarding Medicare Advantage and our empirical setting.

2.1 Medicare Advantage

In response to the increasing costs of Medicare, in 1982 Congress authorized Medicare administrators to engage in a series of trials in which the government handed over management of the medical care of selected groups of Medicare enrollees to private insurers in exchange for a fixed payment that did not vary with the realized medical expenditures of each individual. Though it was not a success initially, it laid the foundation for introducing managed competition in Medicare and went through a series of changes and modernization that led to the formation of the Medicare Advantage program.

Enrollment in MA has increased more than double from 12 million or 26% of total Medicare eligible population in 2011 to 26 million or 42% of Medicare population in 2021 . During this period enrollment grew around 10% every year. At $343 billion per year, it comprises around 46% of total Federal Medicare spending and is one of the fastest growing health sector in the United States.

Enrollment in MA plans takes place during the Open Enrollment Period from October 15 to December 7. Beneficiaries may choose a new plan or switch to a different plan during this period.

Each MA beneficiary has to pay a premium called the Part B premium and may need to pay an additional private plan premium as well. This additional premium is determined by a process where each MA plan must report their operation cost to CMS for providing services in a particular county before the enrollment period. Each county is assigned a benchmark that represents a weighted average of FFS spending in that county. Plans bidding below the benchmark charges a 0 premium while plans which bid above the benchmark charge the difference between the bid and the benchmark as extra premium.

Medicare Advantage allows beneficiaries to choose from differentiated insurance plans which is not possible in traditional Medicare. Where traditional Medicare provides uniform benefits to all enrollees, private insurers compete in terms of prices, plan quality and supplementary benefits and design plans to cater to the needs of different target population, thereby increasing the choice set of beneficiaries. Though this might be considered a desirable feature of the market, it is also necessary to make sure that well informed choices can be made. Thus, in this kind of market publicly available indicator of plan quality is of utmost importance. To serve this purpose, the CMS uses a 5 star rating system in order to measure plan quality.

2.2 Star Rating

Since 2009, the CMS has provided comprehensive data regarding MA plan performance through its Star rating program with the goal to encourage consumers to choose high quality plans and also to incentivize health insurers to improve their service quality. The ratings are assigned at the MA contract level and all plans under the same contract have the same rating. The star rating is an objective measure of plan quality that is calculated based on observable performance scores belonging to the following broad categories.

- Outcome (Improving physical health)

- Process (Cancer screening, Flu vaccination, etc.)
- Patient experience (Customer service, getting appointment quickly, etc.)
- Access (Timely decision about appeals)

The measures come from various sources and comprises of data collected by CMS contractors, CMS administrative data, surveys of enrollees and also data supplied by health and drug plans. The overall score of a contract is calculated as a weighted average of these scores and the ratings are assigned using a clustering algorithm where contracts having similar aggregate scores belong to same cluster and thus have the same rating. The star ratings act as the only measure to assess the quality of MA plans' service.

The star ratings besides being a source of plan quality information for the consumers are also of interest to private insurers offering MA plans as they constitute a source of generating extra revenues. One obvious reason is that if consumers take into account observed ratings while making a plan choice, plans with higher ratings compared to their competitors might capture a larger portion of market share. Also, a higher star rating in a particular market is usually associated with a higher benchmark and a higher rebate percentage the plan faces which increases the plan payment for a given bid, also referred to as Quality Bonus Payments (QBP). This was introduced following the Affordable Care Act of 2010 which mandates that plan payments should be dependent on the quality.

Plan quality have improved in MA over the years, especially after the introduction of QBP as shown in Figure 1. This pattern is indicative of the fact that private insurers respond to these bonuses by improving quality of offered plans.

2.3 Plan Payments

Every MA market is characterized by a CMS assigned benchmark B_{mt} based on which all subsidies are paid. The subscript m denote a particular market and t a particular period. Each plan reports its cost of providing service b_{jt}. For each individual beneficiary i enrolled in plan j, CMS reimburses the plan Reb_{ijt} using the following rule:

$$\text{Reb}_{ijt} = \begin{cases} B_{mt} \times \text{R}_{it} & \text{if } b_{jt} \geq B_{mt} \\ \left(b_{jt} + \lambda_{jt}^{B} \times \left(B_{mt} - b_{jt}\right)\right) \times \text{R}_{it} & \text{if } b_{jt} < B_{mt} \end{cases} \tag{1}$$

where λ_{jt}^{B} is the rebate percentage or the portion of the surplus the plans get to keep and R_{it} is the risk score assigned by the CMS to each individual beneficiary measuring how likely the beneficiary is to incur medical expenses relative to the county benchmark. An average beneficiary in the market receives a risk score of 1. These risk scores are calculated based on individual characteristics and prior medical history.

Plans reporting a cost b_{jt} more than the benchmark B_{mt} receives only the benchmark amount and the difference is charged as an extra premium from the beneficiaries. If the reported cost is less than the benchmark, then the plan receives its reported amount and part of the difference between the benchmark and the reported cost as a reward for cost saving. This rebate percentage is defined by λ_{jt}^{B}.

2.4 Quality Bonus Payments

Star rating of a plan affects its payments through the benchmark and rebate percentage in every market. A plan under a contract with a rating greater than or equal to 4 star has its benchmark increased by 5% (10% in eligible counties). Rebate percentages are 50% for 3 stars or fewer and increased to 65% for 3.5 to 4 star and 70% for 4.5 star and above.

Thus keeping everything else equal, the current payment system rewards plans with higher star ratings favorably. However, these bonuses are paid based on absolute measure and not relative measure. In Section 6 we analyze the effect of the proposed change in the payment rule where quality bonus payments would change from an absolute measure based to a relative measure based.

2.5 Quality Improvement Initiatives

In an effort to evaluate if the quality bonus payments in practice translated to increasing trend in the plan quality that we observe in the data and to understand how the QBP may affect organizations' operations, CMS collected information regarding the quality improvement (QI) activities of MA plan sponsors through a contract-level survey and case studies with selected MA sponsors in 2016 [1].

The majority of survey respondents (88 percent) indicated that the budget for the contract's QI activities increased between 2010 and 2013. Linking survey results about organizations' QI activities to Star Ratings changes, we found that just one QI activity, provider incentive programs, was associated with changes in star ratings from 2013 to 2015. We enumerate some of the most important characteristics and avenue of MA contract's QI initiatives as stated in CMS reports in order to motivate our strategic model of firm choice.

i) MA organization's ratings and their competitors' ratings drive organizational star rating strategies:

This illustrates how competition can mitigate or enhance the effects of QBP incentives and the Star Ratings program more broadly to attain higher star ratings. Respondents noted that in a market where all the competitors are 3-star plans, having a 4.5-star rating is good enough. But in markets where there are high quality contracts on the cusp of very high ratings, they feel acute pressure to achieve 5 stars.

ii) Provider Network formation and provider incentives are an important pathway of improving

[1] https://innovation.cms.gov/files/reports/maqbpdemonstration-finalevalrpt.pdf

ratings:

Most experts in this industry agree that provider network formation is an important aspect of improving star ratings. Over half of MA plan's star ratings are based on physicians delivering appropriate services including providing screening tests, vaccines and managing chronic conditions. Such clinical measures cannot easily be improved by plans without a significant cooperation from primary care physicians and other clinicians. Therefore, significant provider cooperation and buy-in are necessary for improving star ratings.

All MA insurers interviewed focused on star ratings when forming narrow networks, though different insurers took different approaches. One MA insurer that focuses on HMO products said that they narrow primary care networks because they believe primary care drives star ratings. The large national MA insurers said they generally form narrow networks around already high-performing physician groups or hospital systems that have proven track records on quality and utilization. All the health systems echoed the MA insurers' emphasis on star ratings, and the two health systems that partially or fully own an MA plan said their high star ratings were integral to their success in MA. All but one MA expert also agreed that star ratings are a crucial consideration for MA insurers when forming networks.

This discussion motivates our model where firms' action choice represents these QI activities in our empirical setting. In each period, the firm decides whether to invest in these activities. Quality improvement initiatives are costly and improve the quality rating and earns bonus payments in the future period. We use a dynamic model to capture this intertemporal nature of choice and payoff. Specifically, we use dynamic game to capture the strategic interaction between firms as discussed in Section 3.

2.6 Data

We use publicly available data from various CMS sources for our analysis. We use aggregate MA enrollment for every plan in every market. The data reports monthly enrollment which we convert to annual enrollment by taking an average. The Plan Benefit Package data provides plan level information regarding the premium and plan characteristics as provided by the plans during the annual bidding process. The plan payment data provides information regarding the average per month per member Part B payment and the rebate payment to each plan and the average risk score of the beneficiaries enrolled. The landscape folder provides data regarding service contract area and the performance data provides detailed information regarding the star rating and individual measures.

We have 1,50,039 year-county-plan level observations from 2013 to 2016 comprising of HMO and PPO plans. The plans differ in the subsidiary services they offer. Among the observed plans, 38% of the plans provide vision coverage, 62% of the plans provide hearing coverage, and 50% of the plans have dental coverage included. Table 1 shows the summary statistics of the MA markets that we use in our analysis. We select these years as most changes in star ratings are observed to occur during this period after the introduction of the quality bonus payments. The average rating of available plans are observed to increase from 2013 to 2016. The number of observations where rating improves in the next period remains fairly stable across the years. We observe maximum improvement of the quality ratings going from 2013 to 2014. Average MA enrollment went up every year during this period. Average contract revenue in each market which is the sum of the total premium earnings and government subsidies shows an upward trend during these years. The increase in average revenue is due to both expansion of the MA program and also more bonus earning by star rating improvement.

3 Model

We introduce a stylized model of a managed competition setting where firms offer differentiated insurance plans in each market generate revenue by enrolling beneficiaries in a market. The two main components of our model are the beneficiary demand function and the profit function. In each period, a plan's market share is determined by the demand function where the beneficiaries choose from a set of alternatives and their choice depends on the plan characteristics, annual premium, observed star rating, plan level heterogeneity, and the beneficiary's private taste. For each beneficiary a firm enrolls in its plans, it earns a variable profit which comprises of the plan premium, government subsidies, and incurs a marginal cost of providing service. The government subsidies depend on the given market characteristics and the quality ratings, marginal costs depend on the firm characteristics, and the equilibrium plan premiums are set by the firms. In every period, the firms can decide to invest in quality and incurs an investment cost associated with it.

Quality investment choice of the firms determines the quality ratings for the next period. The firms are forward looking and maximize their expected discounted payoff while investing. This payoff depends on the firms' own quality ratings and also that of their competitors and quality investments are strategic. Our model of dynamic game closely follows Aguirregabiria and Ho (2012) and Sweeting (2013).

3.1 Framework

Medicare Advantage firms $f = 1, 2, ..., \mathcal{F}_m$ in a particular market m plays a discrete time infinite horizon game with periods $t = 1, ..., \infty$. Each firm offers a set of plans in each market. Markets are assumed to be independent of each other. In each period, a firm observes its payoff relevant state variables denoted by S_{fmt} which includes firm's own characteristics, competitors characteristics and market characteristics. These state variables are assumed to be public information observed by all the firms in a market. A market is characterized by the CMS assigned subsidy benchmark B_{mt}, total number of MA eligible population M_{mt}, and FFS spending quartile. County benchmarks determine the plan specific subsidy amount using the reported plan cost and the CMS payment rule as described in the previous section. We assume that in each period MA contracts (firms) observe the market characteristics, their own characteristics, and competitors' characteristics and set the premiums of each plan it offers and makes a quality investment choice. Premiums affect the profit of current period whereas investment in quality improvement affects their ratings and consequently payoffs for the next period. We drop the market index m below for notational simplicity.

In each market period, a firm f offers a set of plans $\mathcal{J}_f$ and generates revenue by selling their plans to eligible beneficiaries. The set of firms and plans are assumed to remain the same over time. For each individual beneficiary who enrolls in one of their plans, a firm receives the premium and the per member subsidy assigned by CMS and incurs a marginal cost. The firm also chooses whether to invest in quality improvement. Any decision to improve quality results in an increase in star ratings in the next period and incurs a quality investment cost.

In every period, the firms choose an action $a \in A(S_{ft})$ from a discrete set of possible actions regarding their quality rating in the next period. A firm may decide to improve its rating by half star, one star or not improve at all. The action choices are state dependent as, for example, contracts with a current rating greater than 4 cannot improve their rating by one star in the next period. Each action choice of the firm is associated with private information, independent and identically distributed (i.i.d.) payoff shock ν_{aft}. These shocks are distributed Type 1 extreme value.

The sequence of the firm's decision is as follows

1. Each firm observes payoff relevant state variable S_{ft}
2. Each firm sets a premium for each plan $j \in \mathcal{J}_f$ offered in the market and reports their cost of providing service to CMS

3. Each firm observes the vector of action specific payoff shocks $\nu_{ft} = \{\nu_{aft} : a = 0, 1, 2\}$ and chooses an action $a \in A_{S_{ft}}$ to maximize the discounted sum of future payoffs

4. Each firm earns variable profit $R_{ft}(S_{ft}; \beta^{dd}, \gamma^{mc})$ from beneficiary enrollment and price competition where β^{dd} and γ^{mc} are the demand and marginal cost parameters respectively.

5. Each firm incurs an investment cost for quality improvement $I(a, S_{ft}; \theta)$ and receives a payoff shock ν_{aft}

6. The state variables evolve to the next period according to firms' choices and transition rule

The firm's flow profit function given payoff relevant state S_{ft} is given by

$$\Pi_{ft}(a, S_{ft}, \nu_{ft}) = R_{ft}(S_{ft}; \beta^{dd}, \gamma^{mc}) - I(a, S_{ft}, \theta) + \nu_{aft} \tag{2}$$

I describe later in details each component of the profit function and the state transition rules.

In each period t consumer i in market m chooses a MA plan $j = 0, 1, 2, ..., J_m$ from all available plans offered in a market where $j = 0$ is the outside option of not choosing any MA plan. We let individual utility depend on observed plan characteristics, plan type, and observed and unobserved quality. The utility individual i receives from a plan j in a given period t is given by the following utility function

$$U_{ijt} = \beta^p p_{jt} + \beta^\mu \mu_{jt} + X_{jt}\beta^x + \xi_{jt} + \epsilon_{ijt}, \tag{3}$$

where p_{jt} is the annual plan premium, μ_{jt} is the CMS assigned star rating of the plan, X_{jt} is the vector of plan types and plan characteristics and includes dummy variables indicating whether certain subsidiary services like vision, hearing, and vision, are covered by the plan. ξ_{jt} is plan level characteristic that is observed by the consumers and the firms but unobservable in our model. This captures the plan-market level heterogeneity and also plan qualities that are not captured by the star ratings. ϵ_{ijt} is the beneficiary-plan specific idiosyncratic taste shock assumed to be Type I extreme value distributed. We consider X_{jt} for each plan to be exogenous. Firms choose p_{jt} and

μ_{jt} and are possibly correlated with ξ_{jt}. These two variables are treated as endogenous in out model.

The coefficients β^p, β^μ, and β^x are the demand parameters. The market share for each plan is derived from the individual choice probabilities. A consumer chooses a particular plan if the utility from that plan is greater than all other available options in the market. Under the distributional assumption of ϵ_{ijt} the choice probability is given by the following logit form

$$s_{ij} = Pr(\text{i chooses j}) = \frac{exp(\delta_j)}{1 + \sum_{k=1}^{J_m} exp(\delta_k)}$$

where the plan mean utility δ_j of plan j is given by

$$\delta_{jt} = \beta^p p_{jt} + \beta^\mu \mu_{jt} + X_{jt}\beta^x + \xi_{jt}$$

Most plans in our data are observed to be \$0 plans. It does not however mean that the beneficiaries of these plans pay a \$0 premium. Instead they pay the standard part B premium for traditional Medicare. A positive premium is thus any extra amount the plan charges in addition to this. Since all individuals choosing a plan in our setting are medicare eligible, traditional fee-for-service Medicare or a PFFS plan are considered to be the outside option.

It should be noted that the star ratings are assigned at the firm level in a particular market and not plan level. This means that plans under the same firm uses the star rating of the contract they are under. Let $\mathcal{J}_f$ be the set of plans offered by the firm f. Thus $\mu_{jt} = \mu_{ft} \forall j \in \mathcal{J}_f$.

We assume that ξ_{jt} evolves according to the following AR(1) process:

$$\xi_{jt+1} = \rho^\xi \xi_{jt} + \zeta_{jt}, \tag{4}$$

where $\zeta_{jt} \sim \mathcal{N}(0, \sigma_\zeta)$ can be interpreted as an unanticipated innovation shock that affects demand.

The variable profit is earned by firms by beneficiary enrollment in their MA plans and is given by:

$$R_{ft} = \sum_{j \in \mathcal{J}_f} \{(p_{jt} + Reb_{jt} - mc_{jt}) \times s_{jt} \times M\}, \tag{5}$$

where M is the total Medicare eligible population in the market, s_{jt} is the market share of each plan j obtained from the demand model. The marginal cost of enrolling an extra beneficiary in a plan is assumed to be constant and depends linearly on plan characteristics as follow:

$$ln(mc_{jt}) = x_{jt}\gamma^x + \mu_{jt}\gamma^\mu + \omega^{mc}_{jt}, \tag{6}$$

where ω^{mc}_{jmt} is the unobserved marginal cost component assumed to be i.i.d. distributed.

The amount of subsidy each plan receives per beneficiary is given by the payment equation and depends on the market benchmark, the star rating, and the reported costs[2]. Given the timeline of the game, the equilibrium premium for each plan in a market is determined by maximizing the variable profit R_{ft} with respect to $p_{jt} \forall j \in \mathcal{J}_f$.

In each period a firm takes quality improvement decision and incurs an investment cost $I(a, S_{ft}, \theta)$ based on its choice of action a and parameter θ. We assume the following parametric specification of investment cost:

$$I(a_{ft}, S_{ft}; \theta) = \theta^1 a_{ft} + \theta^2 a_{ft}\mu_{ft} + \theta^3 a_{ft} PS_{ft}$$

We let this investment cost depend on current star rating μ_{ft} and whether quality improvement occurred in the previous period PS_{ft} which takes the value 1 if the firm improved rating in the previous period and 0 otherwise. In the data we observe that most contracts do not improve ratings in consecutive periods. The scope of improvement is usually diminished for a contract which increased its ratings recently as the firms have to find new avenues through which the measures can

[2]The reported cost is assumed to be a function of the true marginal cost. This assumption is based on the fact that the Affordable Care Act mandates each MA plan to have a minimum medical loss ratio of 85% which is observed by the CMS through its auditing process and failure to comply results in punitive actions. Similar assumption has been used in the literature previously by Miller et al. (2019).

be improved. This effect is captured by PS_{ft}.

The star rating for the next period is assumed to evolve based on the firm's action choice as follow:

$$\mu_{ft+1} = \begin{cases} \mu_{ft} + \epsilon^{a_0}, & \text{if } a_{ft} = 0 \\ \mu_{ft} + 0.5, & \text{if } a_{ft} = 1 \\ \mu_{ft} + 1.0, & \text{if } a_{ft} = 2, \end{cases} \tag{7}$$

where ϵ^{a_0} is a discrete random variable with the following probability mass function

$$P(\epsilon^{a_0}) = \begin{cases} P_0^{\epsilon^a}, & \text{if } \epsilon^{a_0} = 0 \\ P_{0.5}^{\epsilon^a}, & \text{if } \epsilon^{a_0} = -0.5 \\ P_1^{\epsilon^a}, & \text{if } \epsilon^{a_0} = -1 \end{cases}$$

where the values of $P_0^{\nu}, P_{0.5}^{\nu}, P_1^{\nu}$ are exogenously given. During estimation they are empirically calculated as some of the contracts are observed to see a reduction in rating[3].

3.2 Value Function and Dynamic Game

We assume that firms use a stationary Markov Perfect Nash Equilibrium in pure strategies in every market. A Markov Perfect strategy Γ_f of a firm is a mapping from (S_{ft}, ν_{ft}) to a_{ft}. A firm's value function given strategies of all firms Γ is given by the following Bellman equation:

$$\begin{aligned} V^{\Gamma}(S_{ft}, \nu_{ft}) = max_{a \in A(S_{ft})}[R_{ft}(S_{ft}; \beta^{dd}, \gamma^{mc}) - I(a, S_{ft}, \theta) + \nu_{aft} \\ + \beta E\{V^{\Gamma}(S_{ft+1})|a, \Gamma_{-f}, S_{ft})\}], \end{aligned} \tag{8}$$

[3]The star rating for a contract are mostly reduced due to institutional reasons difficult to incorporate in the model. Failure to comply with CMS rules or report data on time is associated with a reduction to a one star score for the associated measure which often leads to deterioration in rating.

where $\beta = 0.95$ is the given discount factor assumed and $V^{\Gamma}(S_{ft+1})$ is the firm's value in the particular state before the realization of ν_{ft} takes place. Thus $E\{V^{\Gamma}(S_{ft+1})|a, \Gamma_{-f}, S_{ft})\}$ is the firm's expected future value given the current state, action of the firm and strategies of other firms Γ_{-f}. The expectation is taken over the possible realization of the state variables in the next period where a firm's own star rating evolves depending on firm's action a, the star rating of the competing firms evolve following Γ_{-f}, and all other state variables follow their respective transition rules.

We define the action specific value $v_f^{\Gamma}(a, S_{ft}, \Gamma_{-f})$ as the sum of the flow profit and discounted expected future value at any given state and for a particular action choice as follows:

$$v_f^{\Gamma}(a, S_{ft}, \Gamma_{-f}) = R_{ft}(S_{ft}; \beta^{dd}, \gamma^{mc}) - I(a, \theta) + \beta E\{V^{\Gamma}(S_{ft+1})|a, \Gamma_{-f}, S_{ft}).$$

Under the Type I extreme value distributional assumption of the action specific payoff shocks, the conditional action choice choice probability of a firm can be written as a logistic function of the action specific values as:

$$P_f(a|S_{ft}, \Gamma) = \frac{exp(v_f^{\Gamma}(a, S_{ft}, \Gamma_{-f}))}{\sum_{a' \in A(S_{ft})} exp(v_f^{\Gamma}(a', S_{ft}, \Gamma_{-f}))}. \qquad (9)$$

3.2.1 Approximating the Value Function

The state space in our setting is exceptionally large which poses a problem for solving the value function. A firm's payoff relevant state variables include firm's and competitors own characteristics, characteristics of its competitors, and also market characteristics. Some of these state variables are also continuous variables. Solving for the value function for all states is computationally an infeasible task. In order to address this issue we follow Benitez-Silva et al. (2000), Aguirregabiria (2012) and Sweeting (2013) and use a parametric approximation of the value function.

We assume that the value function can be approximated by linear function of K functions $\phi(\cdot)$. Given any particular state S the value function can be approximated as follows:

$$V(S) = \sum_{k=1}^{K} \lambda_k \phi_k(S) \tag{10}$$

where λ are the linear parameters and $\phi_k(S)$ $k = 1, .., K$ are the K approximating variables as a function of the state variable used for approximating the value function. We call these approximating variables for the value function. Under this assumption, solving for the value function boils down to solving for K linear parameters thereby reducing the computational complexity. We use all the observed states in the data to approximate the value function.

4 Estimation Results

I proceed by first estimating the demand parameters and the plan level unobservables ξ_{jt}. We then back out the marginal costs form firm profit maximization condition and estimate the model of marginal cost. With all the observed and estimated state variables, we estimate our dynamic parameters.

4.1 Estimation of Dynamic Model

We begin our estimation of the dynamic model by defining the expected profit for each state before the realization of action specific shock given some conditional choice probability P_f:

$$\widetilde{\Pi}\left(P_f, S_{ft}\right) = R\left(S_{ft}; \beta^{dd}, \gamma^{mc}\right) + \sum_{a \in A\left(S_{ft}\right)} P_f\left(a \mid S_{ft}\right)\left(-I(a, S_{ft}\theta) + \left(\chi - \log\left(P_f\left(a \mid S_{ft}\right)\right)\right)\right)$$

where χ is the Euler's constant. This formula is derived using the distributional assumption of choice specific payoff shocks. Given the conditional choice probability and firm's state variables, following Aguirregabiria and Mira (2007) the Bellman equation can also be written as:

$$\sum_{k=1}^{K} \lambda_k \phi_k(S_{ft}) = \tilde{\Pi}(P_f, S_{ft}) + \beta \sum_{k=1}^{K} \lambda_k E_{P_f} \left(\phi_k(S_{ft})\right).$$

The linear parameters for the value function approximation can be easily estimated from the above equation using a simple OLS.

We employ an Iterative Nested Pseudo-Likelihood estimation procedure as follows:

1. We start with an initial conditional choice probabilities P^0 by using a reduced form multinomial logit model of observed actions on set of firm characteristics and an initial guess θ^0 of the structural parameter

2. At every step of the iteration we calculate the expected profits given the state variable and conditional choice probability P_{iter} and parameter$\hat{\theta}$

3. Estimate the parameters $\hat{\lambda}^{P_{iter}}$ given the choice probabilities

4. Use $\hat{\lambda}^{P_{iter}}$ to calculate choice specific value function, using (8) to form the pseudo-likelihood function and minimize it for the estimated values of $\hat{\theta}'$

5. Use (8) to update the conditional choice probabilities to P'_{iter}

6. The procedure stops if absolute differences between P_{iter} and P'_{iter} , and $\hat{\theta}$ and $\hat{\theta}'$ are less than the tolerance level set at 10^{-4}

In our demand estimation, apart from the usual price endogeneity of demand model we also deal with the endogeneity of the observed star ratings. As the current plan level unobservable ξ_{jt} is related to previous periods ξ_{jt-1} by an AR(1) process and the current star rating depends on action choices of previous period, these two variables might be correlated.

Some prior literature regarding choice of quality like Fan (2013) uses instruments to address the quality endogeneity. However, we exploit the panel nature of the data and the AR(1) transition assumption of ξ_{jt} to address this issue. We assume that the unanticipated shocks in "innovation" ζ_{jt} is uncorrelated with μ_{jt} as it depends on the action of previous year before the realization of ζ_{jt}. Let Z be the instruments including X and μ. Under this assumption the moment condition $E(Z'\zeta) = 0$ holds true.

From (3), ζ_{jt} can be expressed as $\xi_{jt+1} - \rho^{\xi}\xi_{jt}$ where each of the $\xi_{jt} = \delta_{jt} - \beta^{p} p_{jt} + \beta^{\mu}\mu_{jt} + X_{jt}\beta^{x}$. Thus ζ_{jt} can be written in terms of all the observables and the parameter ρ^{ξ}. Following Sweeting (2013), we estimate the parameters using a 'quasi-difference moment approach'.

The marginal costs are not observed but we use firms' profit maximizing F.O.C. to estimate them by solving the system of linear equations:

$$s_{jt} + \sum_{j' \in J_f} \frac{\partial s_{j't}}{\partial p_j}(p_{j't} + Reb_{j't} + m\hat{c}_{j't}) = 0 \quad \forall \text{j in } \mathcal{J}_f.$$

We then estimate the marginal cost parameters γ^{mc} using OLS

4.2 Estimation Results

This section presents the empirical results of our model using the aforementioned estimation procedure.

Table 2 reports the estimated parameters of our demand model. These estimates in general correspond to sensible priors. For plans with a positive premium the semi elasticity of increasing premium by \$1 is around percent. An increase in star rating by one star leads to a 16 percent increase in market share. Thus we find that beneficiaries value the quality rating in choosing their MA plans. A higher star rating than the competitors leads to increased market share and increased variable profit for the firms. This is indicative of the fact that firms also compete with each other in terms of quality rating to increase enrollment, apart from the financial incentives. We also find that beneficiaries prefer plans that offer dental and hearing coverage but not vision coverage. We also find that beneficiaries prefer PPOs compared to HMOs.

Table 3 reports the marginal cost parameters. We observe that star ratings increase the cost of providing service to each extra beneficiary. Subsidiary coverage like vision, dental, and hearing increase the marginal cost. The coefficient on demand unobservable ξ_{jt} is positive and significant. In addition, cost of providing service is higher for PPO plans compared to HMO plans.

Table 4 we reports the parameters of our dynamic model which are the estimates of improving quality rating of a firm in a market. These estimates report the cost of improving a firm's star rating by half star and are reported in million dollars.

We estimate that the firms undergo a fixed investment cost of \$0.54 million every time they improve their rating. This cost increases by 1.21 million per current star rating. For example, a three star rated contract will face an additional \$3.63 million above the fixed cost. This states that improving rating becomes costlier with increase in current rating of the star. Also the cost of improving star rating in a period goes up by \$1.4 million if the contract improve its rating in the previous period.

Intuitively this makes sense as the avenues to improve quality declines as current quality of the firms improve. Higher rated contracts often employ professionals and consultants to strategize and find ways through which they can improve their rating and our estimates are reflective of these facts.

The quality investment cost parameters also help us explain how the markets have evolved given the "cliff effect" national threshold rule. This rule rewards plans having a star rating of four or above and is only based on this absolute performance measure. From the dynamic parameters it can be seen that the total cost for a 3.5 star rated contract to move to bonus status without any prior quality improvement activity is around \$4.2 million in each market. On the other hand a 2.5 star rated contract moving to 4 star over the course of two years incur a cost of around \$ 10 million. Thus the cost of moving to bonus status for low rated contract is much higher than the marginal contracts

We observe that markets which initially started with better quality plan evolved over the years to have high average plan quality whereas markets which started with poor quality plans seem to have been stuck there. Our dynamic parameters along with the current quality bonus payment policy can thus partly explain the current geographical differences in average plan quality.

5 Counterfactual

We now return to the problem of implementing the competitive bonus payment rule. After estimating the structural model parameters, we explore how markets might evolve in terms of plan rating if quality bonuses are paid to contracts performing better than their peers in the local market.

5.1 Procedure

We begin by adjusting the variable profit of each plan in a market based on the observed star rating. As proposed by CMS, we follow a budget balanced redistribution procedure, where plans having a rating lower than the median star rating of the market get a benchmark reduction of 5% and this deducted amount is redistributed equally to plans above the median star rating as increased benchmark. The rebate rate remains at 50% for plans at or below the median rating and 70% for plans above the median. This change in payment rule is intended to induce more competition among peers in the market where 'being better than the others' in a market fetches more subsidy.

Due to change in quality bonus payment structure, we begin our counterfactual by adjusting the per member subsidy of each plan in a market as stated. With all other plan characteristics in hand, we calculate the new equilibrium prices by iterating over $\frac{\partial s_j}{\partial p_j}$ matrix starting from observed prices with a non-negativity restriction. We match the data precisely when implementing this procedure with the existing payment rule. We then proceed to estimate the market shares given the plan characteristics and the new equilibrium prices.

With the counterfactual variable profits for each observed state of the firm and the parameters for quality investment initiative costs we estimate the new parameters of the value function λ^{count} using an iterative process similar to the one used in the estimation procedure. We begin with a guess of counterfactual conditional choice probabilities P_0^c for each observed state, calculate the expected profit before realization of payoff shocks, estimate λ^{count,P_0^c} and update the conditional choice probabilities using the logit form of the choice specific value functions for the new λ^{count,P_0^c} and estimated $\hat{\theta}$ and continue this iteration until convergence is reached.

We then simulate the market forward based on λ^{count} to see how markets evolve under the new payment rule. We start from 2013, and the previous step provides the equilibrium choice probabilities for observed states for this year. These probabilities and the estimated transition process are used to move the model forward one period. As this process takes the market to a state not observed in the data, from here we move forward by solving for equilibrium choice probabilities for every period we simulate the model forward. [4].

5.2 Simulation Results

We start from the observed states in 2013 and simulate the markets forward. We do this in order to compare the simulated markets with observed data. Figure 4 shows the county average ratings in the United States in 2013. This was the initial period when the rating system and the national threshold bonus payment system was introduced. As we can see that most regions in the United

[4]We solve for the equilibrium choice probabilities in each market by iterating over the best response function. We initialize this iteration with a reduced form estimate of choice probabilities using a simple multinomial logit model of observed action on potential subsidy increase for each possible action if no other firms change and use this model to predict the choice probabilities under the new scheme by recomputing the covariates.

States perform poorly in terms of offered plan quality except regions in the west coast, mid-west and northeast which perform better than other counties. Figure 5 shows the county average rating of 2016 observed in data where we find that certain markets have evolved to have higher average plan quality compared to others like counties in Texas.

It is important to note that the counties with higher average rating in 2016 are mostly the ones which started with better initial condition in 2013. These regional patterns are captured by our model if we simulate it without implementing the new payment policy as shown in Figure 6. Our model predicts well the regions that evolved to have a higher average quality in the data. These results are driven by the initial market conditions, our estimates of value function, structural parameters and the national threshold based quality bonus payment system.

As the initial payment system pays quality bonuses only to plans with a rating greater than four, it is less costly for plans with better initial rating to move to a bonus status. For example, a plan with a 3.5 rating can move to bonus status by increasing its rating by half star only. So a half star increase is associated with an increase in government subsidies. The cost of moving to four star rating is much higher for plans with poorer initial rating. This coupled with the strategic interaction among firms drive the results for our model simulation.

We then introduce the competitive bonus payment system, simulate our model forward, and compare it with observed data. Figure 7 shows the average plan quality for the simulated markets under the competitive bonus payment system in 2016 starting from 2013. The figure illustrates a reduction in regional disparity in plan quality in our counterfactual where 1,853 (65.25%) counties perform better than their observed average rating in 2016. Figure 8 shows the regions that would performed better under the competitive payment system. Low performing regions like west Texas, New Mexico, and Florida. are predicted to improve under the new payment system.

Figure 9 compares the distribution of observed and simulated average county star ratings in the United States in 2016. It can be noted that the distribution shifts rightwards as 67.88% counties are predicted to have an average rating greater than or equal to four star as compared to 48.09% in the data. This is a desirable outcome as the existing payment rule rewards plans having a rating four or higher. The competitive payment rule is predicted to better achieve this goal in the counterfactual. The other key feature of this distribution is that around 40% of counties have an average rating between 4 and 4.25 stars. Our model predicts that under the new payment rules most markets evolve and cluster around this region.

We then analyze which counties perform better under the new payment rule. We calculate for each county the difference between the counterfactual county average rating and the observed mean of 2016. A positive value of this variable signifies that the county improves in terms of plan quality offering under the new payment rule. In Figure 10 we plot for each county the value of their observed average rating in 2016 against the calculated difference as defined above. We observe that most counties that improve have a lower average rating in the data. No county below an observed average rating of 3.5 worsens in the counterfactual. Most of the counties predicted to worsen under the new payment rule have an observed average rating of 4 stars.

This pattern can be indicative of how the firms might allocate resources for quality improvement initiatives under the new payment rule. As explained before, under the existing rule it was more profitable for firms to invest in quality improvement of contracts already performing better but just below the national benchmark. The cliff effect of the current payment policy generates the incentive to do so. However, when the bonus payments are based on relative performance of the contract in a market where the contract just have to be better than its peers, improving the rating of a low performing contract in a low performing market can become profitable. Our counterfactual predictions capture this affect of the competitive bonus payment rule as illustrated.

Finally we analyze how the annual premiums will change under the counterfactual payment rule. The new bonus payment system is budget balanced as no extra dollar amount per beneficiary is injected into the system and are paid as transfers across plans. It is necessary to see how the firms might react in terms of premium under such a payment system. In other words, we would like to see if this predicted increase in quality comes at an increased annual premium.

As shown in Figure 11, the distribution of annual premium does not change much in our counterfactual from the observed data. Most plans in the couterfactual still charges a premium less than $0 . However, the maximum annual premium charged in Medicare Advantage increases but only for a few offered plans. In Table 5, we show that for 24.83% of plans we study, the premium remains the same under counterfactual. These plans are the ones that charge a $0 annual premium. Though around 39.5% of the plans increase their premium, the mean increase in premium is $ 149.19. We also observe that 35.6% of the plans reduce their premium. These are mostly the plans which move into bonus status under the new payment system. The mean reduction is $ 346.92 for these plans. Given the counterfactual predictions, it is safe to state that the new competitive quality bonus payment system does not put any excessive premium burden on the beneficiaries.

6 Conclusion

We study how competition among firms can be exploited in a managed care setting like the Medicare Advantage. While a lot studies regarding managed competition are regarding improving financial efficiency, we explore how competition can be used to provide incentives to firms to improve the quality of service. We introduce a redistribution mechanism of quality bonus payment where in every local market plans are compared to each other in terms of measured quality and bonus payments are made as transfers from low performing plans to high performing plans within the local market. Such a mechanism not only puts pressure on private firms to improve quality it also makes it profitable for them to do so in low performing markets.

We provide a framework to analyze how firms would behave under such a competitive bonus payment system and predict how the markets evolve in terms of offered plan quality. We use a dynamic game model where forward looking profit maximizing firms strategically choose whether to invest in quality improvement. The firms also take into account their competitors behavior as the payoffs for improving quality measure under the new proposed rule depend on their relative performance. We use estimated model parameters to calculate equilibrium quality investment decision of the firms under the new quality bonus payment rule and simulate the model forward to see how they evolve.

Our counterfactual predicts that the average quality of plan offerings improve under this new payment rule. By comparing our simulated market outcomes with the observed 2016 data, we see that 1,853 (65.25%) counties improve their rating with the redistribution bonus payment system. In 2016, we observe that 48.09% of the counties had an average MA plan quality of four or higher. Our counterfactual predicts that this number would go up to to 67.88% under the new bonus payment policy. We also observe that historically poor performing markets perform better under the new policy.

In our model we only consider firm's decision to invest and do not consider entry and exit decision. In reality however, low performing firms may choose to leave the market or merge with better performing firms. Introducing entry and exit decision is a promising extension of our model. Also we do not explicitly model how these quality improvements take place through provider network formation. The ease of improving quality in a market might depend on the existing provider conditions. We leave for our future work to analyze how provider network can improve plan quality and how it is affected by market competition.

7 References

Abaluck, J., Caceres Bravo, M., Hull, P., Starc, A. (2021). "Mortality effects and choice across private health insurance plans."*The quarterly journal of economics,* 136(3), 1557-1610.

Adrion, E.R., 2019. "Competition and health plan quality in the Medicare Advantage market." *Health Services Research*, 54(5), 1126-1136.

Aguirregabiria, V., 2012. "A method for implementing counterfactual experiments in models with multiple equilibria." *Economics Letters*, 114(2),190-194..

Aguirregabiria, V. and Ho, C.Y., 2012. "A dynamic oligopoly game of the US airline industry: Estimation and policy experiments." *Journal of Econometrics,* 168(1), 156-173.

Aguirregabiria, V. and Mira, P., 2007. "Sequential estimation of dynamic discrete games." *Econometrica*, 75(1), 1-53.

Aguirregabiria, V. and Mira, P., 2010. "Dynamic discrete choice structural models: A survey." *Journal of Econometrics*, 156(1), 38-67.

Benitez-Silva, H., Hall, G., Hitsch, G.J., Pauletto, G. and Rust, J., 2000. "A comparison of discrete and parametric approximation methods for continuous-state dynamic programming problems." Working Paper.

Blevins, J.R., 2014. "Nonparametric identification of dynamic decision processes with discrete and continuous choices." *Quantitative Economics*, 5(3), 531-554.

Crawford, G., Shum, M. (2006). "The welfare effects of endogenous quality choice: the case of cable TV." Working paper.

Curto, V., Einav, L., Levin, J. and Bhattacharya, J., 2014. "Can health insurance competition work? evidence from medicare advantage" (No. w20818). National Bureau of Economic Research.

Darden, M. and McCarthy, I.M. 2015. “The star treatment estimating the impact of star ratings on Medicare Advantage enrollments”. *Journal of Human Resources,* 50(4), 980-1008.

Dafny, L. and Dranove, D., 2008. “Do report cards tell consumers anything they don’t already know? The case of Medicare HMOs.” *The Rand Journal of Economics,* 39(3), 790-821.

Decarolis, F., Polyakova, M., Ryan, S. P. (2020). "Subsidy design in privately provided social insurance: Lessons from Medicare Part D." *Journal of Political Economy,* 128(5), 1712-1752.

Draganska, M., Mazzeo, M., Seim,K. (2009). "Addressing endogenous product choice in an empirical analysis of merger effects." *Northwestern University. Economic Inquiry,* 17(2), 177-96.

Fan, Y. (2013). "Ownership consolidation and product characteristics: A study of the US daily newspaper market." *American Economic Review,* 103(5), 1598-1628.

Farley, D.O., Elliott, M.N., Short, P.F., Damiano, P., Kanouse, D.E. and Hays, R.D., 2002. “Effect of CAHPS performance information on health plan choices by Iowa Medicaid beneficiaries” . *Medical Care Research and Review,” 59(3), 319-336.*

Fioretti, M., Wang, H. *(2021). "Performance pay in insurance markets: Evidence from medicare", Working Paper.*

Gruber, J. *(2017). "Delivering public health insurance through private plan choice in the United States." Journal of Economic Perspectives, 31(4), 3-22.*

Handel, B.R. and Kolstad, J.T., *2015. "Health insurance for" humans": Information frictions, plan choice, and consumer welfare." American Economic Review, 105(8), 2449-2500.*

Hoxby, C. M. *(2000). "Does competition among public schools benefit students and taxpayers?".American Economic Review, 90(5), 1209-1238.*

Layton, T. J., Ryan, A. M. *(2015). "Higher incentive payments in Medicare advantage's pay-for-performance program did not improve quality but did increase plan offerings." Health services research, 50(6), 1810-1828.*

Miller, K.S., Petrin, A., Town, R. and Chernew, M., *2019. "Optimal Managed Competition Subsidies" (No. w25616). National Bureau of Economic Research. Working Paper*

Pakes, A., Ostrovsky, M., Berry, S. *(2007). "Simple estimators for the parameters of discrete dynamic games (with entry/exit examples)." The RAND Journal of Economics, 38(2), 373-399.*

Reid, R.O., Deb, P., Howell, B.L. and Shrank, W.H., *2013. "Association between Medicare Advantage plan star ratings and enrollment." The Journal of the American Medical Association, 309(3), 267-274.*

Scanlon, D.P., Chernew, M., McLaughlin, C. and Solon, G., *2002. "The impact of health plan report cards on managed care enrollment." Journal of Health Economics, 21(1), 19-41.*

Sen, A.P., Meiselbach, M.K., Anderson, K.E., Miller, B.J. and Polsky, D. *, 2021. "Physician*

Network Breadth and Plan Quality Ratings in Medicare Advantage." Journal of American Medical Association Health Forum (Vol. 2, No. 7), e211816-e211816.

Sweeting, A., *2013. "Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry." Econometrica, 81(5), 1763-1803.*

Wedig, G.J. and Tai-Seale, M. *, 2002. "The effect of report cards on consumer choice in the health insurance market." Journal of Health Economics, 21(6), 1031-1048.*

8 Appendix: Tables and Figures

Table 1: **Summary Statistics of Medicare Advantage Markets by Year**

Variable	2013	2014	2015	2016
Average Star Rating	3.57	3.74	3.85	3.94
Number of Observed Rating Improvement	5127 (32.2%)	4033 (23.5%)	5489 (30.6%)	
Contract Average Enrollment per County (rounded)	4,205	4,786	5,109	5,415
Contract Average Revenue per County	6,105,121	6,610,965	6,780,367	7,455,344
Number of contract-market observations	19,426	20,616	20,162	20,060

Notes: The reported observations are at year-market-firm level .

Table 2: **Estimates for Demand Parameter**

Variable	Coefficient	S.E.
Annual Premium (per $1000)	-1.02	0.17
Star	0.16	0.08
Vision	2.79	0.13
Hearing	-0.23	0.12
Dental	-0.05	0.013
HMO	-6.76	0.5
PPO	-5.95	0.46

Notes: Estimation of (3) based on 150039 year-market-plan observations. The standard errors are clustered at county level.

Table 3: **Estimates of marginal cost function**

Variable	$ln(mc_j)$
Star	2.13
	(0.002)
Vision	0.66
	(0.01)
Dental	0.11
	(0.017)
Hearing	0.34
	(0.019)
Unobservable ξ_{jt}	0.06
	(0.005)
HMO	0.2
	(0.02)
PPO	1.15
	(0.015)

Notes: Estimation of (6) based on 150039 year-market-plan observations. The standard errors are clustered at county level

Table 4: **Dynamic Parameters for Quality Improvement Investment Cost**

Dynamic Investment Cost Parameters	$ million
Fixed Cost of quality improvement by 0.5 star	0.054 (0.02)
* Current Star Rating	1.21 (0.09)
* Rating Change in previous period	1.41 (0.03)

Table 5: **Difference between Observed and Counterfactual Annual Premium**

Variable	Number of Plans (% of total observations)	Mean Difference in $ (S.D)
Observed Price= Counterfactual Price	8,997 (24.83 %)	0
Observed Price>Counterfactual Price	14,325 (39.53 %)	149.19 (122.63)
Observed Price<Counterfactual Price	12,913 (35.64 %)	-346.921 (192.5)

Notes: This table reports the comparison of observed plan premium and calculated counterfactul plan premiums in 2016.

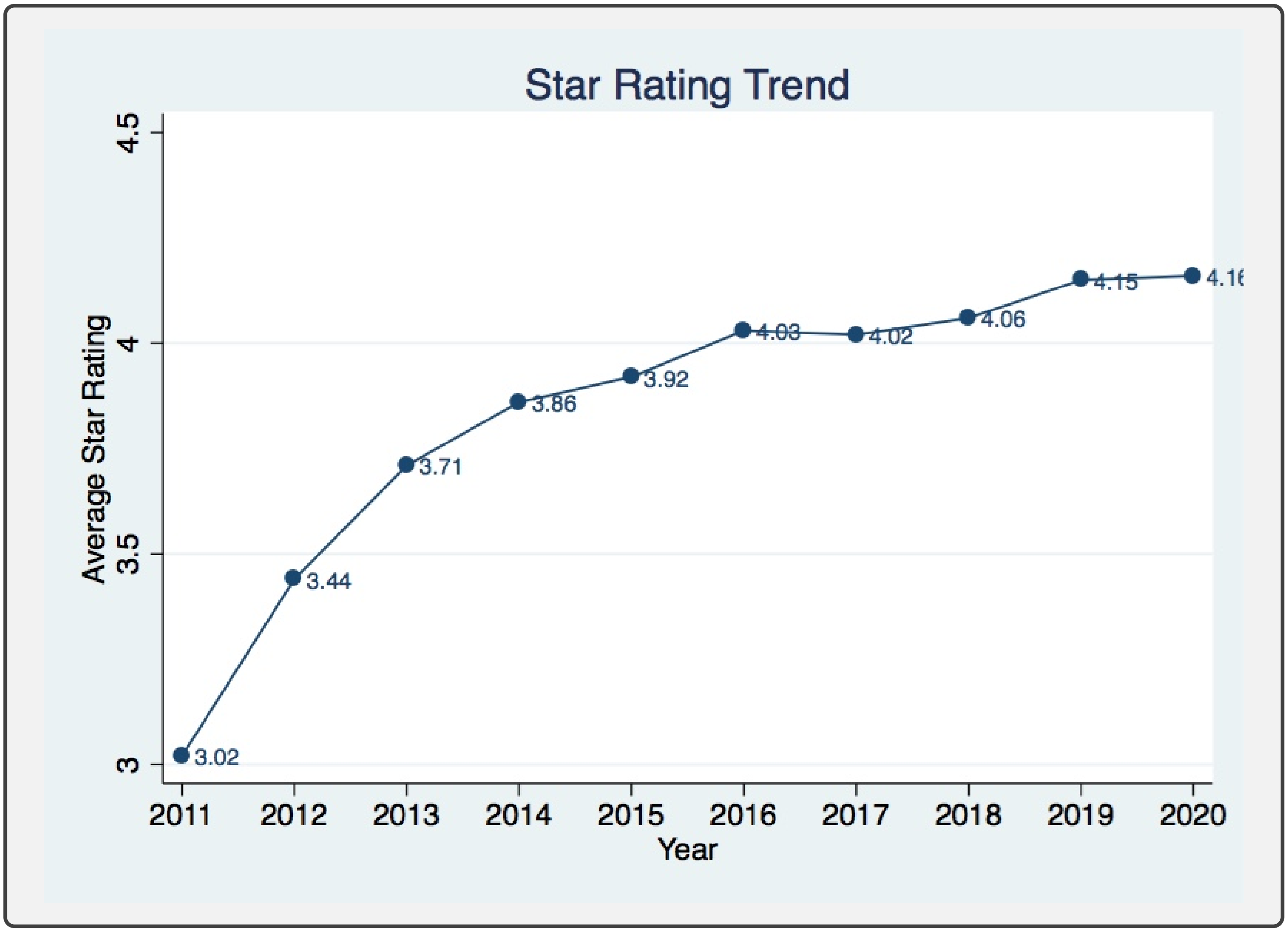

Figure 1: Enrollment weighted average star rating over the years. This figure shows the increasing trend of enrollment weighted average star rating after quality bonus payments are introduced.

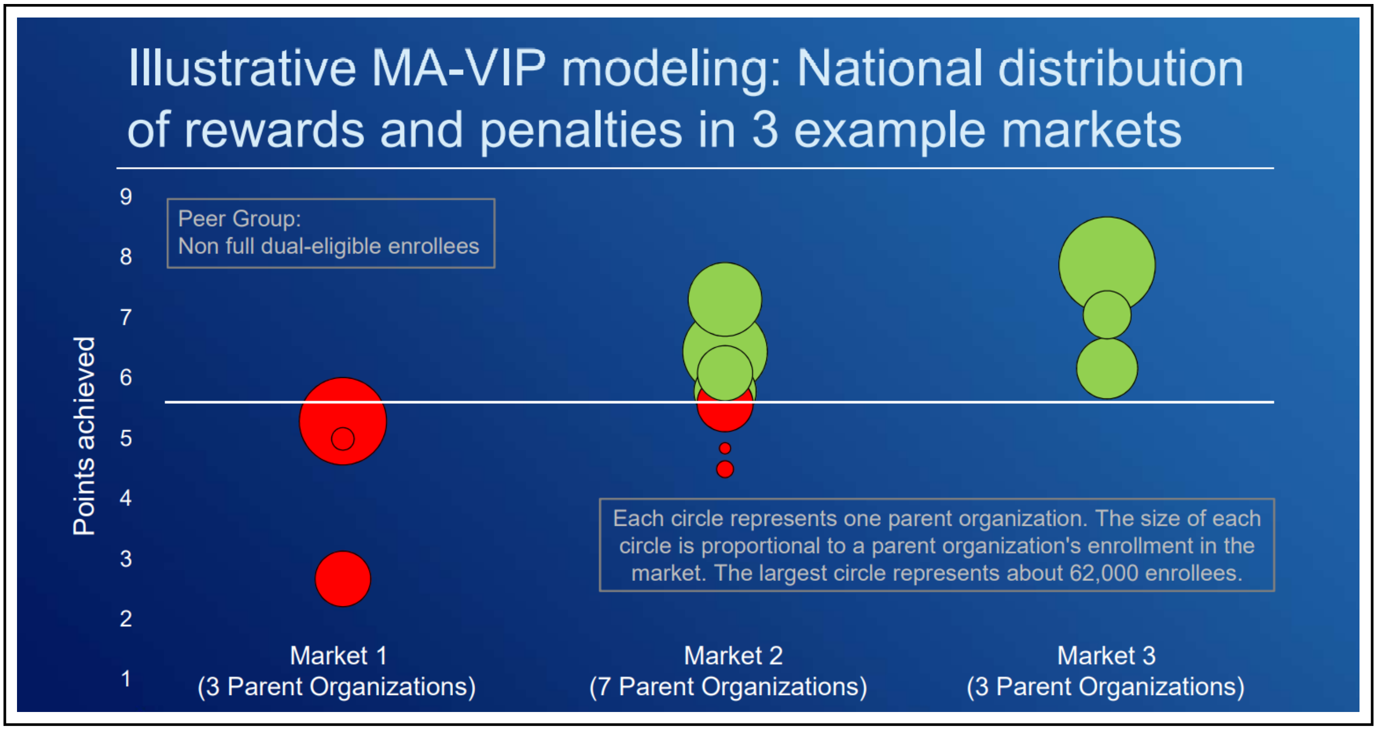

Figure 2: Bonus distribution in example markets for threshold based bonus payment system Source:MedPAC

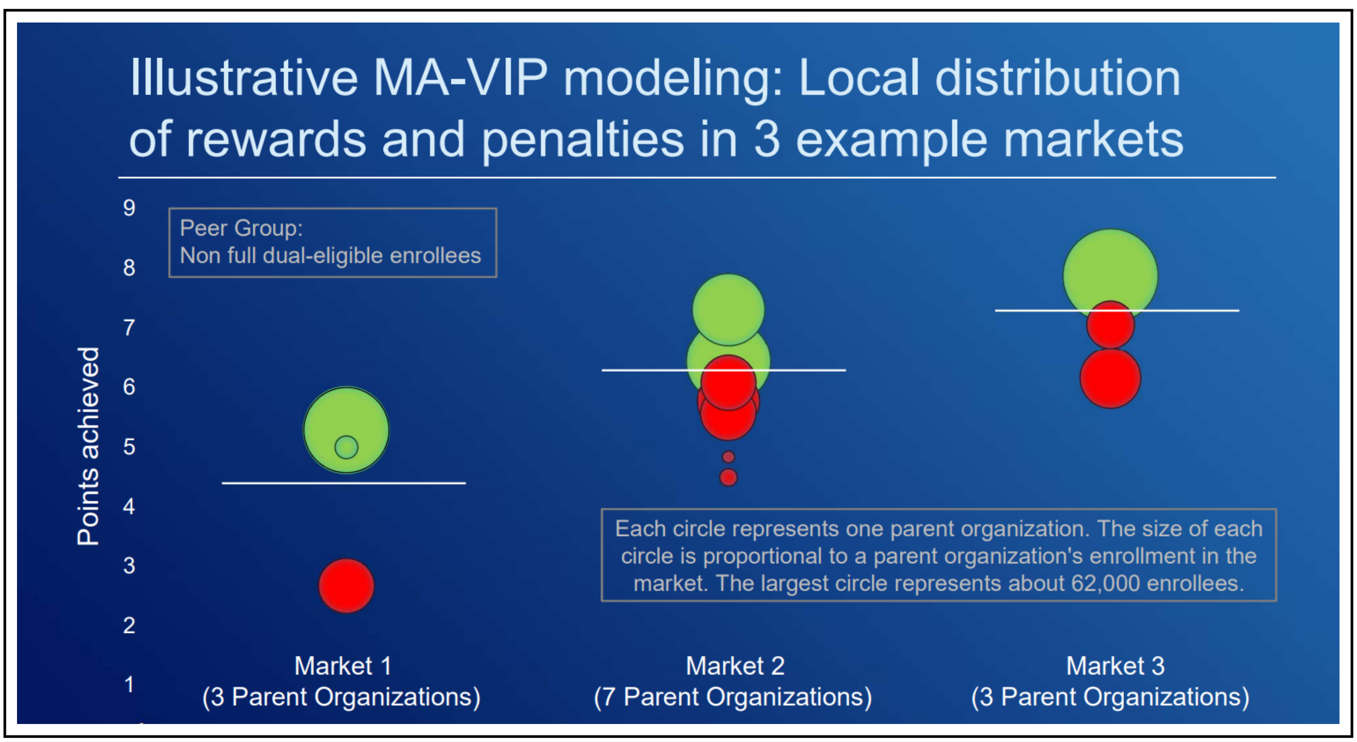

Figure 3: Bonus distribution in example markets for market level comparison based bonus payment systemSource:MedPAC

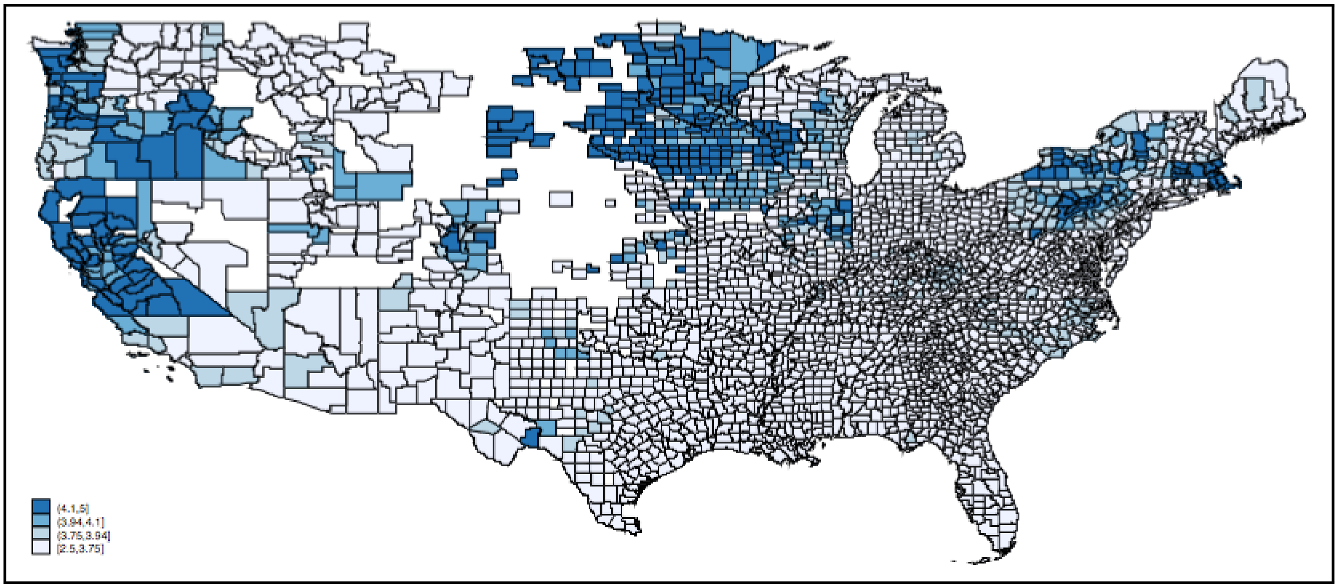

Figure 4: Geographical distribution of average MA plan star rating of counties in 2013

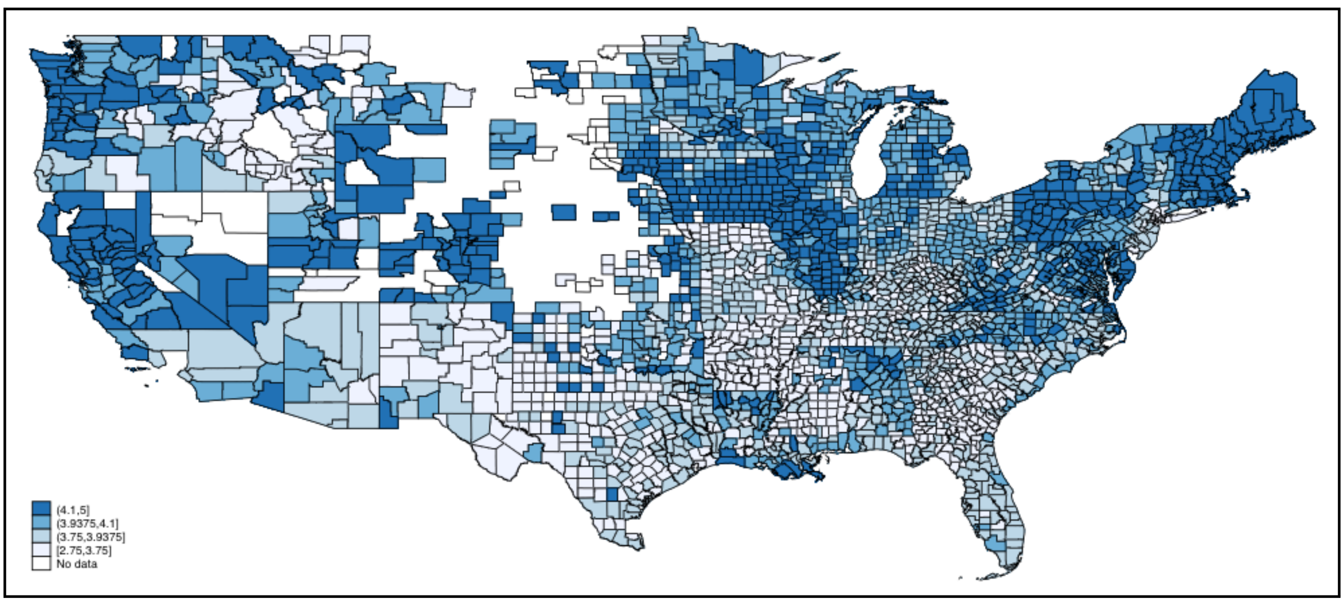

Figure 5: Geographical distribution of average MA plan star rating of counties in 2016

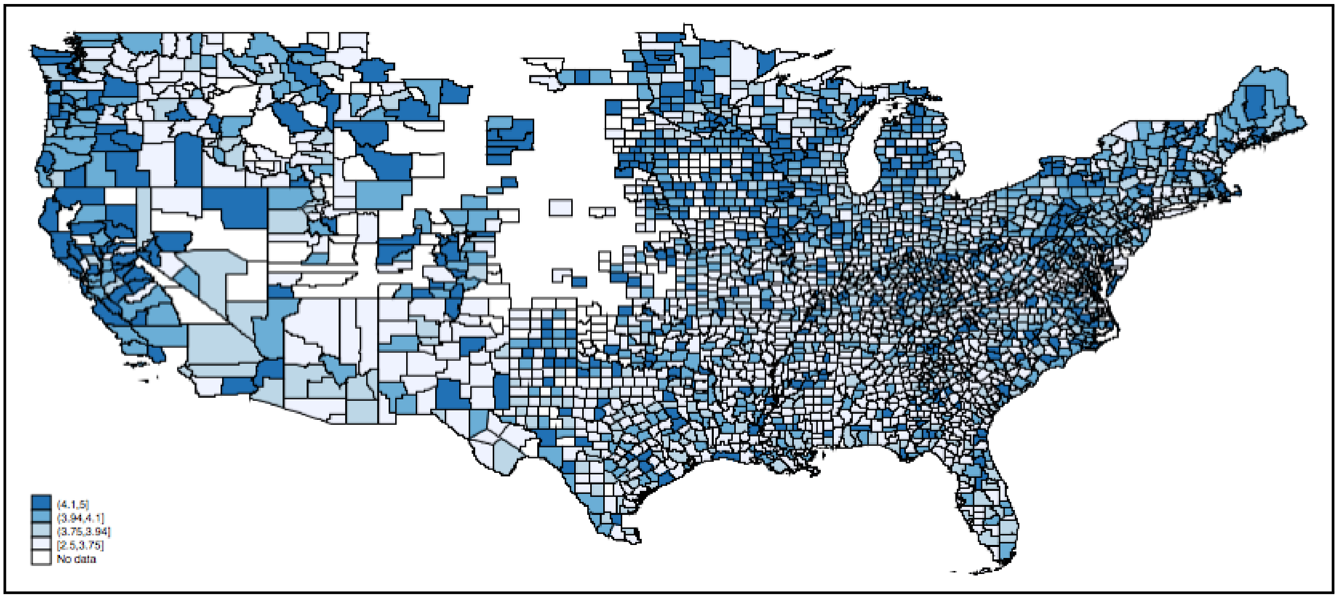

Figure 6: Geographical distribution of model Simulated average MA plan star rating of counties in 2016

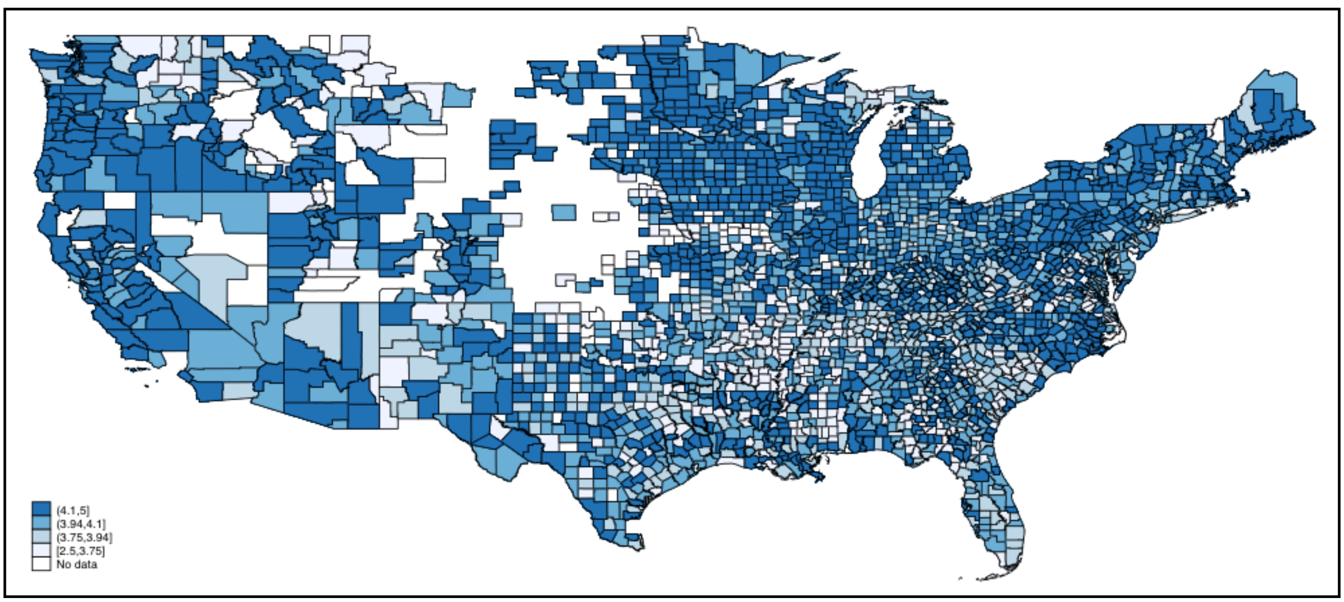

Figure 7: Geographical distribution of counterfactual average MA plan star rating of counties in 2016

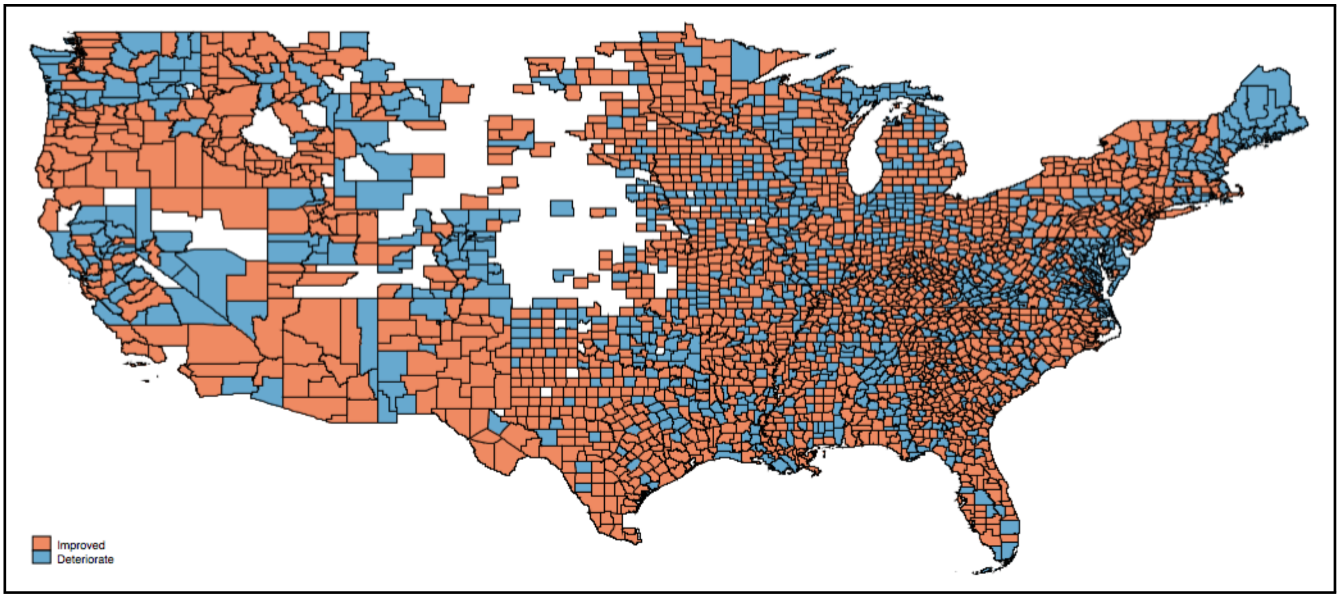

Figure 8: Counties improving mean star rating under the counterfactual payment rule

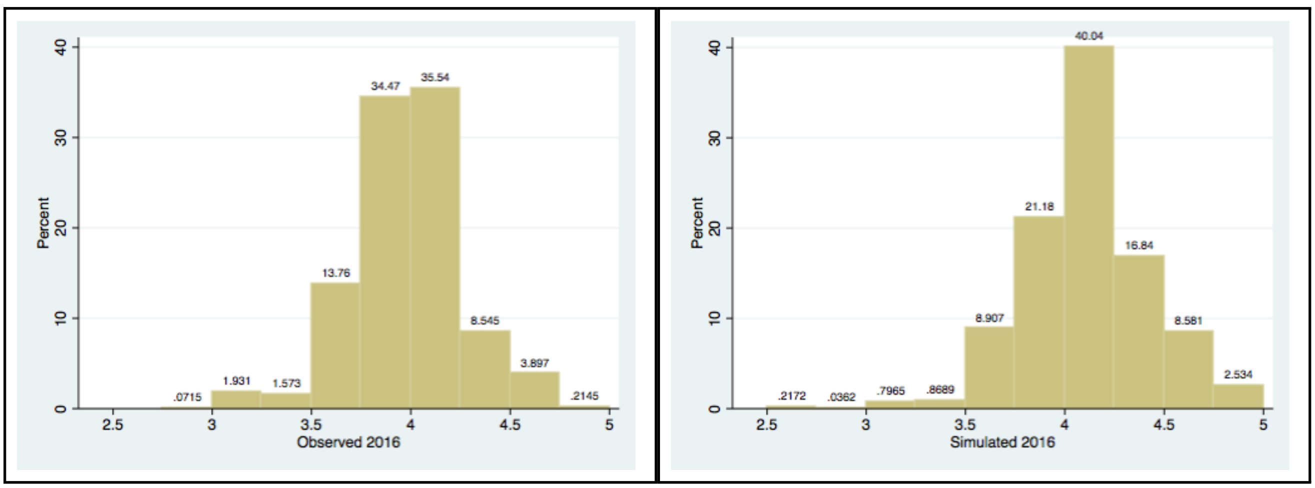

Figure 9: Distribution of mean county star rating in observed data and counterfactual. This figure shows that under the counterfactual payment rule, the distribution shifts to the right and is less dispersed.

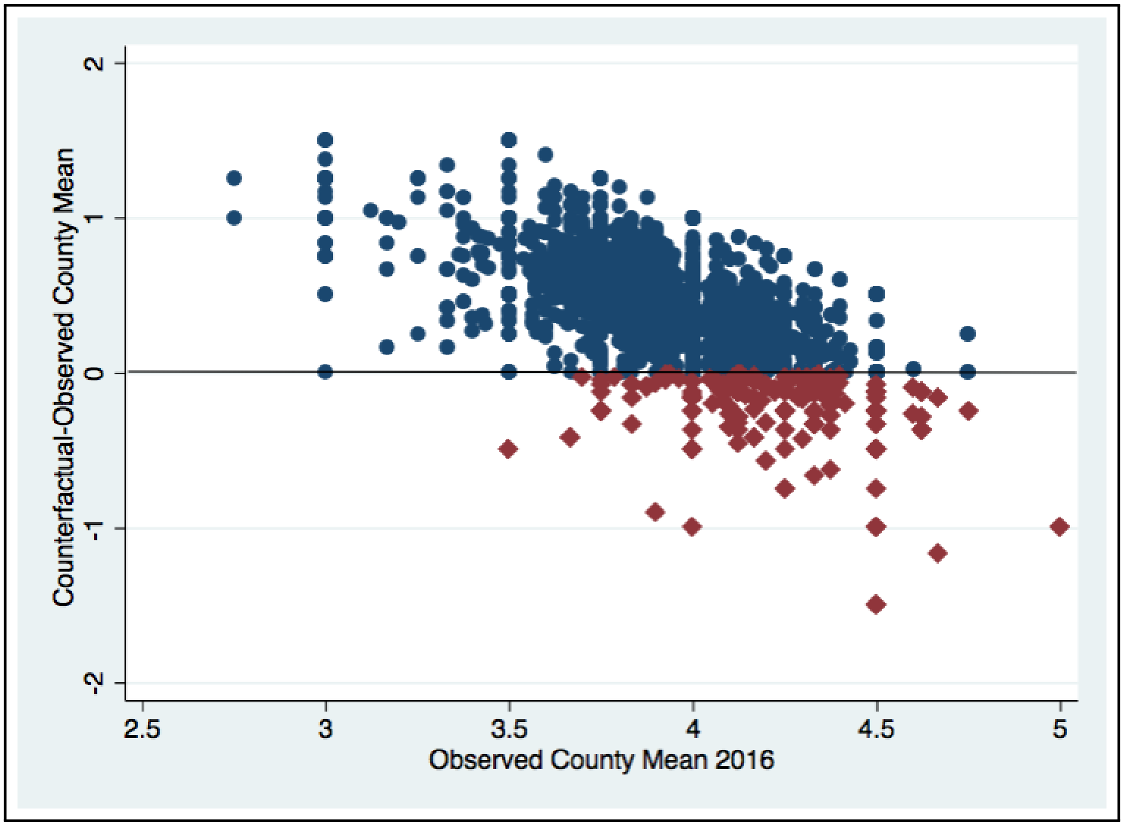

Figure 10: Scatter plot of observed average rating of a county and its difference from the counterfactual prediction. A value greater than zero for the Y axis indicates that the market performs better in the counterfactual.

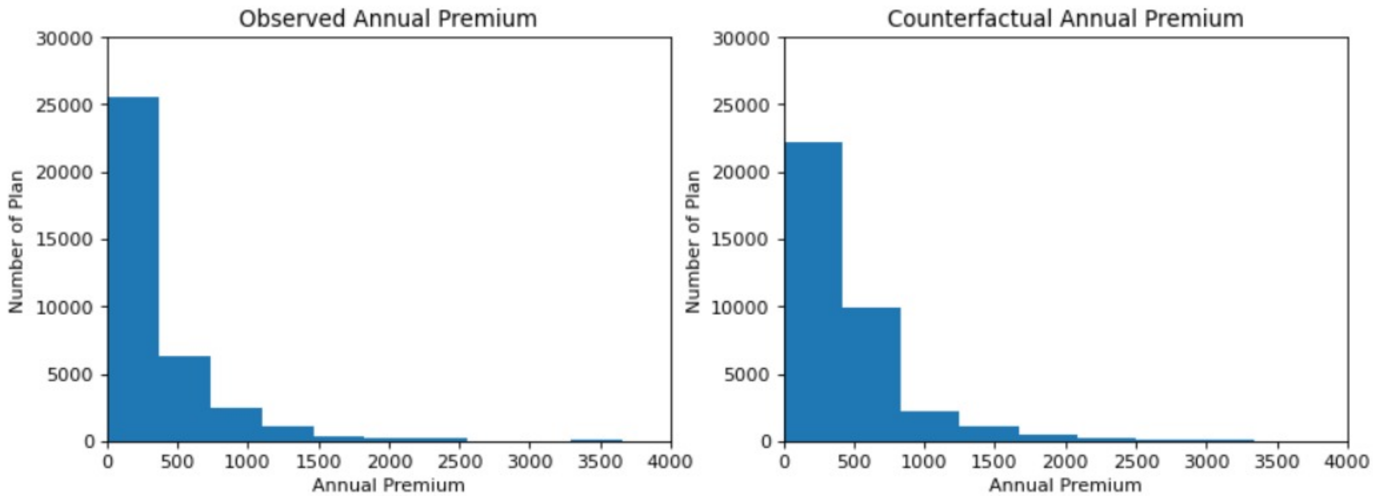

Figure 11: Distribution of Annual Premium in Observed Data and Counterfactual. This figure shows how the distribution of annual premium of MA plans change in the counterfactual.