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RESEARCH ARTICLE

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Open enrollment periods and plan choices

Francesco Decarolis[1] | **Andrea Guglielmo**[2] | **Clavin Luscombe**[3]

[1]Department of Economics and BAFFI-Carefin, Università Bocconi, Milan, Italy

[2]Analysis Group, Boston, Massachusetts,

[3]Amazon.com Inc, Seattle, Washington,

Correspondence
Francesco Decarolis, Department of Economics, Universita Bocconi, Milani, Italy.
Email: francesco.decarolis@unibocconi.it

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Abstract

Open enrollment periods are pervasively used in insurance markets to limit adverse selection risks resulting when enrollees can switch plans at will. We exploit a change in the open enrollment rules of Medicare Advantage to analyze how beneficiaries responded to the option of switching to a 5-star-rated plan at anytime, in a setting where insurers adjusted premiums and benefit design to counterbalance the increased selection risk. We present three findings: Within-year switches to 5-star plans increase by 7–16%; demand for 5-star plans across the years does not decline; and the enrollees who switch to a 5-star plan during the year are in better health status than those who do not switch.

KEYWORDS

health insurance, Medicare, open enrollment periods, periods, risk selection

MSC CLASSIFICATION

I11; I18; L22

1 | INTRODUCTION

The growing economic importance of health insurance markets has increased research to identify market features that can lead to more desirable social outcomes. Several of these studies have involved the design of the Medicare system. With expenditures totalling $646.2 billion in 2015 and growing by 4.5% relative to the previous year, Medicare represents, through its Medicare Advantage and Part D programs, the largest existing case of a publicly funded, but privately provided health insurance system.

As is typical in insurance markets, both Medicare Advantage, covering hospital stays and physician visits, and Part D, covering prescription drugs, have an "open enrollment period" (OEP) during which consumers select a plan that will subsequently provide them with coverage under clearly defined contractual conditions. Among these conditions is the inability for the enrollee to switch plan at will during the coverage period. OEPs play a key role in the stability of health insurance markets as they limit the perverse dynamics produced by adverse selection: beneficiaries remaining uninsured (or choosing cheap, low-coverage plans) when they are healthy and then switching to generous plans when sick.

This paper looks at a 2012 reform of Medicare Advantage under which the OEP rules were changed to allow enrollees to switch at anytime under the sole condition that the destination plan is rated 5 stars (the highest score in the Medicare plan quality rating system). This reform, known as the "5-star Special Enrollment Period" (or 5-star SEP), aimed at increasing enrollment in 5-star contracts.[1] It involves a large share of the Medicare beneficiaries—in 2017, the 5-star SEP was available to 11.5 million individuals.

[1]In Medicare Advantage, enrollees choose plans but the star rating system applies to contracts. Contracts typically include multiple plans. A contract is a particular product type (Health Maintenance Organization, Preferred Provider Organization, or Private Fee For Service) covering a specific service area (i.e., county or group of counties). Within a contract, different plans typically have differences in their benefit package. We use both terms "contract" and "plan," depending on which of the two is most appropriate.

Various demand and supply forces present in the market are likely to limit the possibility of this reform triggering an "adverse selection death spiral" of increasing costs and increasing premiums. On the demand side, both consumer inertia in choosing an insurance plan and the inherent complexity of changing a Medicare Advantage plan—which, as discussed below, implies changing provider network—are likely to reduce plan-switching behavior. On the supply side, there are at least two mechanisms at play. First, Medicare Advantage plans receive risk-adjusted payments. Although it may not be possible to perfectly compensate for all cost, risk adjustment serves to compensate plans receiving an influx of less healthy beneficiaries. Second, insurers can modify both premiums and benefits of their plans' menus.

In a previous study, we analyzed this latter feature by studying how insurers responded to the 5-star SEP (Decarolis & Guglielmo, 2017). By exploiting the geographical variation in the availability of 5-star plans, we identified the causal effect of the 5-star SEP on the distribution of plan characteristics in the markets affected by the reform. We found strong empirical evidence in support of the theoretical predictions of models à la Rothschild and Stiglitz (1976) and Glazer and McGuire (2000) in which plans alter their product in an attempt to attract good risks: Relative to the distribution of competing plans, 5-star plans lower both their premium and their generosity, especially on those margins most valued by the enrollees in worst health conditions. That study, however, left open the question of what the impact on demand has been of the combined effects of free plan switching by enrollees and changes to plan designs by insurers. Answering this question is the main contribution of the current study and is key to understanding the potential effectiveness of using open enrollment rules as a tool to regulate insurance markets with managed competition.

To identify how demand responded to the SEP reform, we use a similar approach to that of Decarolis and Guglielmo (2017). We exploit the geographical variation in 5-star Medicare Advantage plans to compare demand in markets with 5-star plans to that in similar markets where no 5-star plan is offered. Our difference-in-differences (DIDs) strategy is particularly effective when insurers have limited scope to game the star rating system. Therefore, we focus on the first 2 years of the reform (2012 and 2013), when insurers could alter the plan design but not their star rating due to the lag in the timing of the specific measures that compose the rating. We also restrict the control group to plans with a rating no lower than 4 stars to account for the different financial incentives created by the bonuses for higher rated plans introduced by the Patient Protection and Affordable Care Act (ACA; see Layton & Ryan, 2015).

Our main findings are as follows. First, we estimate that the within-year increase in enrollment due to the 5-star SEP ranges from 7% to 16% of the enrollment base of the 5-star plans. This indicates a sizable response by consumers to the new SEP, which involves enrollees from both Traditional Medicare (TM) and other Medicare Advantage plans. Second, we estimate either an insignificant or a positive effect (depending on the model specification) of the reform on enrollment changes across the years. This is indicative of inertia in plan choice: Enrollees do not take advantage of the possibility to stay outside the Medicare Advantage program (or to enroll in the cheapest plans) during the OEP and to switch to 5-star plans only if hit by a health shock. Third, the risk pools of 5-star plans improve, albeit only by a small amount.

The latter finding is not indicative of advantageous selection by itself. Before the reform, 5-star plans tended to have particularly high-risk enrollees. Therefore, their average risk score might have improved because they are bringing in enrollees who, despite being among the high risk enrollees in their original plan, still represent a lower risk than the average 5-star enrollee. Using detailed claims-level data, however, we estimate that the probability of switching to a 5-star plan is negatively associated with measures of poor health. Switchers are also more likely to come from other Medicare Advantage plans than from TM, with or without Medicare Part D.

Therefore, we conclude that the 5-star SEP was effective in steering enrollees toward 5-star plans and that demand increases were not driven by high-cost enrollees. Together with the aforementioned results on the strategic response of insurers (Decarolis & Guglielmo, 2017), these results are informative of the usefulness of designing SEPs as a tool to guide the functioning of health insurance markets. Moreover, they indicate that using this tool requires taking into account both supply and demand responses. Although there is no theoretical literature guiding the design of optimal enrollment periods, as health insurance is increasingly organized in the form of markets with regulated competition, we expect increasing attention to be paid to a market design approach to these markets. A recent example of a study taking this perspective is Einav, Finkelstein, and Tebaldi (2019), who compare subsidies for consumers and risk adjustment for insurers and find that the former are a more effective regulatory tool in markets with adverse selection. With a better understanding of their effects, OEP rules might also become a useful tool to steer the market toward socially desirable goals.

This study is most closely connected to two other existing works on the effects of the 5-star SEP. The first is our supply-side study, (Decarolis & Guglielmo, 2017), discussed earlier.[2] The second, by Madeira (2015), is an early attempt to study behavioral biases among Part D enrollees exposed to the 5-star SEP in 2012. The 5-star SEP reform involved not just Medicare Advantage, but also Medicare Part D—the voluntary program for prescription drug insurance plans. Madeira (2015) studies whether, by removing the typical Part D enrollment deadline, the 5-star SEP could have induced consumers to switch plans less frequently by allowing them to procrastinate. His results suggest that switching rates (across the years) decrease as a result of the policy change in a way that is consistent with a procrastination bias. Our results complement and substantially extend these findings as they look directly at the main aspect of the policy (within-year switches, instead of across-year plan changes) and they do so by using data not only from 2012, but also from 2013.[3] More crucially, by focusing on Medicare Advantage instead of Part D, our analysis benefits from more comprehensive geographical variation of the policy, which involved nearly 180 Medicare Advantage counties but only two Part D regions.[4]

The evidence in this study also complements the very scarce evidence that exists on the effects of OEPs in other markets. In private insurance markets, insurers can often refuse to sell, but this is typically not an option for publicly subsidized health insurer programs like Medicare Advantage or the ACA exchanges. In these markets, OEPs are likely of even greater relevance. Indeed, recent work by Diamond, Dickstein, McQuade, and Persson (2018) shows how high attrition rates in the ACA exchanges are undermining market stability, leading to insurers' exit and higher premiums for enrollees who do not drop out.

Finally, our micro-level evidence on how different groups of consumers are differentially affected by the 5-star SEP is a clean example of the distributional consequences of a recent Medicare reform. Due to its size and organization, the question of the distributional impact of Medicare has received considerable attention in the literature (see, for instance, Bhattacharya & Lakdawalla, 2006; McClellan & Skinner, 2006; and Duggan et al., 2016). In these studies, quantifying the insurance value of Medicare plays a key role in assessing its distributional impacts. In this respect, our findings reveal how even a "small" reform affecting directly just 5-star plans is able to trigger multiple changes in Medicare Advantage, by inducing both supply and demand responses.

2 | INSTITUTIONS: MEDICARE OEPS

The Medicare system consists of a series of interlinked programs aimed chiefly at those aged 65 or older in the United States. TM is composed of Medicare Part A, covering inpatient hospital, skilled nursing, and some home health services, and Medicare Part B, covering physicians' services, outpatient care, and durable medical equipment. This study focuses on the privately provided programs that coexist with TM: Medicare Advantage and Part D. In both programs, private insurers offer a menu of plans to Medicare beneficiaries: Medicare Advantage plans are an alternative to TM and so must not only cover all Medicare Part A and B benefits (except hospice care), but also offer additional benefits. Part D plans complement TM by covering prescription drugs. The two programs are closely connected in many ways, the most evident being that almost all Medicare Advantage plans also include Part D benefits. These latter plans will be denoted below as MAPD. As an alternative to MAPD, enrollees opting for TM, but who want to access the (voluntary) Part D program can purchase stand-alone Prescription Drug Plans (PDPs).

Both MAPD and PDP offer 1-year, renewable coverage coinciding with the calendar year. The OEP is the window of time during which people can enroll in these plans. It typically spans from October to December of the year before the coverage period. Although enrollees are generally required to stay on the same plan for the entire year of coverage, exceptions to the OEP exist. SEPs permit enrollees to change plans when certain circumstances occur. The most common SEPs involve individuals turning 65 during the coverage year, changing residency or entering "low-income enrollee" status. Starting in 2012, an additional SEP was introduced: People eligible for Medicare residing in an area where one or more 5-star Medicare Advantage or Part D plan is offered can switch from their plan (or from TM) to a 5-star plan during the coverage

[2]Related evidence showing insurers' strategic choice of plan features in environments different from the one studied here is offered in Cao and McGuire (2003), Batata (2004), McWilliams, Hsu, and Newhouse (2012), Newhouse et al. (2013), Brown, Duggan, Kuziemko, and Woolston (2014), Polyakova (2014), Carey (2016), and Shepard (2016).

[3]These results also complement the growing literature on demand for insurance. Related works include Nosal (2012) and Miller, Petrin, Town, and Chernew. (2014) for Medicare Advantage and Abaluck and Gruber (2011), Ketcham, Lucarelli, Miravete, and Roebuck (2012), Marzilli Ericson (2014), Ketcham, Lucarelli, and Powers (2014), Abaluck and Gruber (2016), Ho, Hogan, and Morton (2017), Polyakova (2014), Ho et al. (2017), and Heiss, McFadden, Winter, Wuppermann, and Zhou (2016) for Part D. Our analysis is also related to the studies on inertia in employer-sponsored health insurance (Handel & Kolstad, 2015), in auto insurance (Honka, 2014) and in pension plans (Handel & Kolstad, 2015).

[4]Our own analysis on Part D is reported in the Supporting Information for completeness.

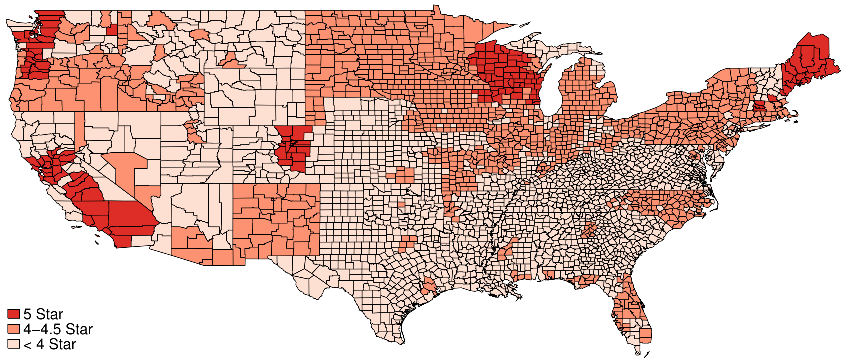


FIGURE 1 Highest rated MAPD contract by county, year 2012. Heat map: Darkest colors indicate counties where the highest rated MAPD has a higher star rating [Colour figure can be viewed at wileyonlinelibrary.com]

year, with the new coverage starting on the first day of the month following the enrollment request. We will refer to this reform as the 5-star SEP. The 5-star plans cannot deny enrollment. Beneficiaries can use this SEP only once per year and can also use it to switch from one 5-star plan to a different 5-star plan. To promote this policy, the Centers for Medicare & Medicaid Services (CMS) has extensively advertised this new SEP rule in its communications to potential enrollees.[5]

In contrast to all other Medicare SEPs, the possibility of a within-year plan switch is entirely dependent on a 5-star plan being offered in the enrollee's area of residency. This "area" differs between Medicare Advantage and Part D plans: For MAPD, it corresponds to a county, whereas for PDP, it corresponds to one of the 34 macro regions partitioning the United States. In 2012 and 2013, nearly 180 counties belonging to 17 different states had at least one 5-star MAPD, whereas only two regions had a 5-star PDP (New York and a macro region formed by seven midwest states). Given the importance of cross-market variation for identifying the effects of the 5-star SEP, the remaining part of this study will focus exclusively on Medicare Advantage, leaving the analysis for Part D to the Supporting Information. Figure 1 illustrates the spatial pattern of 5-star MAPD offerings. Although not present in the south, 5-star MAPDs are present in all other regions. The heat map also reveals the location of counties whose highest rated MAPDs were either 4 or 4.5 stars.

In the post-reform period, seven insurers offer 5-star plans. The main ones are Kaiser, Humana, and Group Health. The case of Kaiser offers another reason why it is important to keep analysis of the 5-star SEP for Medicare Advantage and Part D distinct: Switching plans in response to a health shock is inherently different and less complicated for a PDP than for an MAPD plan. In the case of switching from a different provider to Kaiser, an enrollee would need to change the whole network of primary, secondary, and hospital care. Although the case of Kaiser is extreme, it is clear that for some enrollees, changing care providers might be undesirable, even though they might benefit from some of the high-quality features provided by 5-star plans.

3 | EMPIRICAL STRATEGY

Our strategy for identifying the effect of the 5-star SEP on plan enrollment is based on a DID approach. For MAPD plans, this strategy exploits the fact, documented in Figure 1, that 5-star contracts are offered in only a subset of U.S. counties. We consider all contracts that achieved a 5-star rating in the period 2012–2013 as the DID treatment group (dark red areas in in Figure 1) and all contracts that achieved a rating of 4 or 4.5 stars in the same period and are offered in counties without any 5-star contracts as the control group (light red areas in in Figure 1).

Specifically, the regression model that we estimate is

$$Y_{ict} = \beta D_{it}^{5S} + \alpha_c + \gamma_t + \delta_i + \varepsilon_{ict}, \tag{1}$$

where i indicates the contract, c the county, and t the year. The outcome variable is one of the three variables described in the previous section: (a) the within-year change in enrollment, (b) the across-year change in enrollment, and (c) the plan average risk score. The coefficient of interest is β, the effect on the dependent variable of a dummy equal to one for 5-star contracts after 2011, conditional on fixed effects for the county (α_c), time (γ_t), and contract (δ_i). Various extensions are presented below.

In an ideal scenario, this identification strategy allows the causal effects of the 5-star SEP to be estimated through the random assignment of counties between treatment and control groups. Clearly, however, the observational data that we use fall short of this ideal scenario, and so, there are challenges to interpret β as the causal effect of the policy change.

[5]See, for instance https://www.medicare.gov/sign-up-change-plans/when-can-i-join-a-health-or-drug-plan/5-star-special-enrollment-period

As usual in any DID study, the first and foremost concern is to select an adequate control group. In our setting, 4- and 4.5-star contracts offered in counties that do not have any 5-star plans are a natural control group. First of all, because the regulation separates the geographical markets, a benefit of the proposed DID strategy is that, by selecting the treatment and control groups from different counties, it avoids contamination issues. Furthermore, in the period analyzed, the CMS payment demonstration made the contracts in the control group face similar financial incentives to those in the treatment group, as all payments linked to the star rating were similar for these two groups of plans (Decarolis & Guglielmo, 2017).

Although Figure 1 reveals that the 5-star plans are scattered across many different counties, this clearly does not ensure that their assignment to counties is random. At least two problems related to selection can emerge: Ratings could be subject to manipulations, implying self-selection by the insurers, or even for absent manipulations, counties in the treatment and control groups might differ.

Regarding the first problem, we note that it is hard for insurers to perfectly control their rating. This is due to the institutional features of the Medicare rating system. In particular, the star rating is derived from a combination of nearly 50 individual measures (see list in Table S1). The use of such a large number of measures, together with the fact that both the exact set of measures and the scoring formula change from year to year, implies that insurers do not have full control over their rating. Furthermore, details about the timing of the measures are crucial for understanding why the 5-star SEP should not trigger rating manipulations for 2012 and 2013. Several of these measures enter with a 2-year lag. Because insurers must define their plan offerings in June of the year before the enrollment and because the 5-Star SEP was announced in November 2010, any action aimed at altering the star rating would not take effect before the 2014 enrollment year. This fact is also consistent with the fact that the 2012 and 2013 offering of 5-star plans remained nearly unaltered relative to 2011 in terms of counties served and insurers involved.

Graphical evidence in support of the claim of no rating manipulation is offered in Figure 2. Underlying the discrete scores (appearing in 0.5 increments) that CMS discloses to enrollees and that determine the applicability of the 5-star SEP, there is a continuous measure that summarizes multiple indicators. Five-star plans are those whose overall score is at least 4.75, whereas 4.5-star plans have an overall rating below 4.75, but above 4.25. If we look at this continuous measure in Figure 2, two elements are suggestive of the adequacy of the proposed identification strategy. First, there is no

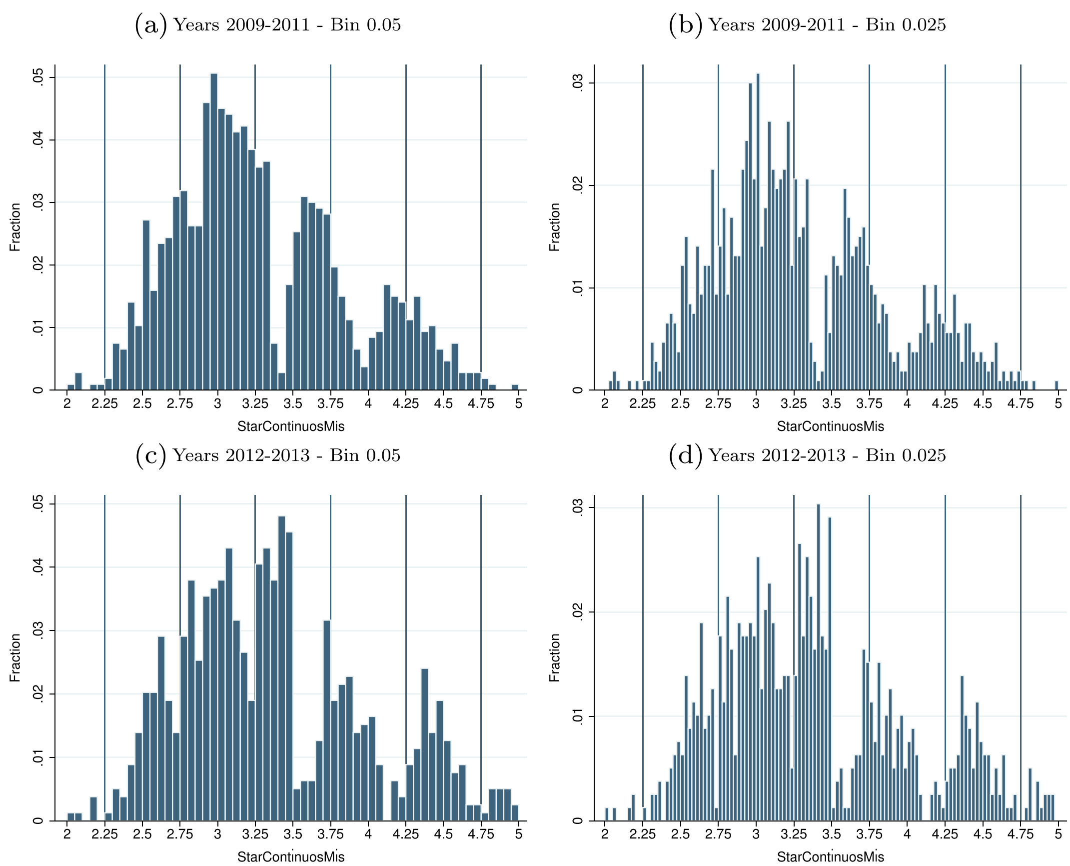


FIGURE 2 Distribution of star rating across contracts [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Descriptive statistics

	Control				Treatment			
Prereform sample: Years 2009–2011	**Mean**	***SD***	**Median**	***N***	**Mean**	***SD***	**Median**	***N***
Total enrollment	1,338.7	4,176.5	196.3	4,796	7129.7	1,7910.4	888	409
Change enrollment, December to January	92.38	378.3	27	4,796	386.0	863.7	117.5	409
Percent of change enrollment, December to January	0.350	0.743	0.147	4,796	0.301	0.721	0.068	409
Premium Part C	497.3	467.0	435.5	4,796	754.9	408.6	838.9	409
Premium Part D	333.9	210.9	348.8	4,796	232.9	140.7	255.6	409
In network MOOP	3,838	1,084.3	3400	1,696	2,781.4	604.8	2682	148
N. top drugs	95.20	5.973	94	4,765	83.17	14.92	90	409
N. unrestricted drug	532.6	130.5	520	4,765	641.4	102.4	641	409
Deductible Part D	44.59	94.41	0	4,796	21.34	61.12	0	409
Risk score Part C	0.965	0.229	0.908	4,796	0.925	0.109	0.965	409
Risk score Part D	0.934	0.111	0.915	4,796	0.882	0.044	0.880	409
Part C OOPC, excellent	823.2	197.7	807.9	4,425	800.2	110.8	801.2	409
Part C OOPC, poor	1,763.5	529.9	1,730.2	4,425	1,632.6	393.2	1,643.3	409
Drug OOPC , excellent	592.2	145.8	597.2	4,425	720.7	151.0	777.3	409
Drug OOPC, poor	1,974.9	645.2	1,972.9	4,425	2,455.9	687.5	2,552	409
Health care quality	4.048	0.788	4	4,658	4.748	0.435	5	397
Customer service	3.809	1.128	4	3,660	4.698	0.492	5	397
Drug access	4.163	0.838	4	4,654	4.952	0.214	5	397
	Control				**Treatment**			
Post-reform sample: Years 2012–2013	**Mean**	***SD***	**Median**	***N***	**Mean**	***SD***	**Median**	***N***
Total enrollment	1,265.5	3,753.6	236	4,300	8,636.0	21,040.4	1,320	263
Change enrollment, December to January	55.68	228.7	13	4,300	569.6	1,364.1	122.1	263
Percent of change enrollment, December to January	0.133	0.327	0.066	4,300	0.101	0.110	0.0674	263
Premium Part C	427.7	423.1	374.3	4,300	632.1	349.8	647.1	263
Premium Part D	310.3	223.8	306	4,300	213.1	165.8	210.4	263
In network MOOP	3,755.6	991.6	3,400	4,026	3,362.9	1,124.3	3,400.0	263
N. top drugs	87.05	3.757	88	4,274	89.31	3.132	88	263
N. unrestricted drug	415.2	123.5	409.4	4,274	415.6	75.30	389	263
Deductible Part D	40.54	89.19	0	4,300	30.68	73.59	0	263
Risk score Part C	0.953	0.196	0.900	4,299	0.907	0.0913	0.930	263
Risk score Part D	0.909	0.0967	0.893	4,299	0.857	0.043	0.854	263
Part C OOPC, excellent	979.0	192.5	998.2	4,033	989.8	121.2	1,009.2	263
Part C OOPC, poor	2,225.2	412.7	2,286.9	4,033	2,172.4	372.3	2,121.5	263
Drug OOPC , excellent	624.8	130.9	618.0	4,033	629.7	207.5	524.8	263
Drug OOPC , poor	2,399.0	546.6	2,367.9	4,033	2,312.6	989.2	2,163.6	263
Health care quality	4.236	0.622	4	4,267	4.817	0.387	5	263
Customer service	3.926	1.033	4	4,219	4.319	1.225	5	263
Drug access	3.908	1.015	4	4,272	4.669	0.929	5	263

Note. The unit of observation is contract/county/year. The top panel includes observations from 2009 to 2011. The bottom panel includes observations from 2012 to 2013. On the left, there are statistics for observations in the control group: the contracts offered in 1,084 counties with no 5-star plans, but at least one 4- or 4.5-star plan in 2012 or 2013. On the right, there are statistics for observations in the treatment group: the contracts offered in 160 counties with at least one 5-star plan in 2012 or 2013.
Abbreviations: MOOP, maximum out-of-pocket; OOPC, out-of-pocket cost.

clear jump in the plan density at the relevant cutoff points, either before or after the reform.[6] Second, most 5-star plans fall short of having an overall continuous score of 5, reaching a score not much higher than 4.75. This is thus reassuring regarding their comparability with lower rated plans.

Regarding the second selection problem, counties in the proposed treatment and control groups might differ irrespective of the lack of rating manipulations. Our strategy for addressing this issue involves controlling for observable differences. Furthermore, to the extent that we can control for both fixed and time-varying unobservables, we gradually expand the model specification to incorporate both contract fixed effects and linear time trends, separately for treatment and control

[6]This is further supported by McCrary tests reported in Figure S1.

counties.[7] As discussed in the next section, when presenting the summary statistics in Table 1, treatment and control groups do indeed differ along several observable characteristics, such as size of the enrollment base and features of the enrollment pool. Hence, to the extent that the selection into the treatment state is based on these observable characteristics, we can address this threat to identification. Therefore, as a robustness check, we also present a matching DID strategy. In this case, the control group observations will be selected to match the characteristics of the treatment group.

4 | DATA

The analysis combines several data sources. In the first part of the analysis, we focus on plan- and contract-level data, whereas in the second, we exploit claims-level data.

The data for the first part of the analysis are publicly available data from CMS. In particular, we obtained monthly enrollment data for the years 2009–2013 at the plan level, as well as plan characteristics and risk scores (both at the yearly level). Also from the CMS files, we obtained the scores that each contract received on each individual measure, which we used to compute the continuous score. Table 1 shows the summary statistics for these data. The three main outcome variables that we analyze are (a) the within-year change in enrollment, (b) the across-year change in enrollment, and (c) the plan average risk score. The first variable is calculated as the difference in the contract enrollment in the last and first month of the year (i.e., $Enrollment_{12/t} - Enrollment_{1/t}$, with j/t indicating the jth month of the year). It captures within-year changes in plan enrollment, and thus, it measures the most direct effect that the policy produces in terms of increased within-year plan switches.[8]

The second outcome variable considers the possibility of plan switching across years. We calculate it as the difference in the contract enrollment in two consecutive years. More precisely, it is calculated as $Enrollment_{1/t} - Enrollment_{12/t-1}$. This variable can capture a strategic response by consumers, namely, greater plan switching during the regular OEP driven by the possibility of switching to a 5-star plan later. The third outcome variable is a proxy for the plan's risk pool. More precisely, we use the mean contract risk score, available from CMS at the yearly level and separately for the managed care (Part C) and prescription drug (Part D) components of the MAPD plans.

The risk score is the key statistic mapping how enrollment composition impacts expected plan costs. In the final part of our analysis, we will look at the demographic characteristics of the switchers to better understand what drives the findings on plan-level risk scores. The summary statistics are immediately suggestive of interesting patterns in the data. In particular, we see that the within-year change in enrollment into treatment plans increases after the 5-star SEP. This is not the case for the control group.[9]

The analysis involving claims-level data, instead, uses the National Bureau of Economic Research, Medicare Part D Research Identifiable Files. These data are a 20% random sample of all beneficiaries. For each beneficiary, we observe information on age, sex, place of residence, health conditions, and plan enrollment. To study within-year switching to 5-star MAPD behavior, we focus on those enrollees residing in counties where 5-star MAPDs were offered in 2012 or 2013. The resulting sample has 2.4 million enrollees for 2012 and 2.5 million enrollees for 2013. In each year, about 0.25% of these enrollees switch to a 5-star MAPD during the year under the 5-star SEP.[10]

5 | RESULTS

This section presents the results separately in four parts. The first three sections look at contract-level outcomes, whereas the fourth presents evidence from the claims-level data.

[7] Our unit of observation is a contract-year-county. In most of the control counties, we observe multiple contracts with 4–4.5 stars. To a lesser extent, we observe multiple contracts also in the treated counties (i.e., we observe seven counties for which there were more than one 5-star plan in either 2012 or 2013).

[8] The data do not allow us to separately observe the part of monthly enrollment due to enrollees turning 65, moving to a different county, or becoming eligible to change plan under any other SEP rule. However, because none of these other SEP rules has been introduced with a timing or a geographical span similar to the 5-star SEP, the proposed empirical strategy will allow us to separately identify the effects of the 5-star SEP.

[9] Table 1 also reveals that both premiums and (several measures of) generosity tend to decline after the reform more for the treatment than for the control group. Details on each measure are reported in the Supporting Information.

[10] We observe 5,502 switching cases in 2012 and 5,667 cases in 2013. To ensure these are all due to the 5-star SEP, we had excluded from the sample individuals changing residency or turning 65 during the year. We exclude from the sample those individuals who cannot switch because they are already enrolled in a 5-star MAPD plan as well as those who never purchase any drug. We also drop individuals with missing values for race in the Medicare files.

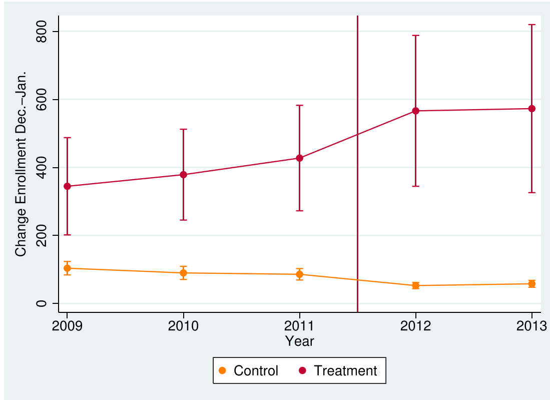


FIGURE 3 MAPD contracts: Within-year enrollment change [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: Evolution of the within-year enrollment variable for both treatment and control contracts.

5.1 | Within-year enrollment for MAPD

The evolution of the average within-year enrollment change is described in Figure 3 for both treatment and control plans. In line with the statistics in Table 1, it shows both a relatively large increase for the treatment group after the 5-star SEP (represented by the straight, vertical line) and a lack of any increase for the control group.

Even before 2012, there is a trend for growth in the treated group, compared with a declining path for the control group. Although for both groups these year-to-year changes are not statistically significant, thus limiting potential bias in the estimate of β, we will also report estimates including group-specific linear time trends in the DID model specification.[11] Nevertheless, because the statistical evidence in favor of a differential trend is rather weak and because it is conceivable that trends might obfuscate the effects of the 5-star SEP if consumers learn over time to exploit the new enrollment flexibility, we will also report estimates from a more parsimonious model without time trends and describe both sets of estimates. As discussed below, the main findings for the contract-level analysis will remain qualitatively the same.

Table 2 displays our DID estimates for the within-year enrollment in MAPD. The dependent variable is thus the within-year enrollment change both in levels (Columns 1–4) and in percentage terms relative to January enrollment (Columns 5–8). We estimate four models. Odd-numbered columns include county and year fixed effects, and even-numbered columns add contract fixed effects. Columns 3, 4, 7, and 8 add a linear trend at state/treatment level. Panel A reports the estimates for the baseline sample: The treatment group has 5-star contracts in 2012 or 2013, whereas the control group contains 4- or 4.5-star contracts in 2012 or 2013 in counties without any 5-star contracts. The next panel reports the robustness check involving a matched-DID estimator.

The estimates in Panel A show that the 5-star SEP has a large and statistically significant effect on the within-year change in enrollment. The effect reported in Columns 1 and 2 implies that the number of enrollees increases on average by 225–235 enrollees. This effect is quite substantial, if, for instance, we compare it with an average value of the dependent variable in the pretreatment period of 386 enrollees. When including time trends, the effect is still present, but its magnitude is attenuated. Columns 5–8 report analogous estimates for the percentage enrollment change. This variable allows the enrollment changes to be normalized by the existing enrollment base. The estimates that we obtain range from 7% to 9% in the more parsimonious specifications and around 16% when including time trends.

To assess the sensitivity of our estimates to the choice of control group, in Panel B, we use the matched-DID strategy described earlier. The estimates obtained are similar in terms of both magnitude and significance to those in Panel A. Not all coefficients of the matched DID, however, lie within the 95% confidence interval of those in Panel A. In particular, the matched DID indicates a larger percentage increase, amounting roughly to a 20% effect, when including trends. Although these estimates are likely the preferable ones as they fully exploit the richness of the data, we take the Panel A estimate of a 15.5% effect as a more conservative estimate.[12]

Finally, it is informative to know in which month of the year enrollees use the SEP. Thus, we consider complementing the above estimates of the December minus January enrollment change with analogous estimates for the other months

[11] The presence of an upward trend for the treatment group can be explained by several factors. CMS has been strongly advertising star ratings as a measure of quality, possibly impacting the evolution of enrollment over time. There is no evidence of trends for the other outcome variables used below.

[12] We tried various specification for the propensity score, and results were broadly comparable with those in Panel B. Details are reported in Tables S1 and S2.

TABLE 2 MAPD contracts: Within-year enrollment change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline sample							
	December to January enrollment change				December to January enrollment % change			
5 stars	224.327***	235.741***	86.860**	86.131**	0.074*	0.089**	0.165**	0.155**
	(50.125)	(48.533)	(39.527)	(37.405)	(0.044)	(0.042)	(0.075)	(0.070)
Observations	9,768	9,768	9,768	9,768	9,768	9,768	9,768	9,768
R^2	.553	.620	.564	.630	.196	.281	.229	.313
	Panel B: Matched sample							
	December to January enrollment change				December to January enrollment % change			
5 stars	145.972***	153.032***	63.519**	60.888**	0.089*	0.099**	0.219***	0.202***
	(25.732)	(25.236)	(25.683)	(24.662)	(0.046)	(0.046)	(0.079)	(0.075)
Observations	7,616	7,616	7,616	7,616	7,616	7,616	7,616	7,616
R^2	.461	.548	.475	.562	.185	.272	.220	.308
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract FE	No	Yes	No	Yes	No	Yes	No	Yes
Time trend	No	No	Yes	Yes	No	No	Yes	Yes

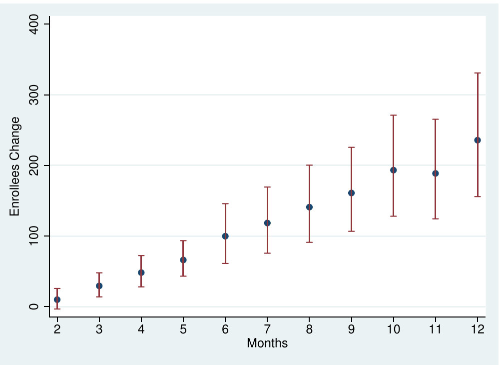
Note. The table reports the difference-in-differences estimates of the effect of the 5-star special enrollment period. The outcome variable is the difference in the contract enrollment between December and January (of the same year) calculated either in levels (first four columns) or as a percentage (latter four columns). The four model specifications considered for each dependent variable differ in the set of controls used, as reported in the block at the very end of the table. Panel A reports the estimates for the baseline sample: treatment group contracts with 5 stars in 2012 or 2013; control group contracts with more 4 or 4.5 stars in 2012 or 2013 in counties without 5-star contracts. Panel B reports the estimates for a sample matched using a propensity score. The probability that a county has a 5-star contract is estimated over a range of socioeconomic, demographic, and health indicators of the counties. Only the county on common support of the propensity score between the treatment and the control groups are included. Standard errors are in parentheses clustered at county level.

Abbreviation: FE, fixed effect.

***$p<0.01$.

**$p<0.05$.

*$p<0.1$.



Notes: Estimate of the effect of the 5-star SEP on within year enrollment change, calculated at all months. The last value on the horizontal axis (12) represents the Dec. minus Jan. enrollment, the next value (11) represents the Nov. minus Jan. enrollment, and so on until (2), which represents the Feb. minus Jan. enrollment. The value for the Dec. minus Jan. enrollment is the same reported in the second column of Panel A in Table 2. All other estimates are obtained using the same specification.

FIGURE 4 MAPD contracts: Monthly enrollment change relative to January [Colour figure can be viewed at wileyonlinelibrary.com]

preceding December. In Figure 4, we plot the estimates obtained for the same specification as in model (2) of Table 2. The effect on enrollment of the SEP appears to increase linearly over time up until October and then it flattens out. Thus enrollees seem to use the new SEP uniformly over most of the year.

5.2 | Across-years enrollment for MAPD

Next, we explore the behavior of consumers across years. In Table 3, we therefore repeat the previous analysis using as a dependent variable the change in enrollment across years.

TABLE 3 MAPD contracts: Across-year enrollment change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline sample							
	January to December enrollment change				January to December enrollment % change			
5 stars	-2.072	0.272	21.254	22.616	0.044	0.039	0.186***	0.204***
	(15.362)	(15.002)	(26.370)	(24.777)	(0.037)	(0.033)	(0.054)	(0.052)
Observations	8,823	8,823	8,823	8,823	8,823	8,823	8,823	8,823
R^2	.079	.121	.088	.130	.143	.219	.148	.225
	Panel B: Matched sample							
	January to December enrollment change				January to December enrollment % change			
5 stars	8.495	10.458	8.776	8.914	0.065	0.057	0.243***	0.261***
	(13.164)	(12.988)	(19.117)	(18.275)	(0.040)	(0.036)	(0.056)	(0.055)
Observations	7,094	7,094	7,094	7,094	7,094	7,094	7,094	7,094
R^2	.138	.190	.167	.220	.118	.204	.124	.212
Year FE	YES	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	YES	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract FE	NO	Yes	No	Yes	No	Yes	No	Yes
Time trend	NO	No	Yes	Yes	No	No	Yes	Yes

Note. The table reports the difference-in-difference estimates of the effect of the 5-star special enrollment period. The outcome variable is the difference in the contract enrollment between January and December (of consecutive years) calculated either in levels (first four columns) or in percentage (latter four columns). Panel A reports the estimates for the baseline sample: treatment group contracts with 5 stars in 2012 or 2013; control group contracts with more 4 or 4.5 stars in 2012 or 2013 in counties without 5-star contracts. Panel B reports the estimates for a sample matched using a propensity score. The probability that a county has a 5-star contract is estimated over a range of socioeconomical, demographic, and health indicators of the counties. Only the counties on common support of the propensity score between the treatment and the control groups are included. Standard errors are in parentheses clustered at county level.

Abbreviation: FE, fixed effect.

***$p<0.01$.

**$p<0.05$.

*$p<0.1$.

The effect of the 5-star SEP is, however, ex ante ambiguous in this case. A decrease in demand for 5-star plans is compatible with consumers acting strategically, that is, enrolling in cheap, low-coverage non-5-star plans, but with the intention of switching to a more expensive 5-star plan if hit by a health shock during the year. The previous estimates in Table 2 indicate that within-year switches do occur. However, this is not enough to also imply that consumers will act strategically in their choice of switching plan across years. In fact, increases in enrollment in 5-star plans across years might be driven by their enhanced promotion by CMS or by lower premiums. Furthermore, inertia in plan choice might imply a lack of changes in across-year enrollment. Empirical evidence by Handel (2013) and related work has revealed how relevant inertia is for health insurance plan choices. But it is noteworthy that, in our setting, inertia might interact in complex ways with the 5-star reform. In the presence of present-biased beneficiaries, it might drive a drop in 5-star plan enrollment across years due to procrastination (as argued in Madeira, 2015). Furthermore, although inertia is sometimes observable through the comparison of the choices of new and continuing enrollees, this is not necessarily the case for the 5-star SEP. In fact, inertia could lead even new enrollees to voluntarily ignore the possibility of "gaming" the system: Selecting a plan during the OEP with the idea of switching to a 5-star plan during the coverage period might be undesirable for those consumers who are aware that their inertial behavior is driven by features like search costs, switching costs, or psychological costs.

The estimates in Table 3 reveal that demand for 5-star plans did not decline across years: There is no specification that results in a negative and significant effect. Statistical significance is achieved only for the estimates involving percentage increase and, within these cases, only for the specifications including time trends (Models 7 and 8). This finding emerges for both the baseline estimates (Panel A) and the matched DID (Panel B). Because we tend to prefer the more complete specifications of Models 7 and 8, we might conclude that there is evidence in favor of an increase in enrollment across years. However, contrary to the within-year demand estimates that systematically lead to very consistent estimates in terms of sign and significance, the lack of stability in the across-years demand estimates suggest that caution should be taken in interpreting the finding as conclusive in terms of any positive effect on across-years demand.

In any case, all estimates indicate that any strategic consideration for consumers to leave 5-star plans was muted by the forces inducing a stronger demand. This finding suggests that the reform was successful in shifting enrollees to 5-star plans

TABLE 4 MAPD contracts: Risk score Part C and D

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Risk score Part C				Risk score Part D			
5 stars	-0.024***	-0.029***	-0.016***	-0.014***	-0.007***	-0.010***	-0.010***	-0.008***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	9,767	9,767	9,767	9,767	9,767	9,767	9,767	9,767
R^2	.349	.949	.354	.953	.349	.930	.354	.935
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract FE	No	Yes	No	Yes	No	Yes	No	Yes
Time trend	No	No	Yes	Yes	No	No	Yes	Yes

Note. The table reports the difference-in-differences estimates of the effect of the 5-star special enrollment period. The outcome variable is the risk score for the managed care (or Part C) component (first four columns) and the prescription drugs (or Part D) component (latter four columns). The four model specifications considered for each dependent variable differ in the set of controls used, as reported in the block at the very end of the table. Baseline sample: treatment group contracts with 5 stars in 2012 or 2013; control group contracts with more 4 or 4.5 stars in 2012 or 2013 in counties without 5-star contracts. Standard errors are in parentheses clustered at county level.

Abbreviation: FE, fixed effect.

***$p<0.01$.

**$p<0.05$.

*$p<0.1$.

in a stable way. Although a positive coefficient can mechanically result from the combination of increased within-year switches in 2012 and the presence of plan switching cost, our estimates remain qualitatively identical if we rule out this channel by excluding 2013 data.

5.3 | Part C and D risk scores for MAPD

The final set of results concerns the effects of the 5-star SEP on the contracts' risk pools. The two dependent variables on which we focus are the yearly average MAPD risk scores that CMS releases separately for the two components of MAPD plans, managed care (or Part C), and prescription drugs (or Part D). Each one of these two measures is normalized to 1 for the average risk of a TM enrollee; the higher the risk score, the higher the risk (and the expected cost) of the enrollee.

Table 4 presents the baseline estimates, separately for Part C (first four columns) and Part D (latter four columns) components. Both the model specifications and the construction of the control group is identical to those described for Tables 2 and 3. All the estimates in this panel show a negative and significant effect on both risk scores. The magnitude of the estimated coefficients is small, but not negligible. Relative to the summary statistics reported earlier, the estimates for the effect on the managed care risk score of the 5-star SEP roughly correspond to one fifth of a standard deviation of the dependent variable. The analogous figure for the prescription drugs component risk score is one fourth of a standard deviation.

There are a few subtle problems related to the timing of the risk score measurement that might affect these estimates. However, additional results reported in the Supporting Information confirm that the risk pool of 5-star plans effectively improved. To explore this feature, we now turn to the claims-level data, which allow us to understand whether the lowered risk score in 5-star MAPD is due to switchers who are healthier relative to the whole Medicare population or only relative to the risk pool of 5-star plans.

5.4 | Additional evidence from claims data

Our analysis of claims-level data is based on estimating the probability of of switching to a 5-star plan. Therefore, we estimate the following logit model:

$$Pr(Switch_{it}) = \Phi[\alpha + \sum_{z\in Z} \beta_z HealthStatus_{itz} + \sum_{j\in J} \gamma_j X_{itz} + \tau_t],$$

where i indexes the enrollee and t the year. Φ is the cumulative density function of the logistic distribution. *HealthStatus* contains Z measures of the health conditions of enrollee i in year t. X contains various additional controls that we will group in three main categories: *Demographics* (sex, age and race), *Financials* (current and last year out-of-pocket cost

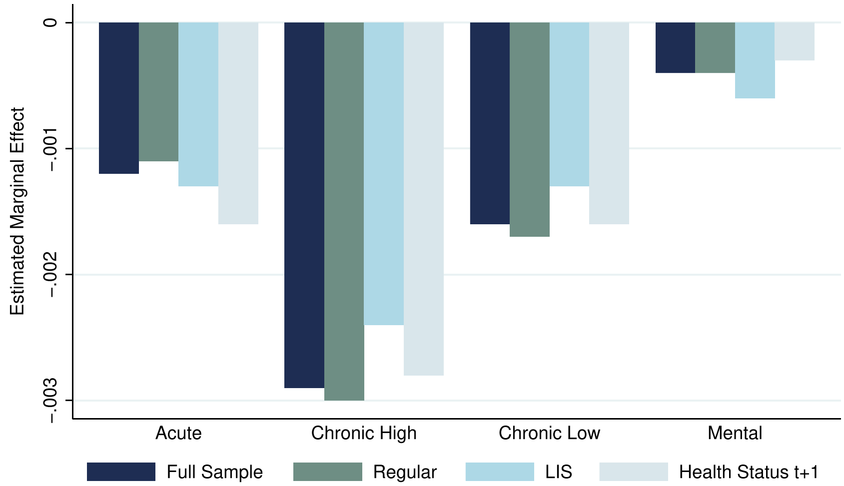


FIGURE 5 Heterogeneity across health groups. LIS, low-income subsidy [Colour figure can be viewed at wileyonlinelibrary.com]

[OOPC]) and *Programs* (indicator variables for whether in January of year *t* enrollee *i* is in MAPD, PDP, or in TM without any Part D plan). We are particularly interested in the estimates of the β_z coefficients as they can provide direct evidence regarding the risk of switchers relative to nonswitchers.

Although we cannot replicate exactly the CMS risk score measures used in the earlier section, the four variables that we use for *HealthStatus* capture most of the health conditions behind the determination of the risk scores. In particular, we consider four variables (*Acute High*, *Chronic Low*, *Chronic High* and *Mental*), which are constructed as follows. Each variable is a dummy variable for the existence of a flag for any of the relevant medical conditions in the chronic conditions component of the master beneficiary summary file. Together, they act as a rough proxy of CMS' risk adjustment. *Acute High* accounts for any severe acute conditions such as heart attacks, strokes, or fractured hips. *Chronic Low* records the presence of chronic conditions that are not debilitating (asthma, diabetes, hyperlipidemia, etc.). *Chronic High* indicates the existence of debilitating chronic conditions (osteoporosis, cancer, etc.). Finally, *Mental* indicates Alzheimer and depression conditions. Because a flag is recorded even if there is only one event in the year triggering one of the diagnoses we consider, this implies that our measures are likely to capture any change in health status that could be also associated with switches to high-coverage, 5-star plans. The means (and standard deviations) for these dummy variables are around 0.8 (0.4) for *Chronic Low* and 0.7 (0.5) for the other three.

In Figure 5, we show the marginal effects for the logit regressions reported in Table 5. For each of the four health conditions, the figure shows the marginal effect estimated for four different samples. The bars in dark blue refer to the first sample, which is the baseline full sample of 2012 and 2013 switchers. All the four measures of adverse health conditions are clearly associated with a decline in the probability of switching. Moreover, the magnitude of the effect associated with *Chronic High* is about twice that of *Chronic Low*. The lower propensity to switch during the year to a 5-star plan among enrollees in worse health is also confirmed across the three subsamples represented with different colors in Figure 5.[13] This evidence is most obviously compatible with the greater difficulties that enrollees suffering from severe chronic disease would face were they to change provider network. As argued in Decarolis and Guglielmo (2017), insurers can enhance these difficulties by reducing the financial generosity of their plans. But even more crucial for chronically ill patients might be the provider network. In this respect, the evidence in Shepard (2016), albeit in a different health insurance context, clearly shows the impacts on these enrollees of insurers' choice to leave out of their network "star" hospitals preferred by these enrollees.

Table 5 reports the logit estimates for different model specifications and sample restrictions. Model 1 includes only the *HealthStatus* measures, whereas the following three models gradually expand the specification to include *Demographics* (Model 2), *Financials* (Model 3), and *Programs* (Model 4). All models also include a constant and a dummy for 2013, both not reported in the table. Models 5 and 6 estimate the same specification of Model 4 for two different subsamples: one excluding low-income subsidy (LIS) enrollees (Model 5) and one including only LIS enrollees (Model 6). Finally, Model 7 uses exclusively 2012 switching data, but replaces the concurrent *HealthStatus* measures with their values in 2013. Models 4–7 are those producing the marginal effects shown in Figure 5.

[13]These are regular enrollees (light green), LIS receivers (light blue), and the 2012 switchers only (grey). For the latter subsample, the model is estimated by replacing the concurrent *HealthStatus* measures with their values in 2013. The idea of this specification is to check whether the enrollees switching in 2012 are more likely to be those in worse health status the following year.

TABLE 5 Logit estimates for 5-star special enrollment period switches

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Regular and LIS enrollees				Regulars	LIS	Health$_{t+1}$
Health Status							
Acute high	-0.58***	-0.60***	-0.60***	-0.53***	-0.51***	-0.52***	-0.70***
	(0.051)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)
Chronic low	-0.69***	-0.73***	-0.71***	-0.71***	-0.78***	-0.52***	-0.69***
	(0.026)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Chronic high	-1.44***	-1.41***	-1.44***	-1.29***	-1.35***	-0.95***	-1.25***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.09)	(0.08)
Mental	-0.26***	-0.23***	-0.23***	-0.18***	-0.20***	-0.22***	-0.11*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)
Demographics							
Female		-0.06***	-0.05***	-0.07***	-0.10***	-0.02	-.07**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.03)
Age		0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black		-0.17***	-0.19***	-0.20***	-0.10**	-0.68***	-0.23***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.06)
Latino		0.55***	0.51***	0.50***	0.17**	0.47***	0.41***
		(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.07)
Asian		1.07***	1.03***	1.06***	1.10***	.60***	1.00***
		(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.06)
Other		0.66***	0.63***	0.65***	0.65***	0.44***	0.62***
		(0.04)	(0.04)	(0.04)	(0.05)	(0.10)	(0.06)
Financials							
OOP			-0.28***	-0.30***	-0.28***	-0.44	0.00
			(0.08)	(0.08)	(0.08)	(0.69)	(0.00)
OOP$_{lag}$			-0.21***	-0.27***	-0.17***	-1.99***	-0.00***
			(0.05)	(0.05)	(0.05)	(0.46)	(0.00)
Programs							
PDP				-0.52***	-0.71***	-0.54***	-0.39***
				(0.04)	(0.05)	(0.07)	(0.06)
No Plan				-0.26***	-0.23***	0.55***	-0.34***
				(0.02)	(0.03)	(0.08)	(0.03)
Observations	4,934,656	4,934,656	4,934,656	4,934,656	4,125,297	809,359	2,211,384
Prob. χ^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. Logit regressions for the probability that an enrollee not enrolled in a 5-star plan in January of 2012 or 2013 switches during the year to a 5-star MAPD under the 5-star special enrollment period. All regressions include a constant and a dummy equal to 1 if the year is 2013 and zero if it is 2012. For readability, OOP and OOP$_{lag}$ are rescaled by 1,000. Standard errors are in parentheses clustered at county level.

Abbreviations: LIS, low-income subsidy; OOP, out-of-pocket; PDP, Prescription Drug Plans.

***$p<0.01$.

**$p<0.05$.

*$p<0.1$.

In addition to what has already been discussed concerning Figure 5, the estimates in Table 5 show a few interesting results. In particular, we find that switchers are more likely to come from other Medicare Advantage plans than from TM, with or without Medicare Part D. Moreover, we estimate a negative coefficient for both the *Black* race indicator and the two OOPC measures. The estimates are also indicative that switchers are more likely to originate from within the MAPD program rather than from the PDP program or from TM without any Part D coverage. The positive estimate on *Age* and *Female*, instead, runs contrary to what would be expected under advantageous selection. Their magnitudes, however, are smaller if compared, for instance, with the effect of the *Black* indicator variable, and in the case of *Female*, the effect is not significant in Model 6. The relevance of the subsampling results in Models 5 and 6 derives from the fact that LIS enrollees have special rights to switch plan within the year. Observing that the estimates are nearly identical for the two subsamples reassures us that our results are not driven by the mere presence of switches by LIS enrollees.

6 | CONCLUSIONS

The 5-star SEP reform that, beginning in 2012, allowed Medicare enrollees to switch at any point in time to a 5-star-rated plans is a rare example of a change in open enrollment rules. It therefore represents a valuable natural experiment to learn about the effects that these kinds of policies can produce and, hence, to what extent they can be used as a tool to guide health insurance markets toward socially desirable outcomes. In the context of Medicare, where as of 2017 more than 11 million beneficiaries were exposed to the effects of the 5-star SEP, this reform appears to have accomplished its intended effects of promoting enrollment into high-quality, 5-star plans without generating an adverse selection death spiral.

The analysis is based on a clean identification strategy exploiting the geographical distribution of plans with different star ratings in the years 2009–2013. Its focus on demand-side questions complements the supply-side analysis of the 5-star SEP presented in Decarolis and Guglielmo (2017). That paper showed a strategic response by the insurers who lowered both the premiums and the benefit generosity of the 5-star plans, whereas our study illustrates how enrollees responded to the combined changes in plan characteristics and the possibility to switch within the year. We find that within-year switching does increase, but this is not associated with a worsening of selection. Indeed, enrollees in poor health are less likely to switch and this explains the reduction in risk scores observed for the 5-star plans.

These results suggest the relevance of two main avenues for future research. First, enrollees' inertia in choosing a plan emphasizes the need to better understand the drivers of plan switching behavior and their interactions with the frequency and length of the OEPs. Second, effective risk adjustment systems need to take into account plan switching behavior associated with the presence of SEPs. This is a factor that should be preeminent in any discussion of SEP reforms involving changes to the set of "life qualifying events" that allow plan switches.

Finally, the external validity of our results will be greater for those markets that, like Medicare, require insurers to accept all enrollment requests. For instance, it would be interesting to consider how our results could contribute to the understanding of recent reforms of the ACA. In fact, as discussed in Dorn (2016), the SEPs in the ACA were designed to allow people who, due to job loss or other factors, needed to obtain marketplace coverage outside of the standard OEP. After the carriers claimed widespread abuse of the SEP by ineligible people, however, CMS tightened the requirements for SEP applicants by requesting to document their eligibility. It would thus be interesting to quantify whether this reform affected both premium and enrollment decisions in the ACA exchanges.

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ORCID

Francesco Decarolis https://orcid.org/0000-0002-8547-7021

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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