Competition and Costs in Medicare Advantage

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December 15, 2015

Job Market Paper

Most Recent Version

Abstract

As of 2010, government expenditure per enrollee in Medicare Advantage (MA) was 13% higher than in Traditional Medicare. I develop and estimate a model of competition among MA insurers to disentangle the sources of this cost discrepancy. Building on the existing literature, in my model, insurers endogenously choose premiums and the generosity of the coverage, taking into account the complex structure of reimbursements and subsidies employed in MA. My estimates reveal considerable heterogeneity in insurer costs. First, HMO plans, compared to PFFS plans, provide more generous coverage with lower costs. Second, the relationship between plan cost and generosity of the coverage varies across type of plans. Further, my estimates imply that MA generates a surplus larger than its cost to the government; however, this surplus is mainly captured by insurers. To identify possible areas for efficiency gains, I run simulations to study the impact of alternative reimbursements policies, such as premium support, on government expenditure, consumer surplus, and insurer profits.

*Andrea Guglielmo, University of Wisconsin – Madison (aguglielmo@wisc.edu). JEL Classification: I11, I18, L22. This research received financial support through the Christensen Award for Empirical Economics. I am extremely thankful to my advisors Alan Sorensen, Ken Hendricks, and Amit Gandhi for all of their support and guidance in the various stages of this project and to Francesco Decarolis for the countless conversations and advice. Thanks to Enghin Atalay, Dan Quint and all participants to the iHEA World Congress 2015, Wisconsin IO Seminars, Student Research Group Workshops, and UW Whitewater seminars. I am grateful to the members of the Medicare Plan Payment Group for sharing their knowledge with me of Medicare Advantage in our numerous email exchanges. Finally, I am thankful to Marguerite Hoving, Nathan Yoder, Mark Colas, Woan Foong Wong, Kegon Tan and countless classmates, friends, and family for all your support. All the remaining errors are mine.

1 Introduction

Managed competition has long been discussed by economists and practitioners as a market driven alternative to single payer systems and traditional employer-sponsored insurance (Enthoven (1978)). The goal is to discipline and spur competition between insurers in order to deliver the highest value for money spent to the beneficiaries. Various examples of systems which implement managed competition exist in countries such as Switzerland and the Netherlands. The primary example of managed competition in the US is Medicare Advantage (MA).

The MA program provides access to subsidized private health insurance to the American elderly, who can opt out from Traditional Medicare (TM) to choose from a variety of plans. These different types of plan, which are known as managed care organizations (MCO), can differ widely as to the way in which healthcare is provided; in particular, MCOs differ with regard to the type of benefits covered, cost-sharing, provider selection and organization, provider payment and service utilization monitoring.[1] Insurers bid to provide the package of services included in TM; these same bids also determine the size of the subsidy they receive for supplemental coverage. Both MA enrollment and the number of plans have been increasing since the early 2000s. As of January 2015, 16 million American senior citizens get their health insurance coverage through MA. Nevertheless, the financial viability of the program has been questioned, as the average cost for Medicare of an enrollee in MA has been 13% greater than TM (see MedPAC (2010)), raising doubts about the efficacy of managed competition in this context. Recently, the Patient Protection and Affordable Care Act (ACA) reformed the payment system of MA, reducing the average subsidy while linking the individual plan subsidy to measures of their previous performance. The CBO (2010) estimates that the reform would save $136 billion over the period 2010-2019.

In this paper, I disentangle the sources of the cost discrepancy between MA plans and TM. There are many possible reasons for the difference. Private health insurance plans might be less efficient than TM and have higher costs; however, the expenditure difference between MA and TM might also be explained by an ill-designed system of payments and subsidies that does not incentivize

[1] For a through treatment of managed care and managed care organizations see Glied (2000)

insurers to reveal their true costs, and instead lets them capture a sizable rent. Moreover, MA plans tend to offer greater coverage, making any comparison of their costs with those of TM, or even those of other MA plans, difficult to interpret. Thus, to make this cost comparison feasible, I develop and estimate a structural model of competition in the MA market which allows me to retrieve consumer preferences, and more importantly, to retrieve MA plans' cost structures. Following Dunn (2010), I allow insurers to freely choose their premium and coverage level, with the latter represented by out-of-pocket cost (OOPC), the non-premium cost paid by MA plan beneficiaries. Moreover, I incorporate the convoluted MA payment system, in which a plan's bid to provide TM services determines the size of its government subsidy for supplemental services, into my model. I am able to simplify this complicated problem by exploiting the regulatory framework, as suggested by Stockley et al. (2014), since it links the amount of coverage that a plan provides to the premium its enrollees pay and the subsidy it receives from the government.

In each market, my model allows me to retrieve not only each plan's marginal cost, but also the derivative of marginal cost with respect to coverage level. As Nevo (2001) and Dunn (2010) do, I assume that insurers follow Bertrand-Nash pricing, enabling me to retrieve such rich cost structures by exploiting plans' first-order conditions. I find that about 37% of MA plans have marginal costs lower than TM, and that different types of MCO have heterogenous marginal costs. Plans that impose tighter constraints on beneficiaries' healthcare choices, through their selection of in-network providers and cost-sharing, have lower costs (55% plans with cost lower than TM) than less restrictive plans do (31% plans with cost lower than TM). Moreover, plans with tighter restrictions on healthcare usage tend to have a greater ability to reduce their cost when increasing enrollees' cost-sharing. I am also able to separate the effect of MA plans' coverage levels on their marginal costs from the effect of the different constraints (i.e., selection of in-network providers and cost-sharing) on beneficiaries' healthcare choices. If they provided the same level of coverage as TM, 64% of MA plans with strong healthcare usage restrictions would have costs lower than TM, while this is true for only 41% of MA plans with less restrictions. This result suggests that the difference in cost between MA and TM is due not only to differences in coverage level but also to systematic differences in the ways in which enrollees are able to access healthcare. My demand and supply estimates imply that MA program generates a net monthly surplus of $86 per enrollee; however, this surplus is mainly captured by insurers. These numbers suggest that there is room for improvement in the way Medicare pays MA plans. I evaluate an alternative payment mechanism, premium support, in which plans receive a flat subsidy for each enrollee. The results suggest that this simple alternative mechanism continues to generate surplus, while reducing government expenditure.

Two recent papers are close to mine in term of approach and methodology. Miller (2014) analyzes competition in the MA market by estimating a structural model in which insurers can set both premium and coverage level. However, the paper does not take into consideration the bidding and subsidization process, which is a key feature of MA. Curto et al. (2014) include the bidding system in their model of competition in the MA market; to my knowledge, they are the only ones to estimate a structural model with this feature. However, their model does not allow insurers to choose their coverage level directly. As discussed above, my paper provides a unified framework which incorporates these relevant features of the MA market, in which insurers both choose their premium and coverage level and take the bidding and subsidization process into account. Moreover, my model allows me to highlight the extent to which plans with different levels of restrictions on enrollees' health care choices have different cost structures. A few other papers perform a similar exercise when analyzing related markets: Lustig (2010) focuses on the MA pre-bidding system; Starc (2014) looks at the market for Medigap insurance and Decarolis, Polyakova and Ryan (2015) analyze the market for Medicare Part D stand-alone drug plans.

This paper contributes to the ever-growing literature that studies MA. Starting from the seminal contribution of Town and Liu (2003), a number of papers have followed a structural approach to study various aspects of the MA market: value of coverage (Dunn (2010)), entry (Maruyama (2011)), drug coverage (Hall (2011)), and advertising (Aizawa and Kim (2013)). My paper is complementary to many recent studies that have employed a reduced-form approach to attempt to quantify the pass-through of the government subsidy and its allocation into coverage by MA plans (Song, Landrum and Chernew (2013); Duggan, Starc and Vabson (2014); Stockley et al. (2014); Cabral, Geruso and Mahoney (2014)). Similarly to Dunn (2010), Lustig (2010) and Miller (2014), I provide structural estimates of the relationship between plan cost and coverage level; however, my model highlights the extent to which different types of MCO may have different cost structures. In this respect, my paper also contributes to a large reduced-form literature (Glied (2000)) that studies the determinant of the cost differences between MCOs and traditional fee-for-services system, providing structural estimates of marginal costs for different types of MCOs. Moreover, this paper is also related to a few recent studies that analyze how insurers react to government regulation in health insurance markets, in particular MA and Medicare Part D (Carey (2014); Decarolis (2015); Decarolis and Guglielmo (2015); Geruso and Layton (2015)).

Finally, my paper contributes to the developing empirical literature on endogenous product characteristics (Crawford (2012); Fan (2013); Wollman (2014)). In the MA market, this type of problem is not trivial because insurers can control a large number of characteristics when designing their plans (e.g. premium, copayment, choice of supplemental services, network size and structure, etc.); thus, it is necessary to reduce the dimensionality of the level of coverage. Previous literature has modeled the coverage as a one-dimensional index function of the various characteristics of the plan (see Lustig (2010) and Miller (2014)). I follow a different approach by using the OOPC as a proxy for coverage, as in Dunn (2010), because it provides a simple but meaningful measure of benefit level: the non-premium cost paid by plan enrollees. Moreover, as suggested by Stockley et al. (2014), I exploit a feature of the payment system which links coverage level, premium, and bid to simplify the insurer optimization problem. This approach is in the spirit of recent empirical work on endogenous product characteristics, which exploits peculiar features of the specific market to simplify the firm's problem (Wollman (2014)).

The paper is structured as follows: Section 2 provides the institutional details of MA. Section 3 describes the data and lays out the descriptive evidence regarding the market. In Section 4, I develop my model and the details of the estimation strategy, and in Section 5, I present my results. Section 6 provides the results of simulations of alternative payment systems. In Section 7 I conclude.

2 Institutional Background

Since the inception of Medicare in the late 1960s, managed care has been seen as an opportunity to achieve two goals, as explained by McGuire, Newhouse and Sinaiko (2011): to better fit Medicare beneficiaries' needs by expanding the set of choices available to them, and to reduce Medicare's costs by exploiting the efficiency of MCOs. However, despite a number of reforms aimed at creating a mechanism to incentivize insurers' entry while reducing overall costs for Medicare, these two goals have never been jointly achieved. The latest iteration of the program, MA, was implemented by the 2003 Medicare Improvement and Modernization Act. Three main features characterize MA compared to previous attempts to incorporate managed care into Medicare: the presence of a wide variety of MCOs available to enrollees, the introduction of risk adjustment, and the use of managed competition, with subsidies and payments determined through a bidding system.

Managed Care Organization

Insurers that want to participate in MA have to contract with the Center for Medicare & Medicaid Services (CMS), choosing a specific service area (e.g. a county or group of counties) and a type of MCO. CMS categorizes each MCO as one of three types according to its degree of network restriction, providers selection and organization, and cost sharing structure: Health Maintenance Organization (HMO), Local Preferred Provider Organization (LPPO) and Private Fee For Service (PFFS).[2] Enrollees in an HMO are usually required to receive their care from providers in the contract's network (except emergency care, out-of-area urgent care, or out-of-area dialysis); if they receive care outside network they are likely to pay full cost. In some contracts, with the point-of-service (POS) option, enrollees may go out-of-network for certain services, for which cost-sharing is usually higher. Furthermore, enrollees have to choose a primary care doctor who functions as a gatekeeper for healthcare: visits to specialized doctors require a referral from the primary care doctor. LPPO contracts are less restrictive than HMOs, and in most cases allow their enrollees access to any provider, but with lower cost-sharing when using doctors, hospitals, and other healthcare providers that belong to the LPPO's network. LPPOs usually do not require enrollees to choose a primary care doctor or obtain a referral for a specialized doctor visit. Finally, PFFS contracts are comparable to Traditional Medicare (TM): enrollees can generally access any provider that accepts Medicare patients, although providers in the contract's network may require patients to bear a

[2]There is a fourth MCO type, Regional Preferred Provider Organization. I will not focus on this type of MCO because CMS payments to insurers are determined using a fundamentally different system from that used in HMO, LPPO and PFFS contracts.

smaller portion of the cost. As with LPPOs, enrollees in PFFS plans do not need to choose a primary care doctor or obtain a referral for a specialty visit.

Within a contract, insurers can offer a number of different plans with different benefit packages (e.g. different premiums, cost-sharing levels, drug coverage, etc.). To qualify for participation in MA, each plan must provide a standard package which covers the same set of services that are available under TM, i.e Medicare Part A and Part B benefits (except hospice care).[3] MA plans may also provide supplemental services, such those not covered under TM (e.g. eye care, hearing care, dental care, etc.), a discount on TM premiums (Part B), lower cost-sharing compared to TM, and/or drug coverage.[4]

Bidding System and Risk Adjustment

Starting in 2006, CMS payments have been determined through a bidding system. Plans submit bids that indicate the price they would charge CMS to provide TM-equivalent coverage for a representative beneficiary in their service area. Payments are then determined by comparing the bid to a benchmark, which is a function of actual TM costs in the counties which make up the plans' service area and projected plan enrollment in those counties.[5] When the bid is lower than the benchmark, the plan gets back 75% of the difference as a rebate. According to program regulation, this rebate must be used to lower premiums, offer supplemental services, or lower cost sharing. When the bid is above the benchmark, CMS pays the benchmark amount, and beneficiaries who enroll in these plans must pay the remaining part as a premium.[6] Both the bid and the benchmark are adjusted by the risk score of the beneficiaries enrolled in the plan. The risk score uses patient information such as age, income, health history, and past utilization to measure the expected cost of an enrollee.

[3]Medicare Part A includes inpatient hospital care, skilled nursing, and some home health services. Medicare Part B includes physicians' services, outpatient care, and durable medical equipment.

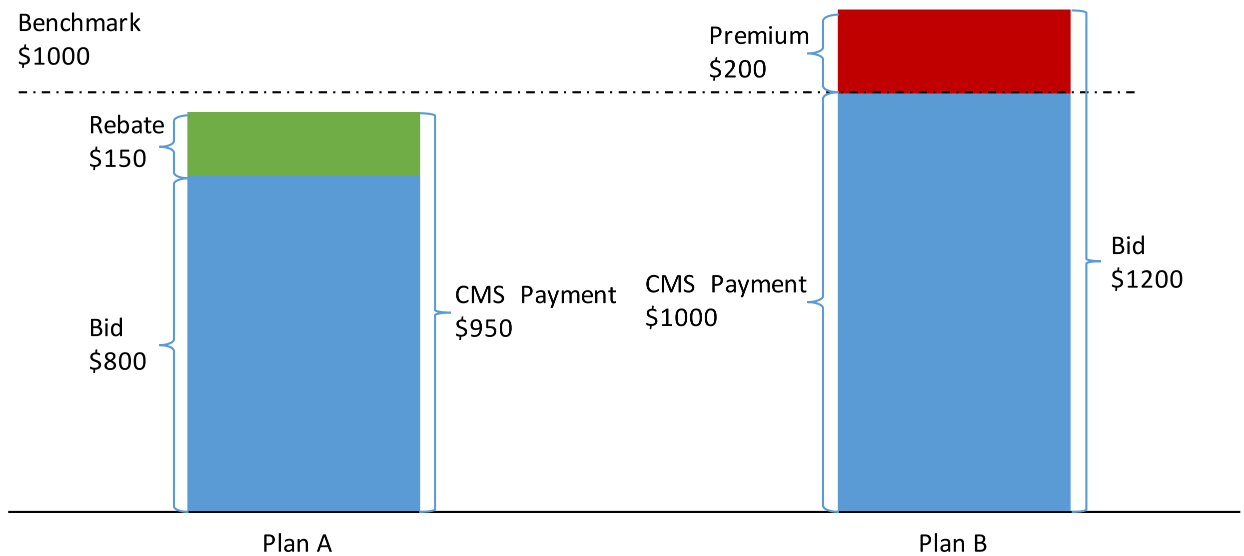
[4]TM enrollees can also access similar types of coverage through separate Medicare programs: Medigap and Medicare Part D. Medigap provides access for TM enrollees to insurance plans that reduce cost-sharing and cover additional services (i.e. health care outside US). TM enrollees can also access drug coverage through the stand-alone Medicare Part D prescription drug plan; similarly to MA, these plans are subsidized by CMS.

[5]Since 2006, benchmarks have been annually updated to the maximum of a national urban or rural floor, an own-county floor, and the previous year's benchmark multiplied by one plus the greater of the national average growth rate of TM costs or 2%. The own-county floor was a forecast based on TM cost data from three to eight years prior.

[6]The total premium paid by enrollees also includes premiums for supplemental coverage (Part C) and, when included, for drug coverage (Part D).

This expected cost is normalized to the average TM enrollee (who has risk score equal to 1).[7]

Figure 1: Bid System - An Example

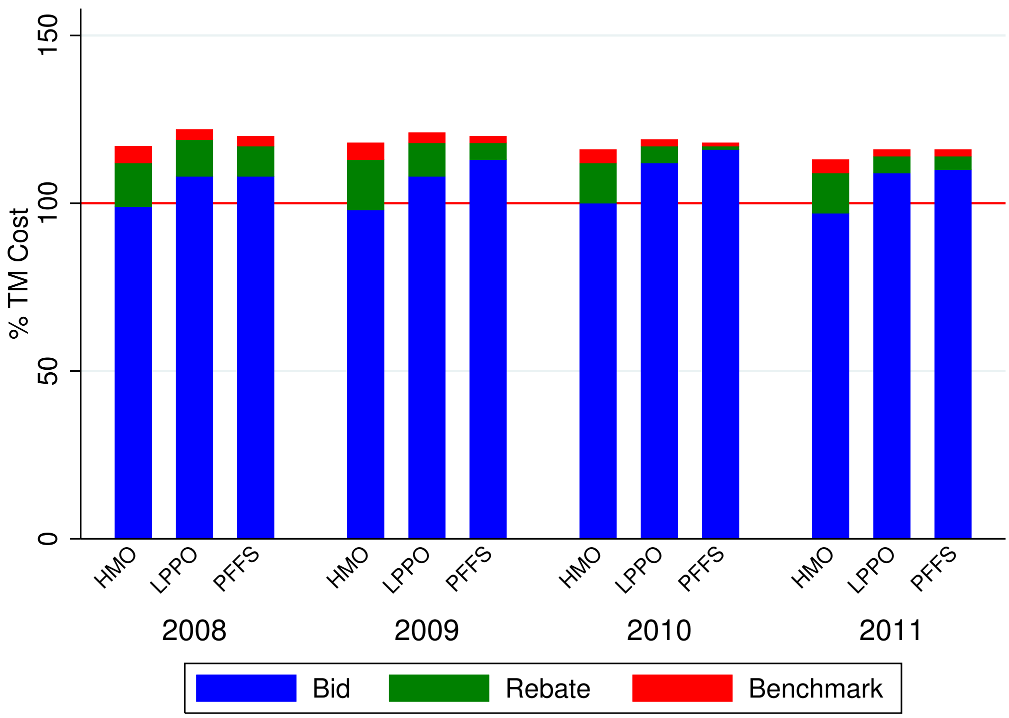


To better understand how the bidding system works, we can consider the example shown in Figure 1. Plan A and Plan B are available only in one county, and the benchmark in this county is $1000. Plan A posts a bid for basic TM services of $800, below the benchmark, and thus receives a rebate of $150 (75% of $200) that must be used to provide supplemental services. Plan B posts a bid of $1200; since this is above the benchmark, enrollees who choose it have to pay a premium of $200. Comparing the overall CMS payment to the two plans, we can see that Plan A receives $950 and Plan B $1000.

The bidding system was initially introduced to spur competition and reduce costs, but it did not deliver the expected outcome. Indeed, in the last few years, MA has been at the center of intense discussion because of the excessive cost of the program, and as of 2010, providing coverage through

[7] Plans also receive a risk-adjusted subsidy for the drug coverage of each enrollee. For Part D, insurers place bids in the amount they would charge CMS to provide basic drug coverage to an enrollee. A national average is constructed weighting these bids by the past enrollment of each plan. CMS provide a subsidy that is roughly 75% of this average and enrollees are responsible of the remaining 25% as base national premium. The individual plan premium would be equal to the sum of base national premium minus the difference between the subsidy and the plan's bid. The subsidy and premium cover only the basic Part D service and plans can also charge a premium for supplemental drug services that are not subsidized by the government. The overall Part D premium would then be the sum of the base premium and supplemental premium.

Figure 2: Payments and Subsidies



Notes: The graph is an elaboration of the data released by the annual MedPAC report to Congress (MedPAC (2008, 2009, 2010, 2011)). Each bar represents the population-weighted average bid, rebate and benchmark.

MA plans costs 13% more than TM (see MedPAC (2010)). Biles, Pozen and Guterman (2009) have estimated that MA plans cost on average \$1,138 more per enrollee than TM, for a total of \$11.4 billion nationally. Figure 2 displays the payment figures released yearly by MedPAC, separating HMOs, LPPOs and PFFSs, drawing a more nuanced picture.[8] It is straightforward to see that the high level at which the benchmarks are set, between 116% and 119.5% of TM cost, fuels the high cost of the MA program; nevertheless, it is worth stressing the difference across different types of MCOs. HMO plans are the only ones that on average bid below the TM cost (specifically, they average 98.5% of it), while LPPOs and PFFSs are above it (109.25% and 111.75% respectively). This is clearly reflected in the rebate figure, which is larger for HMOs; however, even when including their

[8]The data are collected from the annual MedPAC report to Congress, see MedPAC (2008, 2009, 2010, 2011).

rebate amount in their cost, the HMOs are less expensive for CMS than LPPOs and PFFSs. HMOs' total payments are 11.5% larger than TM cost, while LPPOs and PFFSs cost Medicare about 17% and 16.5% more per enrollee than TM. Of course, to correctly interpret these numbers, we have to consider that MA plans typically provide more coverage than TM, with the level of rebate directly affecting these supplemental benefits. In the remainder of the paper, I will document how the rebate and coverage level interact with each other, and how this happens differently across HMO, LPPO and PFFS plans.

The ACA reforms the MA payment system with two objectives. First, it tries to reduce payments, shrinking the wedge between MA plans and TM.[9] Second, it aims to increase the quality of healthcare and the efficiency of MA plans, linking plans' payments to their previous performance.[10] The CBO (2010) estimated that the reform would save \$136 billion over the period 2010-2019. Biles et al. (2012) estimated that if the ACA had been implemented in 2009 there would have been a \$12.7 billion savings on plans' payments. Alternative reforms have been discussed in the legislative and policy arena (CBO (2013)). A few of them propose to turn the entire Medicare system into a premium support program of the same flavor as Medicare Part D. Plans would bid on a package of services with the same level of coverage as TM, which would also be considered a bidder. CMS would pay a flat risk-adjusted subsidy and enrollees would pay a premium, both of which would be a function of the plans' bids.

3 Data

I have assembled a dataset from a number of publicly available sources provided by CMS that covers the 2008-2011 period. It includes monthly enrollment data for each plan and contract at the national and county level, as well as total monthly enrollment in TM and MA at the county

[9]The ACA changes the way in which the benchmark is calculated. Counties are now classified in 4 quartiles depending on their per capita TM cost. The benchmark is a percentage of this cost, which varies between 95% and 115% depending on the quartile (higher cost counties get a lower percentage).

[10]The rebate amount is now related to quality level, with higher-performing plans getting higher rebates – either 70%, 65%, or 50%, depending on the plan's quality. Furthermore, the benchmark is also linked to plans' quality, with better performing plans facing larger benchmarks.

level.[11] The dataset also includes plans' characteristics such as monthly premium, out of pocket cost (OOPC), and if the plan provides prescription drug coverage. The OOPC is a synthetic measure of the enrollee's costs other than the premium. It is constructed by running the one year health history of each individual in the Medicare Current Beneficiaries Survey through the plan coverage structure to calculate the expected OOPC. Individuals are categorized in five groups according to their health status, and the average OOPC per individual in these five different health categories is reported. In my analysis, I use the average across the five different OOPCs as a summary measure of the plan's generosity. On the payment side, the dataset includes the monthly average plan bid, rebate, and risk score for each plan, as well as the benchmark, TM costs, and risk score at the county-year level.[12]

Table 1 reports descriptive statistics on financial and coverage measures at the finest level of observation available, the plan/county/year level. The dataset contains 144,262 observations: 67% of plans are PFFS, while HMOs and LPPOs account for 21% and 12% of the observations, respectively. 63% of these plans provide drug coverage.[13] The average plan charges about \$45 in total premium, although more than 50% of them have a premium lower than \$35. Interestingly, plans' premiums are widely dispersed, with a standard deviation of \$51, and a large difference between minimum and maximum premium charged (-\$96.4 vs. \$427).[14] Looking separately at MA and drug premiums, the former premiums have a highly dispersed right-skewed distribution, and that this is the principal driver of the total premiums' dispersion. The monthly OOPC is less dispersed: medical OOPC has a mean of \$100 and a standard deviation of \$26, while drug OOPC has a mean of \$113 and a standard deviation of \$55. We also observe that similarly to premiums, bids and rebates both have highly dispersed distributions.

[11] CMS does not release enrollment figures for plans/contracts with less than 10 enrollees at the unit of observation (e.g county or country). I impute missing data by cross-checking the data at different levels of aggregation (e.g. enrollment at contract-national level, at contract-county level, plan-county level,etc.).

[12] In the appendix, I further discuss the data collection and provide links to the data sources.

[13] I dropped from the sample: 1) Regional PPO because they do not follow the same set of rules described in Section 2; 2) Any type of MCO not strictly classifiable within HMO, LPPO and PFFS, such as demonstrations, cost plans or any employer-sponsored plans; 3) Plans sold outside the 48 continental states; 4) Special Need Plans; 5) Plans for which I was not able to infer the monthly enrollment at county level; 6) Plans with missing values in the premium and/or OOPC.

[14] The premium variable is centered around the Part B premium; hence, when plans buyback part of the Part B premium, the MA premium will be negative.

Table 1: Descriptive Statistics

	Mean	SD	Min	Median	Max	N
Total Premium	45.07	50.78	-96.40	35	427.2	144,262
MA Premium	31.45	41.48	-96.40	20	398.6	144,262
Drug Premium	21.61	17.49	0	21.80	157.1	90,883
Medical OOPC	100.0	26.34	6.926	102.2	203.2	144,262
Drug OOPC	113.3	55.35	5.675	108.6	261.0	144,262
Bid	729.5	59.94	312.8	722.9	1,134	144,262
Rebate	55.63	41.28	0	51.82	586.1	144,262
Drug Coverage	0.630	-	-	-	-	144,262
HMO	0.212	-	-	-	-	144,262
LPPO	0.116	-	-	-	-	144,262
PFFS	0.672	-	-	-	-	144,262

Notes: An observation is a plan-year-county triple. *MA Premium* also includes the buyback of TM Premium as a negative premium. *Total Premium* is the sum of *MA Premium* and *Drug Premium*. *Rebate* and *Bid* are risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). All statistics reported are calculated over the sample of analysis.

Table 2: Descriptive Statistics by Type of Plan

	HMO N = 30,633			LPPO N = 16,711			PFFS N = 96,918		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Total Premium	36.36	59.27	22	64.56	55.14	52	44.46	45.97	35
MA Premium	23.66	49.92	0	41.34	41.74	32	32.21	37.91	23
Drug Premium	16.84	19.19	13.60	28.05	21.77	27.80	22.00	14.68	22.50
Medical OOPC	86.86	27.23	88.66	91.46	27.14	93.90	105.7	23.91	109.0
Drug OOPC	109.9	56.56	99.65	102.7	54.42	91.10	116.3	54.84	114.5
Bid	712.1	73.22	706.7	732.4	63.88	722.0	734.5	53.19	727.6
Rebate	88.57	52.94	82.95	54.33	37.12	50.90	45.45	31.09	44.17
Drug Coverage	0.754	-	-	0.828	-	-	0.557	-	-

Notes: An observation is a plan-year-county triple. *MA Premium* also includes the buyback of TM premium as a negative premium. *Total Premium* is the sum of *MA Premium* and *Drug Premium*. *Rebate* and *Bid* are risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). All statistics reported are calculated over the sample of analysis.

Table 2 provides the same information separately by type of MCO. As we discussed in Section 2, these three types of MCO are characterized by substantial differences in the degree of access to in and out-of-network providers, cost-sharing, and healthcare management that are likely to be reflected in the coverage and financial characteristics of the plans. HMOs tend to be less expensive, with an average premium of \$36, compared to LPPOs (\$65) and PFFSs (\$44). Moreover, more than 50% of the HMOs do not charge any MA premium, and 3.8% buyback a fraction of the Part B premium.[15] We observe consistent heterogeneity in the availability of drug coverage: a large proportion of HMO and LPPO plans provide drug coverage (75% and 83% respectively) while only about 57% of the PFFS plans have drug coverage. On the financial side, as we have already seen in Figure 2, HMOs bid more aggressively and receive higher rebates, followed in order by LPPOs and PFFSs. Interestingly, more than 10% of plans do not receive a rebate because they bid above the benchmark. The rebate appears to translate into coverage, as HMOs are more generous, with a $89 medical OOPC compared to $91 and $105 for LPPOs and PFFSs.

Table 3: Market Structure Statistics

	Mean	SD	Min	Median	Max	N
Benchmark	784.3	72.28	716.3	750.1	1,320	11,455
TM Cost	724.7	94.86	431.7	717.1	2,386	11,456
MA Share	0.102	0.0930	0.000270	0.0739	0.578	11,456
Plan Share	0.0109	0.0124	9.22e-05	0.00763	0.314	11,456
# Contracts	4.724	3.445	1	4	28	11,456
# Plans	12.59	10.13	1	10	76	11,456
# Plans w/t Drug	7.933	6.299	0	6	50	11,456

Notes: An observation is a market (county-year). *MA Share* reports the total market share of MA plans in the market, while *Plan Share* reports the average market share of MA plans in the market. *TM Cost* is risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). *Benchmark* is the county specific benchmark rate for the average enrollee. All statistics reported are calculated over the sample of analysis.

Table 3 and 4 report the statistics for the MA plans at the market level, county-year. Looking at table 3, we can see that on average, MA accounts for 10% of the Medicare-eligible individuals in each county, but this value goes as high as 54% in certain counties, showing high heterogeneity in the penetration rate of MA. In the average market, enrollees have access to 5 contracts which offer roughly 13 plans, with more than 60% offering drug coverage; however, in the most competitive counties, enrollees have access to as many as 28 contracts, while in the least competitive ones, there may be as few as 1. Table 4 provides further insight looking into the market structure of MA across different types of MCOs. In my sample, PFFSs are present in 91% of markets (county-year), while HMOs and LPPOs are present only in 49% and 41% of the markets, respectively. Furthermore,

[15] Stockley et al. (2014) discuss the potential reasons behind this phenomen arguing that premium and buyback have different salience for enrollees.

Table 4: Market Structure by MCO Type

	HMO # Counties = 5,265			LPPO # Counties 4,715			PFFS # Counties 10,457		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Benchmark	804.9	80.45	800.1	790.0	64.95	791.6	782.0	69.50	747.6
TM Cost	737.8	92.86	731.0	722.4	86.46	718.1	721.2	94.51	713.3
MCO Type Share	0.086	0.099	0.044	0.033	0.040	0.019	0.053	0.050	0.038
Plan Share	0.018	0.022	0.010	0.011	0.014	0.007	0.008	0.010	0.005
# Contracts	2.173	1.979	2	1.679	0.977	1	3.324	2.100	3
# Plans	5.818	5.369	4	3.544	2.674	3	9.268	7.014	8
# Plans w/t Drug	4.388	4.133	3	2.933	2.133	2	5.159	3.406	5

Notes: An observation is a market (county-year). *MCO Type Share* reports the total market share of each MCO type in the market, while *Plan Share* reports the average market share of plans of each MCO type in the market. *Benchmark* is the county specific benchmark rate for the average enrollee. All statistics reported are calculated over the sample of analysis.

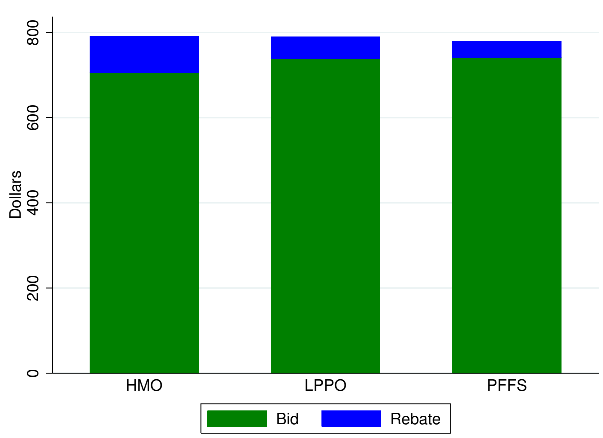
HMOs and LPPOs tend to be in more expensive counties compared to PFFS plans. On average, enrollees have fewer HMO and LPPO plans from which to choose compared to PFFSs, and often they are offered by a smaller set of insurers. Similarly, markets for HMO and LPPO plans tend to be more concentrated, with the average plan accounting between a third and a fifth of the market of each MCO type; this figure is only 15% in the market with PFFS plans, suggesting that the level of competition is diverse across MCOs. Drug plans are more common with HMOs and LPPOs, accounting for more than 90% of those plans enrollees. This figure is lower in the case of PFFS plans, roughly 50%.

Figure 3a reports the average per market (county-year) bid and rebate, weighted by the number of enrollees of each plan. As we have seen, HMO plans tend to have the lowest bid ($709 on average), but once we account for the their larger rebate ($83), HMOs receive the highest total payment. LPPO and PFFS plans, on the other hand, receive average government payments of $790 and $778. However, this difference reverses in sign when accounting for the higher cost level of the markets in which HMOs operate. Figure 3b reports the same information but normalized by the cost of TM in the market, similarly to Figure 2. HMO plans are the only ones that bid below the TM costs on average, and thus receive a larger rebate that theoretically should be invested in larger supplemental services. Figure 4 plots the average per-enrollees market premium and OOPC. HMOs clearly place the lowest monthly financial burden on enrollees, with $28 of premium and $88 of OOPC, followed by LLPOs and PFFSs. The former requires an average of \$41 in premium and \$94 in medical OOPC, while the latter has an average premium of \$32 and medical OOPC of \$115. We can rationalize those figures by looking at the \$152 in average monthly OOPC required by TM. The overall cost for an HMO enrollee – premium plus medical OOPC – is about \$46 less than it would be for TM, on average. The saving are less than half of this for in LLPOs (\$21) and even smaller for PFFSs (only \$5).

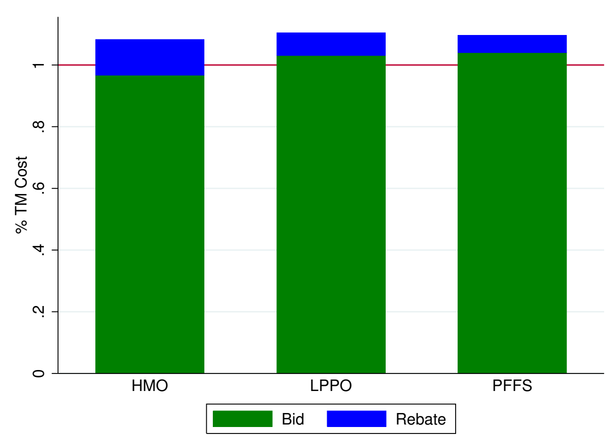
The stylized facts discussed so far suggest an underlying tension between the level of supplemental coverage that enrollees receive and the size of the subsidy, in the form of the rebate, that the government provides for supplemental service. In Figure 5, I plot the relationship between the plans' rebates and their total cost to enrollees (premium plus medical OOPC). In this graph, each circle/diamond/triangle represents the average enrollee cost for HMO/LLPO/PFFS plans with rebates within a \$5 interval. Clearly, the amount of a plan's rebate is negatively correlated with its cost to enrollees. As discussed above, HMOs get larger rebates while placing a lower financial

Figure 3: Bid and Rebate

(a) Levels

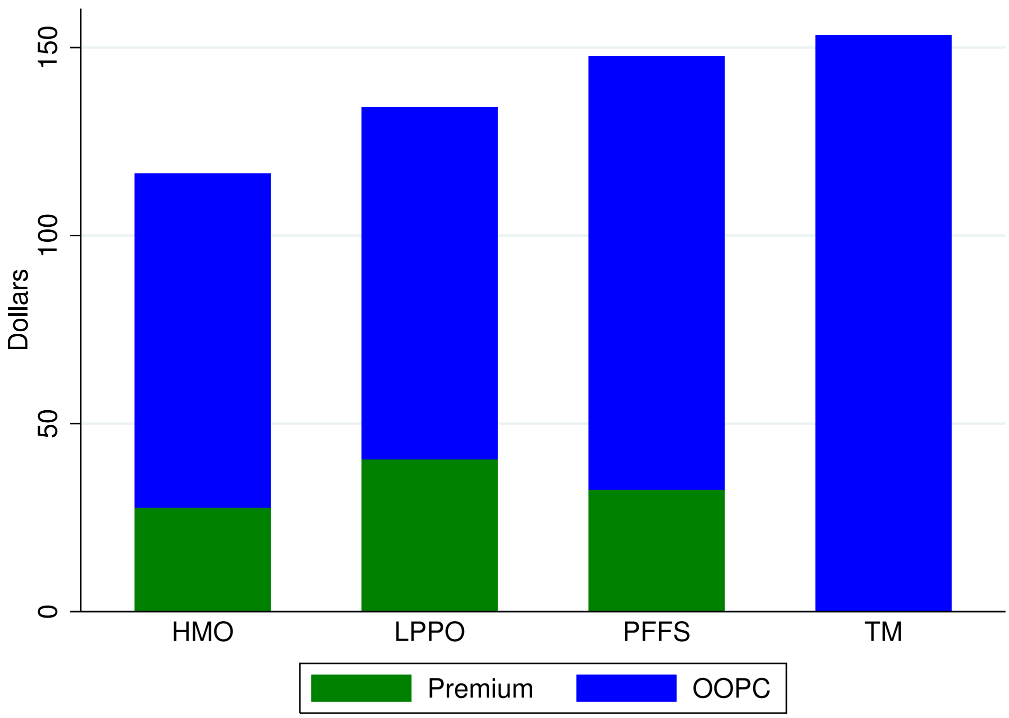


(b) % of TM Cost



Notes: An observation is a market (county-year). Graph 3a reports the average market rebate and bid and Graph 3b reports the average market rebate and bid over the market TM costs by MCO type. Plans' rebate and bid are aggregated at the market level, weighting them by their enrollment. Plans' rebate and bid and market TM costs are risk adjusted and representative of the average Medicare enrollees (risk score equal to 1). The red horizontal line in Graph 3b represents TM costs. All statistics reported are calculated over the sample of analysis.

Figure 4: Premium and OOPC

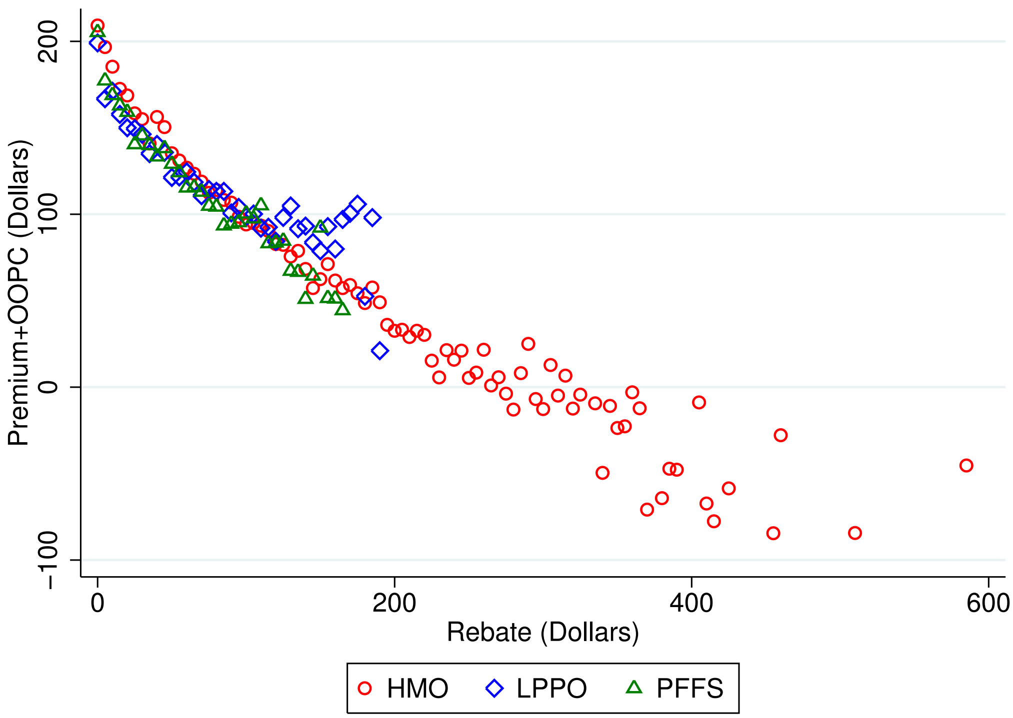


Notes: An observation is a market (county-year). The graph reports the average market MA premium and medical OOPC by MCO type. Plans' MA premium and medical OOPC are aggregated at the market level, weighting them by their enrollment. All statistics reported are calculated over the sample of analysis.

burden on enrollees. The relationship is almost linear and provides strong evidence that the requirement that insurers invest their rebates into supplemental care is frequently a binding constraint. Moreover, the graph also displays that rebates are converted into coverage at a rate lower than one. This result is not surprising given that plan are allowed to spend some of the rebate – the "load factor" – on overhead rather than supplemental services. This reduced form relationship is also in line with with other recent studies that found the pass-through to be around 0.3-0.6 (Song, Landrum and Chernew (2013); Duggan, Starc and Vabson (2014); Stockley et al. (2014); Cabral, Geruso and Mahoney (2014); Curto et al. (2014)).[16]

[16]These studies share the common strategy of exploiting an exogenous variation in the level of the benchmark. The range of estimates can be explained by the fact that each of these studies use a different exogenous variation in the

Figure 5: Rebate, Premium and OOPC



Notes: An observation is a plan-year-county triple. Each circle, square, and triangle reports the average sum of MA premium and medical OOPC for plans among the given MCO type with rebates within a $2.50 interval. Plans' rebate is risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). All statistics reported are calculated over the sample of analysis.

The patterns observed in the data can be rationalized by considering the underlying differences between the different types of MCO and their effects on plans' costs. HMO plans tend to have stronger network restrictions and a higher degree of healthcare management, while PFFS plans allow enrollees access to practically any provider at the same cost-sharing level. LPPOs fall in the middle, with different cost-sharing tiers for in-network and out-of-network providers. This suggests the presence of an underlying trade-off between restrictions on enrollees in terms of network and healthcare usage and plans' costs. It is reasonable to think that the ability of an HMO to curb enrollees' usage of healthcare and steer them toward selected providers, from whom they can negotiate lower service fees, would reduce the overall cost per enrollee in ways that LPPOs and

benchmark and hence estimate different local causal effects.

PFFSs cannot. These stylized facts highlight relevant features of the MA market; hence, I will incorporate them into my modeling and estimation strategy.

4 Model

I want to model the strategic interaction between insurers in their choices of bid, premium, and coverage, with the goal of recovering plans' costs. However, the problem is not straightforward, because the strategy space of the insurers is fairly large given the number of choice variables they can work with when designing their plans (e.g. premium, supplemental services, cost-sharing, etc.). Hence, to make the problem tractable, it is necessary to reduce the dimensionality of plans' coverage level. As already discussed, I follow Dunn (2010) and use OOPC as a synthetic measure of coverage level. This measure has a twofold advantage. First, it provides a simple but meaningful measure of coverage level: the average non-premium cost that beneficiaries would have to pay in a MA plan. Second, it allows me to incorporate in my model the interaction between bid and subsidy in a simple but yet meaningful way. While I use a standard approach on the demand side, in the supply side of the market I carefully incorporate the institutional details of the MA payment system into my model. The rather convoluted payment structure is useful in simplifying the insurers' problem: as highlighted by Stockley et al. (2014), CMS requires insurers to finance their plans' supplemental services either through their rebates or through their premiums, allowing me to reduce the dimensionality of the insurer's problem. I will first explain the demand setting, then move on to the supply side, and finally discuss the key assumptions of my model.

4.1 Demand

For the demand side, I take a standard approach from the literature (Town and Liu (2003); Dunn (2010); Hall (2011); Curto et al. (2014)) and model the enrollee's problem as a one of static discrete choice.[17] Enrollee i's indirect utility from plan j in market m at time t can be written as:

[17] Nosal (2012) and Miller (2014) estimate a dynamic demand model measuring the size of switching costs in MA. Miller (2014) in particular describes the effect of switching costs on plans' choices of premium and coverage level. In my demand framework I address this issue using the age of the plan as a proxy for consumer inertia (see Dunn (2010) and Decarolis, Polyakova and Ryan (2015)).

$$
\begin{aligned}
u_{ijmt} &= \delta_{jmt} + \bar{\epsilon}_{ijmt} \\
\delta_{jmt} &= \alpha_1 pr_{jmt} + \alpha_2 g^{MA}_{jmt} + \alpha_3 g^{Drug}_{jmt} + \beta X_{jmt} + \xi_{jmt} \qquad (1) \\
\bar{\epsilon}_{ijmt} &= \zeta(\rho)_{jmt|MCO} + (1-\rho)\epsilon_{ijmt}
\end{aligned}
$$

δ_{jmt} is the mean utility from plan j for enrollees in market m at time t, while $\bar{\epsilon}_{ijmt}$ is an enrollee specific preference shock. The mean utility δ_{jmt} is composed of two parts. The first of these consists of the observed characteristics such as premium (pr_{jmt}), medical and drug OOPCs (g^{MA}_{jmt} and g^{Drug}_{jmt}), and other observed product characteristics (X_{jmt}). The latter includes the presence of the drug coverage, which I allow to have different effects across different types of MCO, and the ages of the plan and contract; these two variables allow me to control for potential inertia in enrollees' choices of plans. The remaining component is ξ_{jmt}, the unobserved (to the econometrician) characteristics of plan j in county m at time t, which I decompose as $\xi_{jmt} = \xi_{Cs(jm)} + \xi_{s(m)t} + \Delta\xi_{jmt}$. $\xi_{Cs(jm)}$ is the idiosyncratic preference for all the plans in contract C within a state s, and accounts for enrollees' taste for different types of MCO, as well as all those characteristics that are invariant in the short run, across plans within a contract, such as brand name, network size, etc. Some contracts, especially PFFSs, have service areas which cross state lines. In these cases, it reasonable to think that enrollees have different valuations for the same contract in different states: salient features of the contract, such as its network, may differ across states. Furthermore, most health insurance regulation is at the state level, and in private markets, health insurances is generally not allowed to be sold across state lines. Thus, the state is a natural unit of aggregation for health insurance markets. $\xi_{s(m)t}$ is the idiosyncratic preference for all plans sold in year t and state s, and accounts for the state-year specific shift in enrollees' preferences for MA plans. $\Delta\xi_{jmt}$ captures the remaining heterogeneity not accounted for in the contract-state and year-state specific preference components.

α_1, α_2 and α_3 represent enrollees' sensitivity to premium and OOPC. As discussed by Dunn (2010), if enrollees can perfectly predict their medical expenditure, then $\alpha_1 = \alpha_2$. It is unlikely, however, that enrollees would be able to perfectly predict their health status and thus their medical expenses. Risk averse enrollees would be willing to trade a higher premium for more certainty in their OOPC, implying that $\alpha_1 < \alpha_2$. In this discussion, I have implicitly assumed that the OOPC is a perfect predictor of enrollees' medical costs, or equivalently, that individuals do not have additional information about their health status. This is a strong assumption, and it is more reasonable to assume that the g^{MA} is approximation of enrollees' expectation of future medical expenses. Under this less stringent assumption, the attenuation bias induced by the measurement error in the OOPC could induce $\alpha_1 > \alpha_2$. Thus, ex-ante, we do not know the relationship between them. The discussion in the previous paragraph extends to the relationship between α_3 and α_1 as well.

I assume a nested logit structure for the preference shock: ϵ_{ijmt} is drawn from an i.i.d Type I Extreme Value distribution and $\zeta(\rho)_{jmt|MCO}$ is drawn from a unique distribution with parameter ρ such that the preference shock $\bar{\epsilon}_{ijmt}$ also has a Type I Extreme Value distribution.[18] $\zeta(\rho)_{jmt|MCO}$ represents the idiosyncratic preferences of enrollees for the different types of MCOs (i.e. HMO, LPPO and PFFS) relative to TM. We can interpret the nesting parameter ρ as the degree to which valuations for plans are correlated within an MCO type. It varies between 0 and 1, with larger ρ implying greater substitutability between plans of the same type. When $\rho = 1$ plans of the same type are perfect substitute, while with $\rho = 0$ the model collapses into a standard logit.

It follows from the nested logit assumption that the market share for plan j in market m at time t (s_{jmt}) can be written as:

$$s_{jmt} = \frac{\exp\left(\frac{\delta_{jmt}}{(1-\rho)}\right)}{\sum_{k \in MCO(j)} \exp\left(\frac{\delta_{kmt}}{(1-\rho)}\right)} \times \frac{\left[\sum_{k \in MCO(j)} \exp\left(\frac{\delta_{kmt}}{(1-\rho)}\right)\right]^{(1-\rho)}}{\exp\left(\delta_{0m}\right) + \sum_{K \in MCO} \left[\sum_{k \in K} \exp\left(\frac{\delta_{kmt}}{(1-\rho)}\right)\right]^{(1-\rho)}} \tag{2}$$

where $MCO(j)$ is the type of plan j, $MCO = \{HMO, LPPO, PFFS\}$ is the collection of types of MCOs and K defines each element of this collection. The first term of the market share equation represents the market share of plan j within its MCO type. The second term represents the market share of that MCO type in the overall markets. δ_{0m} is the mean utility of the outside option.[19]

[18] See Cardell (1997). This model is equivalent to a model with a random coefficient on a dummy identifying the MCO types.

[19] My model includes year-state fixed effect allowing the mean utility of MA to varies across different markets. I normalize the variance of the preference shock to 1. Moreover, my model makes an additional simplification by giving

Estimation and Identification:

The demand model generates a linear estimating equation (Berry (1994)):

$$\ln\left(\frac{s_{jmt}}{s_{0mt}}\right) = \alpha_1 pr_{jmt} + \alpha_2 g_{jmt}^{MA} + \alpha_3 g_{jmt}^{Drug} + \beta X_{jmt} + \rho ln(s_{jmt|MCO}) + \xi_{Cs(jm)} + \xi_{s(m)t} + \Delta\xi_{jmt} \tag{3}$$

Equation 3 can be estimated through standard OLS, but the estimates would be biased because the within-MCO type market share ($s_{jmt|MCO}$) is clearly endogenous. Moreover, the unobserved product characteristic ($\Delta\xi_{jmt}$) is likely to be correlated with premium and OOPC. I therefore leverage various features of the data to estimate equation 3 using an instrumental variables (TSLS) approach. Exploiting the fact that each observation represents a plan/year/county triple allows me to identify $\xi_{Cs(jm)}$ and $\xi_{s(m)t}$: I observe multiple plans within the same contract across different markets, where a market is a couple county-year, so I am able to estimate separate fixed effects for each contract-state and state-year pair.

For the nesting parameter (ρ), I use two instruments typically used in the literature. For each county-year I calculate the number of plans of each type, and the number of plans with drug coverage of each type.[20] The underlying identifying assumption requires the number of plans in the market to be uncorrelated with $\Delta\xi_{jmt}$, which in turn requires the overall market structure to be exogenous.

I tackle the endogeneity of premium and OOPC in three ways. First, I exploit the fact that I observe plans belonging to the same contract in different counties. Thus, for each plan I calculate the minimum premium and OOPC (maximum rebate) over other plans which are in the same contract, but which have a non-overlapping service area (i.e. Hausman, Leonard and Zona (1994), Nevo (2001) and Dunn (2010)). The identification relies on the fact that plans which are in the

beneficiaries only one outside option. Beneficiaries enrolled in TM can also decide to buy drug coverage through stand-alone Part D plans and additional insurance coverage through a Medigap policy. Modeling enrollees' choices from among these outside options is outside the scope of this paper.

[20] These type of instruments have been proposed in the literature (Town and Liu (2003); Dunn (2010); Curto et al. (2014)). I also tried using the number of contracts for a MCO type: the results are comparable, but I preferred the number of plans for two reasons. First, it is a more direct measure of competitive pressure in the market. Second, I observe greater variation in the number of plans compared to the number of contracts.

same contract, and therefore share same network and parent organization, are likely to share a common cost component. This cost component would be correlated with these plans' premiums, OOPCs and rebates. However, these premiums, OOPCs and rebates must not be correlated with $\Delta\xi_{jmt}$, the plan-market specific unobserved characteristic. Second, following Hall (2011), I use the average premium, OOPC, and rebate of competing contracts in other counties. In particular, for each competing contract, I only select plans that do not directly compete with plan j and belong to the same type of MCO. The premiums of competing contracts will be correlated with the common cost component in the market, but uncorrelated with the plan-market specific change in quality, $\Delta\xi_{jmt}$. Finally, I also use as instruments the average age of plans and contracts in the market within plan j's MCO type. These instruments, as the nest instruments, rely on the assumption that entry and market structure are fixed.

4.2 Supply

I model competition as a game in which insurers can choose plans' bids, MA premiums, and OOPCs. Since the payment system requires insurers to finance their plans' supplemental services either through their rebates or through their premiums, following the insight of Stockley et al. (2014), I reduce the dimensionality of the insurer's problem by imposing the constraint that any difference in the medical OOPC between TM and an MA plan must be covered by either its premium or rebate. I directly model this linkage between bid, rebate, and coverage level for three reasons. First, as previously explained, CMS requires that any additional coverage beyond TM-level must be financed through plan's rebate and/or premium. Second, the data show a trade-off between rebate/premium and medical OOPC, as well as a trade-off between rebate and premium. Finally, a model that does not include any link between rebate and coverage level would deliver unrealistic equilibria, predicting that optimal bids are either at the benchmark or above, when in fact roughly 90% of the plans have bids below the benchmark.

The insurer's profit maximization problem for contract C can be written as (dropping the market subscript m and t):[21]

[21] I assume that risk-adjustment is perfect, and thus when solving the profit maximization problem, the insurer considers the expected marginal cost of each additional enrollee. For sake of brevity I also omit drug coverage variables

$$\begin{aligned}
\underset{\{b_j, pr_j^{MA}, g_j^{MA}\}}{\text{Max}} \quad & \pi_C = \sum_{j \in C} (b_j + pr_j^{MA} + 0.75(B_j - b_j)\mathbb{1}\{B_k \geq b_j\} - mc_j(g_j^{MA}))Ms_j(pr, g^{MA}, \mathbf{X}, \xi) \\
\text{s.t.} \quad & g^{TM} - g_j^{MA} = \gamma_1 pr_j^{MA} + \gamma_2 0.75(B_j - b_j)\mathbb{1}\{B_j \geq b_j\} \quad \forall \quad j \in C \\
& pr_j = pr_j^{MA} + \mathbb{1}\{B_j \leq b_j\}(b_j - B_j)
\end{aligned} \tag{4}$$

Insurers can choose three variables: b_j is the plan bid, the cost of covering TM services; pr_j^{MA} is the premium for supplemental coverage – Part C – minus the buyback of the Part B premium; and g_j^{MA} is the medical OOPC for the plan j. As already discussed, insurers bid against benchmarks B_j, each of which is a function of TM costs in the service area of plan j; 75% of the difference between the benchmark and the bid is given to the insurer as a rebate. If the bid is above the benchmark, enrollees have to pay the difference as a premium. Therefore the premium (pr_j) paid by plan j's enrollees in this case would be $pr_j^{MA} + b_j - B_j$. When choosing the level of OOPC, insurers must finance any difference between TM and their plans using either premiums or their rebates from CMS. However, increases in a plan's rebate or premium do not need to translate into decreases of OOPC on a dollar-for-dollar basis; instead, they are scaled by the parameters γ_1 and γ_2. As we discussed in previous sections, insurers are allowed to charge an overhead when using the rebate to increase the level of supplemental coverage. Moreover, my measure of the level supplemental coverage – the difference between TM and MA plan OOPC – is an only approximation of a plan's actual supplemental coverage level; thus, plans may spend part of their premiums and rebates on supplemental coverage in a way that I am unable to observe. Also note that, as we observed in the data section, the pr_j^{MA} can be negative since the insurer can buyback part of the Part B premium. Additionally, M the is the size of the market, represented by the Medicare eligible population, and g^{TM} is the medical OOPC for TM.

From the constraint, it is clear that a plan's premium is a function of its OOPC and bid, so the insurer's problem reduces to finding the choice of bids and OOPCs which maximizes profits. The

(g^{Drug} and pr^{Drug}), given that in my model I abstract from the insurers choice of premium and coverage level for Part D.

Nash equilibrium is then given by the solution to the system of bid and OOPC first-order conditions (FOC) for each plan in the market:[22]

$$
\begin{aligned}
\frac{\partial \pi}{\partial b_j} := \sum_{k \in C} & \left(b_k + \frac{1}{\gamma_1}(g^{TM} - g_k^{MA}) + \left(1 - \frac{\gamma_2}{\gamma_1}\right) 0.75(B_k - b_k)\mathbb{1}\{B_k \geq b_k\} - mc_k(\cdot) \right) \\
& \times \left(0.75 \frac{\gamma_2}{\gamma_1} \frac{\partial s_k(\cdot)}{\partial pr_j^{MA}} \mathbb{1}\{B_k \geq b_k\} + \frac{\partial s_k(\cdot)}{\partial pr_j^{MA}} \mathbb{1}\{B_k \leq b_k\} \right) \\
& + s_j(\cdot) \left(1 + 0.75 \left(\frac{\gamma_2}{\gamma_1} - 1 \right) \mathbb{1}\{B_j \geq b_j\} \right) = 0
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
\frac{\partial \pi}{\partial g_j^{MA}} := \sum_{k \in C} & \left(b_k + \frac{1}{\gamma_1}(g^{TM} - g_k^{MA}) + \left(1 - \frac{\gamma_2}{\gamma_1}\right) 0.75(B_k - b_k)\mathbb{1}\{B_k \geq b_k\} - mc_k(\cdot) \right) \\
& \times \left(\frac{\partial s_k(\cdot)}{\partial g_j^{MA}} - \frac{1}{\gamma_1} \frac{\partial s_k(\cdot)}{\partial pr_j} \right) + s_j(\cdot) \left(-\frac{1}{\gamma_1} - \frac{\partial mc_j(\cdot)}{\partial g_j^{MA}} \right) = 0
\end{aligned}
$$

Estimation and Identification:

I do not impose the supply structure on the demand estimation; instead, I use my demand estimates to calculate the implied marginal cost and derivative with respect to coverage level (see Nevo (2001) and Dunn (2010)). The first step is to retrieve the conversion parameters for premium and rebate from the constraint:

$$
g_t^{TM} - g_{jt}^{MA} = \gamma_{1MCO(j)t} pr_j^{MA} + \gamma_{2MCO(j)t} 0.75(B_j - b_j)\mathbb{1}\{B_j \geq b_j\} + \eta_{jt} \tag{6}
$$

I allow the γ_1 and γ_2 to vary across year (t), and the type of MCO ($MCO(j)$). The error term η_{jt} is i.i.d and accounts for the fact that OOPC is an approximation of the actual coverage level. As explained in Section 2, each insurer can allocate their rebate toward buying out Part B or D premium, reducing cost-sharing, or providing supplemental service (e.g., hearing coverage, dental coverage,

[22] I assume the existence of a pure strategy Nash Equilibrium. The proof of the existence of equilibrium is outside the scope of the paper; however, Gallego and Wang (2014) prove the existence and uniqueness of the equilibrium in markets in which multi-product firms compete *a* la Bertrand and consumers are characterized by nested logit demand.

etc.). I estimates these parameters through OLS, where an observation is a plan/county/year triple.

I then calculate marginal costs using the demand and constraint estimates. First, I retrieve the implied marginal costs using the bid FOCs. Let $D_{pr}s$ be the derivative matrix of the vector of market shares with respect to the vector of premium pr. I define the ownership matrix Ω such that each element of it is:

$$\Omega_{jk} = \begin{cases} 1, & \text{if j and k} \in C \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where j and k =1, ..., J with J being the number of plan sold in the market. Then, I define $D^*_{pr}s$ as the point-wise product of Ω and $D_{pr}s$ ($\Omega * D_{pr}s$). Thus, with a slight abuse of notation, I can then rewrite the insurers' bid FOCs in vector notation and solve the resulting system of linear equations to calculate the markup and therefore the marginal costs vector:[23]

$$\begin{aligned} mc = &\left(b + \frac{1}{\gamma_1}(g^{TM} - g^{MA}) + \left(1 - \frac{\gamma_2}{\gamma_1}\right) 0.75(B-b)\mathbb{1}\{B \geq b\}\right) \\ &+ \left(0.75\frac{\gamma_2}{\gamma_1}\mathbb{1}\{B \geq b\}D^*_{pr}s - \mathbb{1}\{B \leq b\}D^*_{pr}s\right)^{-1} s(\cdot) * \left(\mathbf{1} + 0.75\left(\frac{\gamma_2}{\gamma_1} - 1\right)\mathbb{1}\{B \geq b\}\right) \end{aligned} \tag{8}$$

Let $D_{g^{MA}}s$ be the derivative matrix of the vector of market shares with respect to the vector g^{MA} of OOPCs. Then, I define $D^*_g s$ as the point-wise product of Ω and $D_g s$ ($\Omega * D_g s$). The vector of derivatives of marginal costs with respect to coverage is:

[23] We should notice that the FOC is not continuous for a bid at the benchmark, and would not hold with equality. Therefore, the standard inversion method would not work for plans with such a bid, and moreover would potentially affect all plans within a contract. Unfortunately, due to aggregation in the data, I cannot identify these plans that bid at the benchmark but only those plans with zero rebate. Thus, in order to retrieve plans' marginal costs I assume that all plans with zero rebate did bid above the benchmark. These plans account for roughly 10% of the sample of my analysis.

$$\nabla mc_g = \left(\frac{D_g^* s - \frac{1}{\gamma_1} D_{pr}^* s}{s(\cdot)} \right) \times \left(b + \frac{1}{\gamma_1}(g^{TM} - g^{MA}) + \left(1 - \frac{\gamma_2}{\gamma_1}\right) 0.75(B-b)\mathbb{1}\{B \geq b\} - mc \right) - \mathbf{1}\frac{1}{\gamma_1} \tag{9}$$

4.3 Discussion

In this section, I first compare my model to the existing literature, then discuss the simplifying assumptions that I make in my model and estimation procedure.

My model allows insurers to jointly set their plans' premiums and coverage levels while accounting for the constraints imposed by the payment system which make the size of the government subsidy endogenous, as suggested by Stockley et al. (2014). As discussed in the introduction, recent studies that have analyzed the MA market have focused only on one of these two variables, bid or coverage level. Miller (2014) allows insurers to jointly set premiums and coverage levels, but takes the subsidy as exogenous. However, in choosing a plan's bid, insurers determine the size of their rebate, which is highly correlated with the plan's coverage level.[24] The FOCs of my model (5) highlight this link between bid and coverage level and a failure to account for the endogenous rebate would bias the retrieved cost structures of the plans. We can see that when insurers bid below the benchmark, which is the case for roughly 90% of plans, their bid FOCs differ from those on price in a traditional Bertrand-Nash model of oligopoly.[25] Moreover, given that the ratio of γs can be either smaller or larger than one, it is not even straightforward to sign the direction of the bias. Similarly, looking at the coverage level FOC we can see how not accounting for the endogenous rebate could bias the retrieved derivative of the marginal costs as well.[26] Curto et al. (2014) incorporate the

[24] Miller (2014) also offers a different approach from mine on the demand side. He uses dynamic a demand model in which enrollees face a switching cost when changing plan and shows that failing to account for enrollees' inertia could bias marginal cost estimates downward by as much as 20%.

[25] The standard Bertrand-Nash oligopoly FOC for the MA market would be

$$\frac{\partial \pi}{\partial pr_j} := \sum_{k \in C} \left(b_k + pr_k^{MA} + 0.75(B_k - b_k)\mathbb{1}\{B_k \geq b_k\} - mc_k(\cdot)\right) \frac{\partial s_k(\cdot)}{\partial pr_j^{MA}} + s_j(\cdot) = 0$$

[26] If we did not consider the constraint, the FOC for coverage level would be

$$\frac{\partial \pi}{\partial g_j^{MA}} := \sum_{k \in C} \left(b_k + pr_k^{MA} + 0.75(B_k - b_k)\mathbb{1}\{B_k \geq b_k\} - mc_k(\cdot)\right) \frac{\partial s_k(\cdot)}{\partial g_j^{MA}} - s_j(\cdot)\frac{\partial mc_j(\cdot)}{\partial g_j^{MA}} = 0$$

MA bidding system into their model, with insurers having a single choice variable (bid), but do not directly model insurers' supplemental coverage decisions (premium and/or coverage level). As in my model, if a plan's bid is above its benchmark, enrollees pay the difference as a premium. However, in their model, if the plan's bid is below its benchmark, the rebate amount enters directly into consumers' utility functions as a proxy for the corresponding increase in coverage level that CMS requires. Two assumptions underly their interpretation of the rebate as increase in the level of coverage: first, that enrollees must equally value a reduction of one dollar in premium as one dollar less of coverage, and second that, each dollar of rebate must translate into a dollar of coverage. If these two assumptions did not hold, their retrieved marginal costs would be biased. As already discussed, plans can use their rebate to either decrease premiums or increase coverage levels, and when doing the latter, apply a fraction of the rebate to their overhead expenses, making the conversion rate between rebate and coverage level lower than one; moreover, as shown by Dunn (2010), enrollees value increases in coverage level differently from equivalent decreases in premiums. I will further comment enrollees' willingness to substitute between for premium and coverage level when discussing my results.

The demand side of the model is simple and requires only market level data to be estimated. One might worry that this approach cannot fully capture the heterogeneity in enrollees' preferences, particularly in how willing they are to bear OOPC, and thus deliver biased estimates. For example, the OOPC is calculated for five different health levels, but it is impossible for me to know which of the five health statuses of the OOPC is the correct proxy for a specific enrollee's health status. Unfortunately, I cannot sign the bias in this case; it could be negative or positive, depending on whether I over or underestimate the health status of the enrollees in the market. However, we should notice that within a county-year, the plans' ordering with respect to OOPC tends to be stable across health levels. The standard deviation of plans' OOPC rankings within a county-year is less than 1 for about 60% of the plans.[27] Therefore, using the mean OOPC would likely generate negligible bias given that the plans' generosity rankings are comparable across the health status levels.

[27] I report a histogram showing how standard deviations of plans' county-year OOPC rankings are distributed in the appendix (Figure A.1).

On the supply side, my model abstracts from the choice of Part D premium and coverage level, because I feel that introducing a choice of drug coverage level would complicate the model without adding further insight.[28] Insurers that want to provide drug coverage must submit a separate bid to CMS, following regulations that are as convoluted as those for MA. The two bids for MA and Part D are submitted by insurers independently from each other and should represent the revenue necessary for the plan to cover the two services separately. On the demand side, I still account for enrollees' preferences over the drug premium and OOPC levels for those plans that include drug coverage. The main concern with this approach is the potential presence of (dis)economies of scale on the supply side for plans that provide drug coverage, which could bias my retrieved plans' cost structures. I will address this issue in the results section by testing for differences in cost between plans with and without drug coverage. With respect to Part D, I cannot account for the allocation of plans' rebates to Part D services while estimating the conversion parameters in the constraint. However, MedPAC provides estimates of the rebate usage during 2009 and 2010, and report that only 17-23% was used for Part D services, including Part D premium buyback (MedPAC (2009, 2010)). Similarly, Curto et al. (2014) shows that in the period from 2007 to 2011, only 12.5% of rebate dollars were allocated to Part D coverage.

I also assume that risk-adjustment perfectly corrects payments for differences in enrollees' health. Historically, MA plans were characterized by advantageous selection (McGuire, Newhouse and Sinaiko (2011)), but more recent studies have argued that selection is now limited, and potentially concentrated within risk categories (McWilliams, Hsu and Newhouse (2012); Newhouse et al. (2013); Brown et al. (2014)). Moreover, Curto et al. (2014) find that at the margin, changes in bids have limited effects on the plans' risk pools.

Finally, I make a strong but necessary assumption in measuring coverage levels through OOPCs alone. Even under the tight regulations implemented by CMS, insurers are able to manipulate a number of their plans' characteristics and implement highly refined strategies that may not be fully captured by the measures of OOPC (Carey (2014); Decarolis and Guglielmo (2015)). An alternative

[28] For a analysis of the drug side of Medicare (Part D), Decarolis, Polyakova and Ryan (2015) look at the market for stand-alone drug plans and conduct an exercise comparable to mine.

approach would be to estimate a demand model with as many plan characteristics as possible, then measure a plan's coverage level as single index function of the utility value of these characteristics (Lustig (2010); Miller (2014)). Neither approach is perfect, but I believe that OOPC provides two fundamental advantages. First, it is extremely easy to interpret: OOPC measures the non-premium cost that beneficiaries pay as part of a MA plan. Second, it allows me to incorporate the link between rebate and coverage level into the model in a clean and transparent way by comparing the OOPCs of MA plans with those of TM.

5 Results

5.1 Demand Estimates

Table 5 reports the estimates of the nested logit model expressed in equation 3. I estimate three different specifications of the model in which I allow nesting and/or medical OOPC coefficients to vary across different types of MCO (i.e. HMO, LPPO and PFFS). I provide two sets of estimates of the premium and OOPC coefficients: OLS estimates (odd columns) and TSLS estimates (even columns). The former are good benchmarks to evaluate the importance of the instrumental variables strategy for estimating these coefficients. I transform the drug OOPC by subtracting TM drug OOPC, so that when a plan has no drug coverage the transformed drug OOPC will be equal to zero. Each specification include contract-state and year-state fixed effects, plan and contract age, and a drug coverage dummy for each type of MCO. The standard errors are clustered at the contract level.

In the baseline specification (columns 1-2), estimates of the main coefficients of interest, ρ, α_1, α_2, and α_3, are statistically significant and have the expected sign; moreover, they are comparable to those in the literature (Town and Liu (2003); Dunn (2010); Hall (2011); Maruyama (2011); Curto et al. (2014)).[29] We can observe that the TSLS estimates for the premium and medical OOPC

[29]Previous studies have found premium coefficients between -0.005 and -0.012 and nesting parameters between 0.296 and 0.658. The closest benchmark for my model is Dunn (2010), who finds smaller sensitivity to medical OOPC (-0.020 vs. -0.008) and price (-0.010 vs. -0.005), and higher within-nest substitutability (0.415 vs. 0.658). The differences in these estimates can be explained by his different unit of analysis: he uses data aggregated at the contract level, while I use data at the plan level. These previous studies use contracts as their unit of aggregation because of data limitations (plan-level data was not available before 2006) and/or censoring (CMS does not disclose

coefficients are larger than those from OLS, whereas the drug OOPC coefficient estimate is smaller; this difference is likely due to the correlation of premium and OOPC with $\Delta\xi_{jm}$.[30] The estimates on the medical OOPC coefficient seem to suggest that enrollees may be risk-averse: the average enrollee would be willing to trade $2 today to reduce its medical OOPC by $1.

Columns 3 and 4 report the results of a model allowing for heterogenous coefficients on medical OOPC. The model is particularly appealing given the differences across MCO types in observed OOPC levels, healthcare usage restrictions, and cost-sharing structure.[31] I find that enrollees in HMOs have a higher sensitivity to medical OOPC compared to enrollees in LPPOs and PFFSs. These differences are not only statistically significant (with TSLS estimates) but also economically meaningful. The ordering of the OOPC sensitivities suggests that beneficiaries who experience higher disutility from OOPC prefer plans with lower OOPC. This model delivers a larger estimate of the premium coefficient, implying more elastic demand, but a nearly identical nesting parameter. To further test for the presence of heterogeneity in consumer preferences across MCO types, I also allow the nesting parameter to vary across types. The ordering of the nesting coefficients implies that HMOs are less substitutable than LPPOs and PFFSs, which is reasonable given differences in network restrictions and cost-sharing between MCO types and TM. I cannot reject the hypothesis that all three of these coefficients are identical.[32] The coefficients on the control variables have the expected sign in each specification and are generally statistically significant.[33] For the remainder

enrollment figures for plans with fewer than 10 beneficiaries). As discussed by Gandhi, Lu and Shi (2014), both data features could generate less elastic demand. In this paper, I use data at plan level and impute missing data by cross-checking the data at different levels of aggregation (e.g. enrollment at contract-national level, at contract-county level, plan-county level, etc.).

[30] The instruments for the nesting parameter are highly significant, with F-statistics above 111. On the other hand, those for premium and OOPC may raise the issue of the instruments' weakness, since their F-statistic is 3.1. I reestimate the model using Limited-Information-Maximum-Likelihood (LIML), which is robust to weak instruments. The results of the LIML estimation are comparable to those from Table 5. For further details, please refer to Tables A.1, A.2, A.3, and A.4 in the appendix.

[31] As in the baseline specification, the first stage for the nesting parameter is strong, with an F-statistic of 83. For premium and OOPC, I augmented my instruments by interacting the own and competitor rebate and medical OOPC instruments with the MCO type. The joint F-statistic is 2.9, but the LIML estimator provides qualitatively similar results.

[32] For this specification the standard weak instruments testing reveal issues in both the OLS and TSLS specification, with F-statistics equal to 11.6 and 2.3 respectively. The LIML estimates confirms this suspect, being qualitatively different from those in Table 5.

[33] Older plans tend to have higher enrollment; drug coverage increases market share for HMOs and LPPOs, but decreases it for PFFSs. The latter result reflects differences in the availability of drug plans across different types of

of the paper, I will focus on the TSLS results of the heterogenous medical OOPC sensitivity model (column 4).

In the bottom of Table 5, I report the average semi-elasticities for premium and OOPC.[34] In the preferred specification, Column 4, the semi-elasticity for premium is -0.02; therefore, for an increase of \$1 in premium would generate a drop in enrollment of 2%. Demand is more elastic with respect to OOPC: an increase of \$1 in OOPC would generate a drop in enrollment of 4.2%. Unsurprisingly the semi-elasticity for medical OOPC is widely heterogenous across types of MCO. The semi-elasticity for HMOs is almost three times as large as that for LPPOs and PFFSs: a \$1 increase in OOPC would generate a drop in enrollment of 8.4% for HMO plans, but only a 2.8% drop for LPPOs and only a 3.1% drop for PFFSs.

These results provide evidence that, as shown by Dunn (2010), coverage (as captured by OOPC) is a major factor in enrollees' plan choices, and therefore is meaningful to consider in firms' choice problems. Moreover, enrollees' medical OOPC valuations are highly heterogenous, suggesting that different types of MCOs may follow different pricing strategies.

5.2 Supply Estimates

The first two rows of Table 6 report the range of estimates for γ_1 and γ_2, the parameters in the constraint that convert plans' premiums and rebates into their coverage levels. I separately estimate these parameters by type of MCO (HMO, LPPO and PFFS) and year.[35] Different types of MCOs may have different cost structures and therefore they would be able to convert premiums and rebates into coverage levels at different rates. The increase in coverage level generated by \$1 of rebate or premium is on average less than \$1; more specifically, it is between \$0.4 and \$0.8. We can rationalize these results by considering that plans are allowed to apply a certain level of overhead costs in the cost of supplemental services (MedPAC (2010)), implying that, on average, the conversion rate of premium and rebate into coverage is expected to be less than one. The third row of Table 6 reports the range of the ratio of γ_2 to γ_1. Whether this ratio is above or below one

MCO.

[34]Semi-elasticities are more easily interpretable for the large portion of the sample with negative or zero premium.

[35]Table A.5 reports the details of the estimates and standard errors of the γ's

Table 5: Demand Estimates

	Baseline		Het. OOPC		Het. OOPC-Nest	
	IV Nest	IV All	IV Nest	IV All	IV Nest	IV All
	(1)	(2)	(3)	(4)	(5)	(6)
Nest - ρ	0.330***	0.415***	0.321***	0.412***		
	(0.045)	(0.046)	(0.054)	(0.055)		
Nest HMO - ρ_{HMO}					0.376***	0.515***
					(0.040)	(0.066)
Nest LPPO - ρ_{LPPO}					0.261***	0.335***
					(0.063)	(0.078)
Nest PFFS - ρ_{PFFS}					0.320***	0.383***
					(0.083)	(0.112)
Premium	-0.008***	-0.010***	-0.008***	-0.013***	-0.008***	-0.013***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Medical OOPC - α_2	-0.011***	-0.020***				
	(0.004)	(0.005)				
Medical OOPC HMO - α_{2HMO}			-0.015***	-0.054***	-0.015***	-0.057***
			(0.003)	(0.012)	(0.003)	(0.013)
Medical OOPC LPPO - α_{2LPPO}			-0.012***	-0.019**	-0.012***	-0.021**
			(0.003)	(0.009)	(0.003)	(0.010)
Medical OOPC PFFS - α_{2PFFS}			-0.010	-0.019***	-0.010	-0.019***
			(0.006)	(0.005)	(0.006)	(0.005)
Drug OOPC - α_3	-0.009***	-0.007***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Drug Coverage - HMO	0.373*	0.581***	0.369*	0.484**	0.287	0.294
	(0.200)	(0.213)	(0.204)	(0.224)	(0.225)	(0.297)
Drug Coverage - LPPO	0.415*	0.634***	0.410*	0.520**	0.516*	0.611*
	(0.231)	(0.241)	(0.235)	(0.247)	(0.268)	(0.327)
Drug Coverage - PFFS	-0.679***	-0.374*	-0.703***	-0.492**	-0.703***	-0.531*
	(0.161)	(0.225)	(0.156)	(0.246)	(0.162)	(0.291)
Plan Age	0.419***	0.375***	0.424***	0.384***	0.417***	0.372***
	(0.060)	(0.059)	(0.066)	(0.053)	(0.060)	(0.055)
Contract Age	-0.576	-0.657	-0.579*	-0.762	-0.571*	-0.765
	(0.357)	(0.468)	(0.350)	(0.494)	(0.341)	(0.503)
Observations	144,246	144,246	144,246	144,246	144,246	144,246
R-squared	0.546	0.613	0.538	0.575	0.511	0.484
F-Statistics	111.066	3.104	82.817	2.921	11.626	2.320
Mean Semi-Elasticity Premium	-0.0107	-0.0168	-0.0106	-0.0201	-0.0106	-0.0207
Mean Semi-Elasticity OOPC	-0.0162	-0.0325	-0.0158	-0.0417	-0.0159	-0.0457

Notes: The regression also includes fixed effects for contract-state and state-year. In the odd columns, the nest is instrumented using the number of plans of a type, and the number of plans with drug coverage of a type in county-year; in column 5, the instruments are interacted with MCO type dummies. In the even columns premium and OOPC are also instrumented and I expand the set of instruments to include: the minimum premium and OOPC (maximum rebate) from plans in the same contract, but with non-overlapping service areas; the average premium, OOPC, and rebate of plans in competing contracts of the same MCO type but with non-overlapping service areas; the average age of plans and contracts in the market within each MCO type. A dummy is added when the first two instruments are not available. In column 4 and 6 these instruments using rebate and medical OOPC are interacted with MCOs type dummies. The standard errors are clustered at the contract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

have implications on the bidding strategy of insurers. When $\frac{\gamma_2}{\gamma_1}$ is lower than one the effect of \$1 increase in the bid on insurers profits would be different compared to the standard Nash-Bertrand oligopoly. In particular, the effect of a bid increase on both intensive and extensive profit margin would be dampened by $\frac{\gamma_2}{\gamma_1}$ being less than one. Vice-versa, when $\frac{\gamma_2}{\gamma_1}$ is larger than one the effect of a bid increase on both intensive and extensive profit margin would be magnified. Roughly 30% of PFFSs have $\frac{\gamma_2}{\gamma_1}$ larger than one, while HMO and LPPO plans always have a ratio smaller than one.

Using the estimates of the γs together with the demand estimates, I am able to retrieve the marginal cost and its derivative with respect to medical OOPC implied by my model for each triple of plan/county/year, as explained in Equations 8 and 9.[36] My approach, similar to Nevo (2001) and Dunn (2010), allows me to generate such a rich cost structure without imposing any parametric assumptions other than Bertrand-Nash equilibrium. Exploiting this richness, I can not only compare MA plans costs to TM, but also study the heterogeneity in cost structures across MA plans, and in particular, between different types of MCOs.

Table 6: Supply Estimates

	HMO	LPPO	PFFS
γ_1	[0.538,0.609]	[0.612,0.793]	[0.368,0.749]
γ_2	[0.495,0.608]	[0.534,0.667]	[0.490,0.669]
$\frac{\gamma_2}{\gamma_1}$	[0.921,0.997]	[0.823,0.908]	[0.893,1.508]
Marginal Cost	738.7	738.3	742.2
Der. Marginal Cost	-5.112	-1.513	-1.406
Profit	85.70	89.84	69.95

Notes: Rows 1 through 3 reports the range of estimates of γ_1 and γ_2, and their ratio, as described in Equation 6, by MCO type. Rows 3 through 6 report the average plan's marginal costs, derivative of the marginal costs with respect to coverage, and profits by MCO type. An observation is a plan-year-county triple; all statics reported are calculated over the sample of analysis.

The last three rows of Table 6 report the values of marginal cost, derivative of marginal cost with respect to medical OOPC for the heterogenous-OOPC model (column 4), and profits by MCO

[36] I make a simplifying assumption when retrieving the marginal cost of plans that are sold in multiple markets: I assume that premium and coverage are determined at the market level, instead of the plan level. The retrieved marginal costs do not seems to differ substantially within plan: the average within-plan standard deviation of marginal cost is roughly \$8 and the coefficient of variation is 1%. These results offer reassurance of this assumption's limited impact. On the other side, it is reasonable to think that the same plan, may have different marginal costs in different markets, because even with the same contract and plan providers may have different negotiated fees.

type.[37] The average marginal cost for MA plans is \$741, and there is limited heterogeneity across MCO type. HMO and LPPO plans are slightly more efficient, their per enrollee marginal costs are \$739 and \$738 compared to \$742 for PFFSs. HMOs and LPPOs generate the most profit per enrollee, which translates into a larger markup (12-12.5%), while PFFS plans' markup is approximately 9.5%. These estimates are similar to the average markup of 13% given in MedPAC's 2010 annual report. (MedPAC (2010))[38]

The derivative of marginal cost with respect to OOPC paints a different picture: a \$1 increase in OOPC decreases plan costs by \$2.2 on average. There is a large degree of heterogeneity in the ability of MCOs to control their costs by changing their medical OOPC. For every \$1 increase in OOPC, an HMO's marginal cost drops by \$5.1 on average, while for LPPO and PFFS plans this figure is much smaller at only \$1.5 and \$1.4. The heterogeneity in the elasticity with respect to medical OOPC leads to these results, with HMOs facing an average demand elasticity about three times as large as that faced by the other MCOs. The fact that a \$1 increase in OOPC enables plans to reduce their costs by more than \$1 suggests presence of adverse selection and/or moral hazard. I cannot directly disentangle which of the two is the driving force; however, given the presence of risk-adjustment, it is reasonable to believe that moral hazard could be the main driver. Moreover, given that OOPC is a synthetic measure of coverage – a highly multidimensional object – changes in OOPC should not be literally interpreted at their dollar value. For example, an increase of \$10 in expected OOPC could be generated by an increase in copayment of \$10 or a reduction in available free preventive care services; these two changes are likely to have different effects on enrollees' health care usage, and thus, on plans' marginal costs.

In Figure 6a, I plot the kernel densities of marginal costs across different types of MCOs. The median LPPO and HMO plan costs \$723 per enrollee while the median PFFS plan costs \$729. We can observe another interesting fact, HMOs' marginal costs tend to be more dispersed, with a standard deviation of \$81; those of PFFSs tend to be less so, with a standard deviation of \$65;

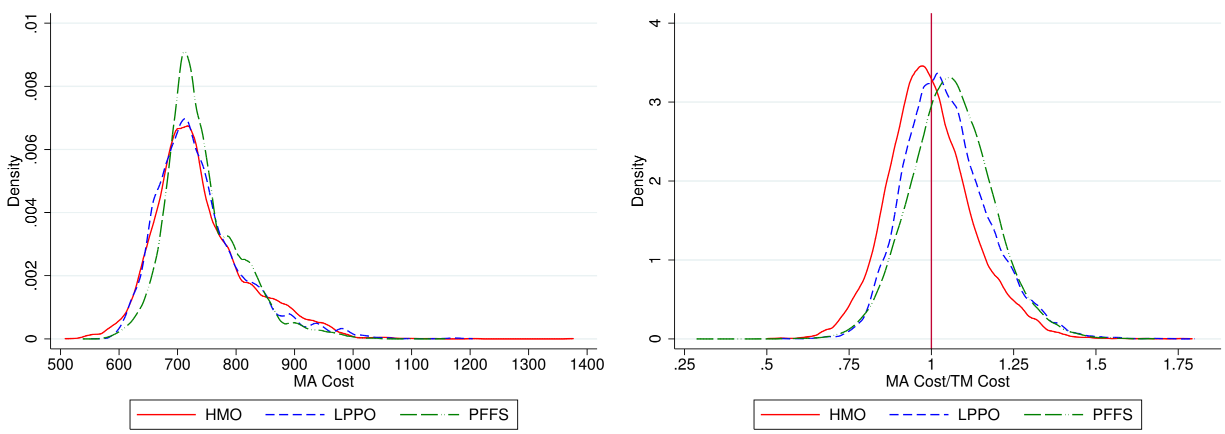
[37] Results from the baseline specification are comparable to those discussed in this section.

[38] I calculate the marginal cost implied by my model when the bidding process is shut down and the rebate is taken rebate as exogenous. Under this scenario, the average marginal cost is \$17 larger, with wider differences for HMOs (\$22) and LPPOs (\$23) than PFFS (\$15). The size of the bias is roughly 2%-3% of the size of the marginal costs.

LPPOs sit in the middle with a standard deviation of $77. To further explore the relationship between cost and MCO types, I plot the kernel densities of the ratio between marginal costs and county TM cost across different types of MCOs in Figure 6b. This measure is particularly appealing because it accounts for differences in the geographic penetration of different MCO types, normalizing their marginal costs over a common unit of measurement, TM costs. We have seen in previous sections that HMO plans, and to lesser extent LPPOs, tend to be concentrated in counties with higher TM costs and therefore higher benchmark. Using this measure, it is more clear that HMOs are the most efficient MCO, followed by LPPOs and then PFFSs. In particular, 55% of the HMO plans cover beneficiaries for a cost that is lower than that of TM. This percentage drops to 39% for LLPOs, and even further for PFFSs, to 31%.

Figure 6: Distribution of Marginal Cost By Plan Type

(a) MA Plans Marginal Cost (b) Ratio MA Plans Marginal Cost and TM Cost



Notes: An observation is a plan-year-county triple. Graph 6a plots the kernel density (bandwidth $7.5) of the plans' marginal costs separately by MCO type. Graph 6b plots the kernel density (bandwidth 0.0075) of the ratio plans' marginal costs and TM costs in their market, again separately by MCO type. Marginal costs are calculated as in Equation 8. TM costs are risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). The red vertical line in Graph 6a represents TM costs. All statistics reported are calculated over the sample of analysis.

These results paint an intriguing picture in which HMOs provide higher coverage while incurring lower costs. This makes sense if we consider the peculiar characteristics of each different type of MCO. As already discussed, HMOs are characterized by strong network restrictions and differential cost-sharing for provider in versus out-of-network. This allows HMO plans to better control their cost per enrollee by curbing the healthcare usage of their enrollees and/or negotiating lower fees with in-network providers. By design, these tools are less sharp for LPPOs, and even more so for PFFSs, because healthcare choices of their beneficiaries are less constrained by cost-sharing and network breadth. In the next section, I delve deeper into this comparison of costs by disentangling the contribution of coverage level from the heterogeneity in costs across types of MCOs.

5.3 Cost Function

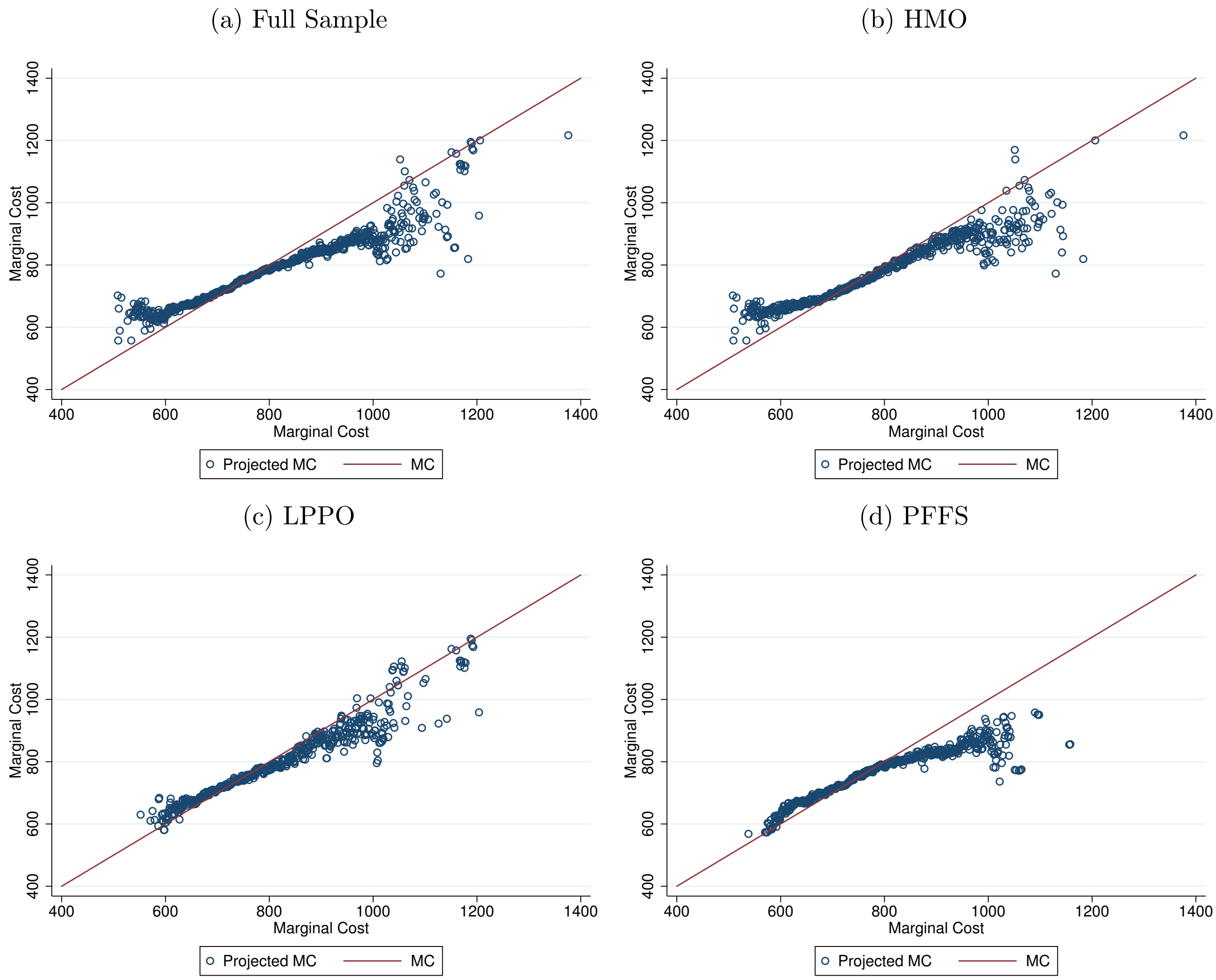
I can use the marginal costs implied by my model to estimate marginal costs as a function of coverage level. These hedonic estimates have a twofold benefit. First, it allows me to compare the marginal costs of MA plans with TM at the same coverage level as TM. Second, it allows me to run counterfactuals choosing different levels of coverage. Define the marginal cost of plan j as:

$$mc_{jmt} = f\left(g_{jmt}^{MA}\right) + \theta_B B_{mt} + \theta_A Age_{jmt} + \theta_{Cs(jm)} + \theta_{s(j)t} + \theta_{PD} + \theta_0 + \varepsilon_{jmt} \tag{10}$$

$f(\cdot)$ is an unknown function of OOPC that traces the effect of changes in the level of OOPC on marginal costs. I account for variation in marginal costs not accounted for by OOPC by controlling for additional plan characteristics. $\theta_{Cs(jm)}$ is a fixed effect for contract C in state s; similarly to the role of the fixed effect in my demand model, it captures the underlying heterogeneity in cost level across different contracts in different states. This difference can be due to differences in providers' network structures or local market characteristics. θ_B is the coefficient on the county benchmark, that I use to further control for local cost factors. $\theta_{s(j)t}$ captures heterogeneity in plans' costs across states and years. As already discussed in the data section, plans seem to cluster on a premium of zero, θ_0 represents the effect on marginal cost of zero premium. I would suggest that they cluster here because if they charge or buyback a premium, it is an additional bill that insurers have to produce, that entails an additional cost. Moreover, plans that include drug coverage may potentially experience (dis)economies of scale when providing it, which are accounted for by θ_{PD}. I also include as control the plans age at market level, the effect is measured by the coefficient θ_A. Finally, ε_{jmt} accounts for the remaining heterogeneity not captured by $f(\cdot)$ or the other controls.

I approximate $f(\cdot)$ with a spline and select number of knots and degree of the spline through

Figure 7: Goodness of Fit Hedonic Regression



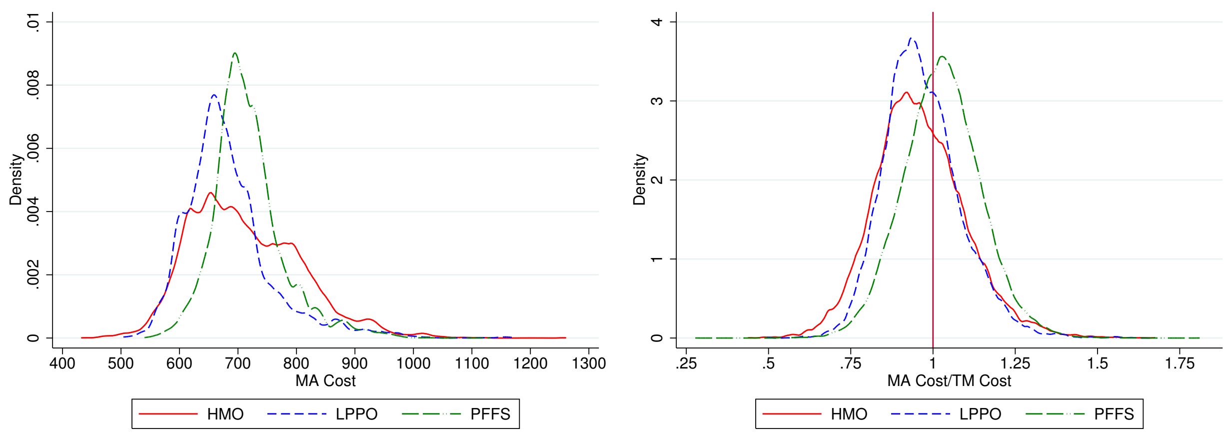
Notes: An observation is a plan-year-county triple. The graphs plot the projected marginal costs calculated as in Equation 10 against the implied marginal costs from Equation 8 by MCO type. Each circle represents the average projected marginal costs within \$1 of the marginal cost. All statistics reported are calculated over the sample of analysis.

cross-validation.[39] I estimate the model separately for each type of MCO. Figure 7 plots the

[39]I use a n-fold cross-validation criterion: for each contract, I estimate the spline using all the data but those from this contract, and then calculate the out of sample prediction error of the model for this contract. I repeat the algorithm for each contract, and then calculate the cross-validation criterion using the out sample prediction errors. I use the contracts as unit of analysis because given the presence of fixed effects at contract-state level, I identify $f(\cdot)$ using within contract-state variation. I allow a maximum number of 10 knots and split the OOPC variable in equally sized groups according to the number of knots. The cross-validation criterion suggests a specification with a quadratic polynomial with 7 knots for HMO, a linear polynomial with 2 knots for LPPO, and a quadratic polynomial with 2 knots for PFFS.

Figure 8: Marginal Costs with TM Coverage

(a) MA Plans Marginal Cost (b) Ratio MA Plans Cost and TM Cost



Notes: An observation is a triple plan-year-county. Graph 6a plots the kernel density (bandwidth \$7.5) of the plans' marginal costs, separately by MCO type. Graph 6b plots the kernel density (bandwidth 0.0075) of ratio of plans' marginal costs and the TM costs in their market, separately by MCO type. Marginal costs are calculated as in Equation 10, setting coverage at the same level as TM. TM costs are risk adjusted and representative of the average Medicare enrollee (risk score equal to 1). The red vertical line in Graph 6a represents TM costs. All statistics reported are calculated over the sample of analysis.

predicted marginal costs from my hedonic regression against the marginal costs retrieved from my model for the entire sample and each MCO type separately. Each dot represents the average predicted marginal costs within \$1 of the given marginal cost. The overall fit of the model is good: it slightly underestimates marginal costs for the upper tail of marginal costs distribution and overestimates them for the lower tail; the correlation coefficient between predicted and implied marginal costs is above 0.81 for each MCO type. The model also provides information regarding two plans' features discussed previously. First, plans that provide drug coverage incur \$5-\$15 in additional cost per enrollee. Second, plans that do not charge a premium save \$17-\$25 dollar per enrollee, suggesting the existence of an administrative cost in charging/rebating premiums.

Using the hedonic regression, I can calculate the cost for an MA plan to provide a coverage level identical to TM. In Figure 8, I repeat the same exercise as in Figure 6. Looking at Figure 8a, we can see that LPPO plans tend to have lower marginal costs (\$683), followed by HMOs (\$712) and PFFSs (\$718)[40] However, as discussed above, given the difference in geographic penetration

[40]The calculation of the MA plans's marginal costs excludes both the effect of drug coverage and zero premium.

of MA plans across the US, it is reasonable to normalize marginal cost by TM cost at the market level. From Figure 8b, it is clear that HMO and LPPO plans are able to provide the same level of coverage as TM at lower cost, and that more of them can do so than PFFSs: 64% of HMOs and LPPOs have cost lower than TM, while only 41% of the PFFS do. This exercise suggests that the difference we observed in plans' marginal cost cannot be solely explained by differences in their coverage levels. Indeed, heterogeneity across type of MCO is one of the main forces driving the cost differences between them.

5.4 Welfare Analysis

The next step in my analysis is to evaluate the welfare impact of MA, calculating the difference between the government expenditure on MA and consumer surplus plus insurers' profit. I calculate consumer surplus excluding the value of the drug coverage ($DC_{jm} = \alpha_1 pr_{jm}^{Drug} + \alpha_3 g_{jm}^{Drug} + Drug_{jm}$) in order to extrapolate only the surplus generated by the MA part of the coverage. The consumer surplus from MA coverage in a market m is:[41]

$$CS_m = \frac{1}{\alpha_1} \ln \left[1 + \sum_{K \in MCO} \exp \left((1-\rho) \ln \left(\sum_{k \in K} \exp \left(\frac{\delta_{km} - DC_{jm}}{1-\rho} \right) \right) \right) \right] \tag{11}$$

Table 7 reports the average monthly per enrollee and the total welfare impact of MA. I aggregate profit and government cost of each plan, weighting them by their enrollment, and follow a similar process for county level variables such as TM costs and consumer surplus. The surplus generated is \$133 per enrollee; about two-thirds of it is captured by insurers in the form of profits. As already discussed, MA plans are more expensive for the government than TM; each MA enrollee costs \$47 more than a TM enrollee, a cost difference which is generated by the rebate.[42] These numbers imply that the average welfare improvement generated by the MA program is equivalent to roughly \$86 per enrollee. We can interpret the magnitude of these numbers by looking at the overall impact of the MA program, which this estimate implies has generated a \$31 billions increase in total welfare

[41] Similarly to Town and Liu (2003), I scale consumer surplus by the total market share of MA.

[42] These figures differ from those previously discussed due to their different weighting: MA plans tend to have more enrollees in areas in which they have a cost advantage compared to TM. Graphs 3a and 3b display the average rebate and bid across all markets, in which each plan is weighted by its enrollment in the market.

from 2008 through 2011. It also worth noticing that the surplus generated is allocated to the MA participants (enrollees and insurers). Given the additional cost to the government of running the program compared to TM, CMS is implicitly subsidizing MA enrollees over TM ones. Moreover, MA is not generating nearly as large of an increase in consumer surplus as it is in total welfare, because most of surplus is captured by insurers.

Table 7: Welfare Impact of MA

	Per Enrollee (Dollar)	Total (Billion Dollar)
Profit (1)	88.10	32.30
Consumer Surplus - No Drug (2)	44.81	16.43
Total Surplus (A=1+2)	132.91	48.73
Rebate (3)	82.43	30.22
Bid (4)	739.6	271.2
TM Cost (5)	774.7	284.0
Total MA Cost (B=3+4-5)	47.33	17.42
Total Welfare Impact (A-B)	85.58	31.31

Notes:The first column reports the average monthly values for the variables of interest in the period 2008-2011, while the second column reports the total of those variables over the same period. Each plan is weighted by its enrollment.

Although at first my estimates suggest that the MA program is generating value, a careful look at the demand and supply estimates would suggest that there is room for improvement in the program. How could we address these points? We saw that different types of MCOs have highly heterogenous trade-offs between marginal cost and enrollee coverage level, and that this is a main driver of consumer surplus; therefore, an alternative design of the MA market which enhanced those differences could generate greater gains in surplus for each dollar of government expenditure. The next section will explores the potential gains (or losses) from an alternative payment policy for MA.

6 Counterfactual Analysis

In this section, I run a few counterfactual simulations which implement an alternative payment policy for MA, premium support, that has been widely discussed both before and after the implementation of the ACA (CBO (2013)). In particular, I focus on a simplified version of the premium support program in which each plan receives a flat subsidy identical to the cost of TM in their market. Plans bid their costs to provide a coverage level equal to TM (or higher) and if the bid is above the subsidy, enrollees have to pay the difference between the two as a premium. When the plan's bid is below the cost of TM, the difference between its bid and the subsidy is paid back to the plan's enrollees. Under this mechanism, the average government expense per enrollee would be identical regardless of the fraction of enrollees choosing MA over TM.

Table 8: Welfare Impact of Premium Support

	Data	CF1	CF2	CF3
	g^{MA}	g^{MA}	$g^{MA} = g^{TM}$	$g^{MA} = 60\% g^{TM}$
Premium	29.14	-3.105	-35.71	10.88
Medical OOPC	89.17	85.75	151.9	92.24
Marginal Cost	761.8	745.3	707.9	750.1
Consumer Surplus - No Drug	45.31	25.41	25.14	24.34
Profit	87.79	72.48	67.02	73.54
TM Cost	769.1	820.8	810.7	812.8
Bid	738.2	817.7	775.0	823.6
Rebate	82.25	0	0	0
MA Share	0.168	0.155	0.043	0.177

Notes: The first column (Data) reports average monthly values for the variables of interest. The second columns (CF1) reports these averages for a premium support program in which plans offer the same coverage level as they do in the data. The third column (CF3) reports these averages for a premium support program in which each plan offers the same coverage level as TM. The fourth column (CF4) reports these averages for a premium support program in which each plan offers 60% of the TM coverage level. Each plan is weighted by its enrollment during the period 2008-2011. Unlike Table 7, this table excludes 120 markets for which the results of the counterfactuals were unstable from the sample.

Table 8 reports the results of these counterfactual simulations. I report the enrollment-weighted averages of premium, marginal cost, medical OOPC, consumer surplus, profit, TM cost, bid, government subsidy (rebate), and MA market share in three alternative scenarios. In the first one, insurers offer the same packages they offer in the data, but payments are made according to the premium support system. In the other two scenarios, the payment system is also premium support, but each plan is constrained to offer the same coverage package – 100% or 60% of TM medical OOPC.

The results of these counterfactual exercises provide a few interesting insights. Plans' profits drop by roughly 16-24%, mainly due to two factors: a decrease in product differentiation across plans, especially with respect to TM, and the drop in government subsidy. In counterfactuals 2 and 3, plans have the same level of coverage and can only compete on premium; however, the drop in plans' profits is larger in counterfactual 2 ($67), where plans offer the same coverage as TM, than in counterfactual 3 ($74), where MA plans offer lower OOPCs than TM. Comparing counterfactual 1 to the data, we can also observe how the decrease in the size of subsidy plays a significant role in the reduction of profits. The change in government subsidy also affects the geographic penetration of MA plans. We observe a dramatic change in the penetration of MA plans across markets: MA plans now have larger enrollment in counties with higher TM cost (from $769 to $821), where they have a cost advantage compared to TM ($821 vs. $745). This is a reasonable outcome for my simulations given that low TM cost counties have the largest spread between TM cost and MA benchmark.[43] Moreover, consumer surplus decreases by about 44-46% on average because enrollees no longer receive an additional government subsidy when they choose MA plans and thus have to pay the full cost through higher premium. For enrollees, the main attraction of MA plans is the additional coverage that they provide compared to TM; in fact, if MA plans provided the same level of coverage as TM, their market share would only be 4%. Overall, we observe that even without the additional government subsidy for supplemental services – the rebate – the surplus generated is still sizable (between $95 and $98 per enrollee-month).

My counterfactual simulations suggest that there is room for improvement in the design of the MA payment system, because they are likely to represent a lower bound for the welfare gains achievable. The ACA seems to go in the correct direction, reducing the spread between benchmark and TM cost. Moreover, it is reasonable to think that a complete redesign, and potentially a simplification, of the MA's system of payments and subsidies would be welfare enhancing. Clearly, my counterfactual exercises abstract from any additional effects of the introduction of a premium support program and reduced payment amounts, such as changes in the portfolio of plans offered and/or entry and exit decisions by insurers in the MA market.

[43] As explained in footnote 5, the benchmark grown faster than TM cost for counties with low TM cost because their benchmarks were updated using either the national TM cost growth rate or the rural/urban floor.

7 Conclusion

In the last few decades, MA has played an increasing role in providing access to health insurance to the American elderly. Despite the program's goals of exploiting competition between private insurers to reduce Medicare's costs, as of 2010, the cost to Medicare of the average MA enrollee was 13% larger than that of the average TM enrollee.

In my paper, I disentangle the sources of this cost discrepancy between MA and TM. I develop and estimate a structural model of demand and supply in the MA market, in which I allow insurers to freely choose their premium and coverage level, with the latter represented by the non-premium cost paid by MA plans' enrollees (OOPC). My model incorporates the convoluted MA payment system, in which a plan's bid to provide TM services determines the size of its government subsidy for supplemental services. I exploit this link to simplify insurers' choice problems to the task of finding optimal coverage levels and bids. Using my model, I am able to retrieve a rich cost structure that includes plans' marginal costs and the derivatives of their marginal cost with respect to coverage level.

My estimates indicate that about 37% of the MA plans can provide a level of coverage equal to or greater than that of TM for a lower cost. Furthermore, I find that different types of MCO have widely heterogenous cost structures. Plans that impose stronger constraints on beneficiaries' healthcare choices, like HMOs, have lower costs and greater ability to reduce their costs by increasing beneficiaries' cost-sharing. My demand and supply estimates imply that MA program generates a monthly surplus of \$133 per enrollee, with two-third of this surplus captured by insurers; accounting for government expenditure, the monthly net welfare change generated by MA is \$86 per enrollee. These numbers suggest that there is room for improvement in the way Medicare pays MA plans. I evaluate an alternative payment mechanism, premium support, in which plans receive a flat subsidy for each enrollee equal to the TM cost for that market. This simple alternative mechanism still generates surplus for enrollees and firms, while reducing overall government expenditure. My results also suggest that while the reduction of the overall subsidy level for MA implemented by the ACA could be a step in the right direction, a complete redesign of the payment-subsidy system should be a topic of discussion in the policy arena because it could generate savings for the government without substantially affecting welfare.

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Appendix

A.1 Data

The dataset was assembled from data made publicly available by CMS (Center for Medicare and Medicaid Services):

- The Plan Payments files contain the average risk score, payment and rebate for each plan. The County Payment files provide the same type of information at the county level disaggregated to the different type of plans offered.

  https://www.cms.gov/Medicare/Medicare-Advantage/Plan-Payment/Plan-Payment-Data.html

- The Contract/Plan/State/County (CSCP) files provide monthly enrollment for each plan at the county level.

  https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/Monthly-Enrollment-by-Contract-Plan-State-County.html

- The State/County/Contract (SCC) files provide monthly enrollment for each contract at the county level.

  https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/Monthly-MA-Enrollment-by-State-County-Contract.html

- The Service Area files provide the availability of each contract at county level.

  https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/MA-Contract-Service-Area-by-State-County.html

- The MA Penetration Rate files include the Medicare population at county level.

  https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/MA-State-County-Penetration.html

- The FFS file contains the TM costs at county level.

  https://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/FFS-Data.html

- The Rate Book files contain the benchmarks at county level

  https://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Ratebooks-and-Supporting-Data.html

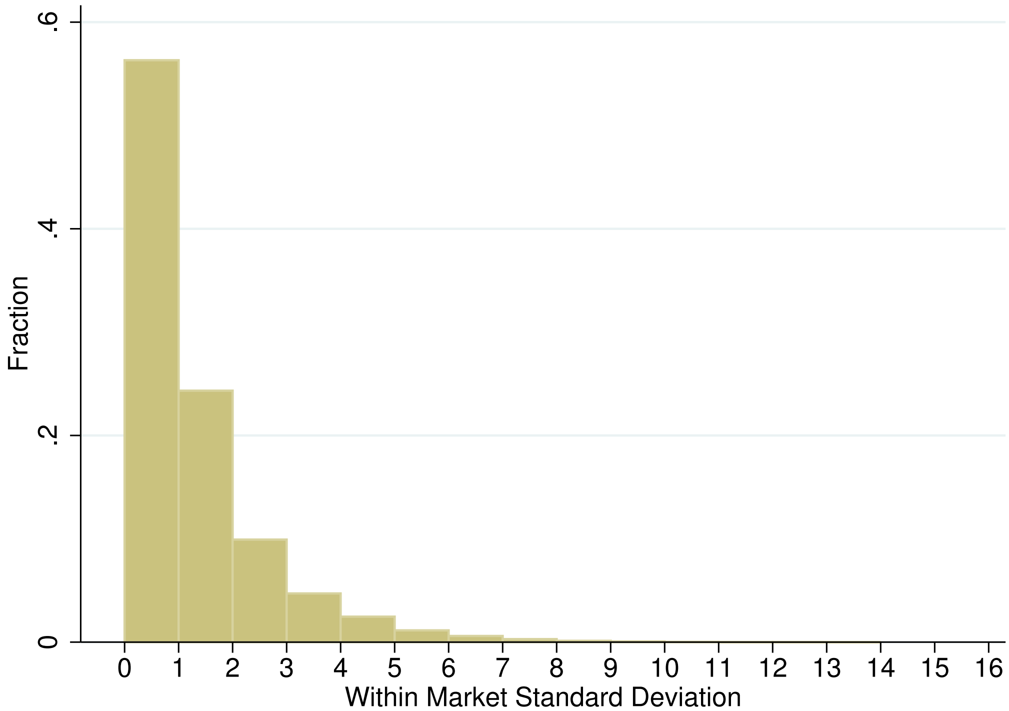
- The Landscape files provide information regarding premium, presence and type of prescription drug coverage, and presence and type of extra coverage gap.

  https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovGenIn/index.html

- I received the OOPCs database from directly from CMS archive.

A.2 Additional Results

Figure A.1: Standard Deviation OOPC Ranking



Notes: The histogram reports the within-market plan standard deviation in the OOPC ranking. Each bin represent the fraction of plan with standard deviation less than that value.

Table A.1: Demand Estimates - LIML

	Baseline		Het. OOPC		Het. OOPC-Nest	
	IV Nest	IV All	IV Nest	IV All	IV Nest	IV All
	(1)	(2)	(3)	(4)	(5)	(6)
Nest - ρ	0.326***	0.364***	0.316***	0.342***		
	(0.046)	(0.057)	(0.055)	(0.074)		
Nest HMO - ρ_{HMO}					0.371***	0.588***
					(0.041)	(0.102)
Nest LPPO - ρ_{LPPO}					0.247***	0.324***
					(0.064)	(0.087)
Nest PFFS - ρ_{PFFS}					0.304***	0.136
					(0.087)	(0.224)
Premium - α_1	-0.008***	-0.008**	-0.008***	-0.010**	-0.008***	-0.009
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.006)
Medical OOPC - α_2	-0.011***	-0.018***				
	(0.004)	(0.006)				
Medical OOPC HMO - α_{2HMO}			-0.015***	-0.064***	-0.015***	-0.087***
			(0.003)	(0.017)	(0.003)	(0.027)
Medical OOPC LPPO - α_{2LPPO}			-0.012***	-0.026**	-0.012***	-0.042**
			(0.003)	(0.013)	(0.003)	(0.027)
Medical OOPC PFFS - α_{2PFFS}			-0.010	-0.019***	-0.010	-0.018**
			(0.006)	(0.006)	(0.003)	(0.020)
Drug OOPC - α_3	-0.009***	-0.007***	-0.009***	-0.009***	-0.009***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Drug Coverage - HMO	0.375*	0.560**	0.371*	0.410	0.278	-0.280
	(0.201)	(0.228)	(0.206)	(0.257)	(0.231)	(0.559)
Drug Coverage - LPPO	0.417*	0.621**	0.413*	0.448	0.522*	0.111
	(0.232)	(0.256)	(0.236)	(0.276)	(0.275)	(0.558)
Drug Coverage - PFFS	-0.683***	-0.452*	-0.709***	-0.630**	-0.719***	-0.925*
	(0.162)	(0.243)	(0.157)	(0.292)	(0.166)	(0.484)
Plan Age	0.420***	0.401***	0.426***	0.418***	0.421***	0.404***
	(0.060)	(0.066)	(0.067)	(0.062)	(0.061)	(0.070)
Contract	-0.577	-0.592	-0.580*	-0.706	-0.571*	-0.642
	(0.358)	(0.426)	(0.351)	(0.464)	(0.343)	(0.459)
Observations	144,246	144,246	144,246	144,246	144,246	144,246
R-squared	0.541	0.572	0.532	0.492	0.529	0.270

Notes: The regression also includes fixed effects for contract-state and state-year. In the odd columns, the nest is instrumented using the number of plans of a type, and the number of plans with drug coverage of a type in county-year; in column 5, the instruments are interacted with MCO type dummies. In the even columns premium and OOPC are also instrumented and I expand the set of instruments to include: the minimum premium and OOPC (maximum rebate) from plans in the same contract, but with non-overlapping service areas; the average premium, OOPC, and rebate of plans in competing contracts of the same MCO type but with non-overlapping service areas; the average age of plans and contracts in the market within each MCO type. A dummy is added when the first two instruments are not available. In column 4 and 6 these instruments using rebate and medical OOPC are interacted with MCOs type dummies. The standard errors are clustered at the contract level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.2: First Stage - Premium and OOPC OLS

VARIABLES	(1) Col.1 Nest	(2) Col. 3 Nest	(3) Nest HMO	(4) Col. 5 Nest LPPO	(5) Nest PFFS
# Plans	-0.076***	-0.074***			
	(0.007)	(0.009)			
# Plans w/t Drug	-0.038***	-0.039***			
	(0.010)	(0.011)			
# Plans - HMO			-0.130***	0.001	-0.002
			(0.009)	(0.001)	(0.002)
# Plans - LPPO			-0.006*	-0.097***	-0.006
			(0.004)	(0.037)	(0.006)
# Plans - PFFS			-0.004	-0.001	-0.058***
			(0.002)	(0.001)	(0.012)
# Plans w/t Drug - HMO			0.026***	-0.001*	-0.005*
			(0.007)	(0.001)	(0.003)
# Plans w/t Drug - LPPO			0.001	-0.081**	0.003
			(0.004)	(0.033)	(0.009)
# Plans w/t Drug - PFFS			0.007***	0.003***	-0.064***
			(0.003)	(0.001)	(0.022)
Total Premium	-0.008***	-0.008***	-0.002**	-0.000	-0.005***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Medical OOPC	-0.013**				
	(0.006)				
Drug OOPC	-0.012***	-0.012***	-0.002***	-0.001***	-0.008***
	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)
Medical OOPC - HMO		-0.016***	-0.009***	-0.001**	-0.007***
		(0.003)	(0.002)	(0.000)	(0.003)
Medical OOPC - LPPO		-0.017***	-0.004**	-0.007**	-0.007**
		(0.004)	(0.001)	(0.003)	(0.003)
Medical OOPC - PFFS		-0.011	-0.003**	-0.000	-0.006
		(0.009)	(0.002)	(0.000)	(0.010)
Drug Coverage - HMO	0.916***	0.927***	1.158***	-0.062**	-0.630***
	(0.235)	(0.229)	(0.176)	(0.030)	(0.223)
Drug Coverage - LPPO	0.826***	0.828***	-0.154*	2.060***	-0.833***
	(0.279)	(0.275)	(0.082)	(0.280)	(0.259)
Drug Coverage - PFFS	-0.510**	-0.502**	-0.192**	-0.098***	0.020
	(0.207)	(0.208)	(0.082)	(0.036)	(0.370)
Plan Age	0.465***	0.465***	0.217***	0.064***	0.181***
	(0.069)	(0.068)	(0.042)	(0.016)	(0.046)
Contract Age	-0.499	-0.489	-0.229**	-0.048***	-0.160
	(0.336)	(0.319)	(0.112)	(0.018)	(0.205)
Observations	144,246	144,246	144,246	144,246	144,246
R-squared	0.168	0.169	0.237	0.237	0.093

Notes: The regression also includes fixed effects for contract-state and state-year. Column 1 reports the first stage regression of the model in column 1 of Table 5. Column 2 reports the first stage regression of the model in column 3 of Table 5. Columns 3 through 5 report the first stage regressions of the model in column 5 of Table 5. The standard errors are clustered at the contract level *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: First Stage - Premium and OOPC TSLS (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MODEL		Col. 2						Col. 4		
VARIABLES	Nest	Tot. Premium	Med.OOPC	Drug OOPC	Nest	Tot. Premium	Med. OOPC - HMO	Med. OOPC - LPPO	Med. OOPC - PFFS	Drug OOPC
# Plans	-0.056***	-0.673**	-0.371***	-0.232***	-0.057***	-0.651**	0.078***	0.023*	-0.389***	-0.206***
	(0.006)	(0.323)	(0.133)	(0.074)	(0.006)	(0.269)	(0.024)	(0.012)	(0.101)	(0.065)
# Plans w/t Drug	-0.047***	-0.701**	0.207	0.464**	-0.047***	-0.752**	-0.180***	-0.002	0.337***	0.487**
	(0.013)	(0.340)	(0.136)	(0.185)	(0.013)	(0.296)	(0.063)	(0.018)	(0.099)	(0.189)
Min. Total Premium	0.002	0.167**	-0.140***	-0.009	0.002	0.213**	-0.021	-0.027**	-0.103***	-0.007
	(0.003)	(0.074)	(0.027)	(0.017)	(0.003)	(0.086)	(0.018)	(0.013)	(0.032)	(0.018)
Min. Drug OOPC	-0.004***	-0.046	-0.003	0.500***	-0.004***	-0.047	-0.006	-0.006	0.002	0.508***
	(0.001)	(0.043)	(0.017)	(0.035)	(0.001)	(0.045)	(0.008)	(0.004)	(0.015)	(0.035)
Min. Medical OOPC	-0.002	-0.260*	0.177	0.015						
	(0.003)	(0.150)	(0.112)	(0.048)						
Max Rebate	0.001	0.036	-0.023	0.012						
	(0.001)	(0.049)	(0.023)	(0.024)						
Min. Medical OOPC - HMO					0.004	-0.215	0.054	-0.012	0.131**	-0.136**
					(0.002)	(0.150)	(0.034)	(0.010)	(0.059)	(0.054)
Min. Medical OOPC - LPPO					0.002	-0.189	-0.015	0.179***	0.130**	-0.100**
					(0.003)	(0.153)	(0.027)	(0.046)	(0.057)	(0.050)
Min. Medical OOPC - PFFS					-0.004	-0.211	0.009	0.001	0.143	0.050
					(0.003)	(0.180)	(0.019)	(0.007)	(0.106)	(0.052)
Max Rebate - HMO					0.000	0.051	-0.020	-0.002	0.010	0.019
					(0.001)	(0.051)	(0.014)	(0.004)	(0.016)	(0.022)
Max Rebate - LPPO					0.000	0.094	0.032	-0.096***	0.006	-0.016
					(0.002)	(0.080)	(0.020)	(0.026)	(0.017)	(0.030)
Max Rebate -PFFS					0.001	0.093	0.019	-0.014**	-0.043	0.028
					(0.003)	(0.103)	(0.019)	(0.007)	(0.041)	(0.032)
Missing Own IV	-0.331	-27.968*	14.764	26.025***	-0.268	-20.357	1.919	-1.196	14.025**	23.869***
	(0.306)	(16.596)	(9.716)	(8.572)	(0.293)	(18.514)	(3.057)	(0.957)	(6.547)	(7.901)
Rival Mean Total Premium	0.003*	-0.297**	-0.069	-0.026	0.003*	-0.226**	0.021	-0.022**	-0.036	-0.026
	(0.002)	(0.147)	(0.047)	(0.028)	(0.001)	(0.088)	(0.017)	(0.010)	(0.025)	(0.027)
Rival Mean Drug OOPC	-0.001	-0.049	-0.006	0.133***	-0.001	-0.039	0.000	-0.007	0.002	0.121***
	(0.002)	(0.044)	(0.013)	(0.031)	(0.002)	(0.043)	(0.010)	(0.005)	(0.007)	(0.032)
Rival Mean OOPC	0.002	-0.276**	0.128*	0.149***						
	(0.002)	(0.124)	(0.069)	(0.039)						
Rival Mean Rebate	0.002	-0.027	0.035	0.005						
	(0.002)	(0.049)	(0.047)	(0.026)						
Rival Mean Med. OOPC - HMO					0.005*	-0.279***	0.066*	-0.039*	0.013	0.085***
					(0.002)	(0.090)	(0.038)	(0.023)	(0.058)	(0.030)
Rival Mean Med. OOPC - LPPO					0.002	-0.117	-0.104***	0.149***	0.019	0.079**
					(0.003)	(0.091)	(0.036)	(0.028)	(0.059)	(0.031)
Rival Mean Med. OOPC - PFFS					0.005	-0.220	-0.190***	-0.058**	0.651**	0.146**
					(0.005)	(0.222)	(0.069)	(0.024)	(0.276)	(0.068)
Rival Mean Rebate - HMO					0.003*	-0.039	0.003	-0.009	0.011	-0.017
					(0.002)	(0.053)	(0.032)	(0.010)	(0.017)	(0.026)
Rival Mean Rebate - LPPO					0.004**	-0.079	0.082***	-0.104***	0.034	-0.000
					(0.002)	(0.074)	(0.028)	(0.029)	(0.026)	(0.027)
Rival Mean Rebate - PFFS					-0.001	0.386	0.034	-0.036*	0.260	0.011
					(0.006)	(0.403)	(0.038)	(0.019)	(0.239)	(0.050)
Rival IV Missing	0.667*	-47.858***	9.555	23.556***	0.803**	-35.280***	2.063	-4.803	5.268	15.215***
	(0.344)	(17.021)	(8.757)	(5.126)	(0.355)	(11.734)	(4.866)	(3.313)	(7.238)	(4.857)
Mean Age Plans	-0.586***	-4.989**	-1.283**	-0.053	-0.592***	-5.533**	1.338***	-0.120	-2.136***	0.142
	(0.048)	(2.054)	(0.605)	(0.339)	(0.054)	(2.326)	(0.367)	(0.278)	(0.523)	(0.314)
Mean Age Contracts	-0.048***	0.501**	0.045	0.074	-0.047**	0.513**	-0.144	-0.008	0.178***	0.050
	(0.018)	(0.239)	(0.123)	(0.085)	(0.018)	(0.240)	(0.122)	(0.028)	(0.063)	(0.079)
Drug Coverage - HMO	1.197***	33.213***	-2.611	-19.982***	1.152***	35.000***	0.713	-1.719**	-2.142	-19.459***
	(0.285)	(7.418)	(3.318)	(6.215)	(0.305)	(7.462)	(2.020)	(0.805)	(2.503)	(6.561)
Drug Coverage - LPPO	1.162***	30.726***	-2.789	-21.252***	1.134***	32.079***	-0.283	-2.114	-1.195	-21.259***
	(0.327)	(6.289)	(3.672)	(7.778)	(0.348)	(6.433)	(1.221)	(2.394)	(2.676)	(8.186)
Drug Coverage - PFFS	-0.057	23.898***	1.052	-35.689***	-0.068	25.449***	1.668	-1.052*	0.629	-36.177***
	(0.351)	(5.991)	(2.328)	(4.342)	(0.351)	(5.905)	(1.113)	(0.631)	(2.011)	(4.504)
Plan Age	0.603***	0.438	0.169	-0.571	0.603***	0.616	-0.026	-0.424	0.704	-0.457
	(0.061)	(1.620)	(0.591)	(0.417)	(0.061)	(1.691)	(0.358)	(0.269)	(0.446)	(0.393)
Contract Age	-0.083	-38.500*	-5.113	-14.956**	-0.073	-42.281*	-0.492	0.043	-7.676	-14.088***
	(0.237)	(19.692)	(9.460)	(5.956)	(0.201)	(23.029)	(0.950)	(0.323)	(10.945)	(4.575)
Observations	144,246	144,246	144,246	144,246	144,246	144,246	144,246	144,246	144,246	144,246
R-squared	0.155	0.152	0.056	0.942	0.157	0.158	0.056	0.135	0.147	0.943

Notes: The regression also includes fixed effects for contract-state and state-year. Columns 1 through 4 report the first stage regressions of the model in column 2 of Table 5. Columns 5 through 10 report the first stage regressions of the model in column 4 of Table 5. The standard errors are clustered at the contract level *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: First Stage - Premium and OOPC TSLS (2)

VARIABLES	(1) Nest -HMO	(2) Nest - LPPO	(3) Nest - PFFS	(4) Tot. Premium	(5) Med. OOPC - HMO	(6) Med. OOPC - LPPO	(7) Med. OOPC - PFFS	(8) Drug OOPC
# Plans - HMO	-0.131***	-0.000	0.001	0.225	-0.403***	0.029**	0.056*	-0.025
	(0.009)	(0.001)	(0.002)	(0.217)	(0.110)	(0.014)	(0.033)	(0.090)
# Plans - LPPO	-0.029***	-0.102***	-0.016***	-0.647	0.035	0.211	-0.070	0.325
	(0.006)	(0.036)	(0.006)	(0.423)	(0.087)	(0.284)	(0.095)	(0.656)
# Plans - PFFS	0.001	-0.000	-0.044***	-0.737**	0.137***	0.019	-0.469***	-0.286***
	(0.001)	(0.000)	(0.006)	(0.293)	(0.029)	(0.013)	(0.132)	(0.075)
# Plans w/t Drug - HMO	0.027***	-0.000	0.001	-0.752***	-0.047	0.001	-0.059*	-0.192
	(0.008)	(0.001)	(0.003)	(0.291)	(0.152)	(0.014)	(0.031)	(0.150)
# Plans w/t Drug LPPO	0.008	-0.079**	0.014*	0.168	0.023	-0.559*	-0.020	-0.526
	(0.006)	(0.033)	(0.007)	(0.399)	(0.069)	(0.331)	(0.073)	(0.926)
# Plans w/t Drug PFFS	0.004*	0.002	-0.069***	-1.552***	0.042	0.029	0.435**	1.165***
	(0.002)	(0.001)	(0.025)	(0.439)	(0.041)	(0.019)	(0.178)	(0.273)
Min. Total Premium	-0.001	-0.001**	0.004	0.211**	-0.021	-0.027**	-0.102***	-0.004
	(0.001)	(0.000)	(0.003)	(0.083)	(0.017)	(0.012)	(0.032)	(0.019)
Min Drug OOPC	0.000	-0.000	-0.004***	-0.033	-0.010	-0.006	0.001	0.497***
	(0.000)	(0.000)	(0.001)	(0.042)	(0.008)	(0.004)	(0.015)	(0.035)
Min Med. OOPC - HMO	0.003*	0.000	0.002	-0.245*	0.065*	-0.011	0.127**	-0.123**
	(0.002)	(0.000)	(0.002)	(0.144)	(0.033)	(0.010)	(0.059)	(0.055)
Min Med. OOPC - LPPO	-0.003**	0.005***	0.001	-0.207	-0.009	0.179***	0.128**	-0.091*
	(0.001)	(0.001)	(0.002)	(0.149)	(0.027)	(0.046)	(0.057)	(0.051)
Min Med. OOPC - PFFS	-0.002**	0.000	-0.001	-0.240	0.018	0.002	0.142	0.068
	(0.001)	(0.000)	(0.003)	(0.174)	(0.019)	(0.007)	(0.105)	(0.053)
Max Rebate - HMO	-0.001**	-0.000	0.001	0.048	-0.020	-0.002	0.014	0.027
	(0.001)	(0.000)	(0.001)	(0.049)	(0.014)	(0.004)	(0.015)	(0.021)
Max Rebate - LPPO	0.000	-0.002	0.002	0.093	0.032*	-0.097***	0.007	-0.014
	(0.001)	(0.002)	(0.001)	(0.077)	(0.019)	(0.026)	(0.017)	(0.030)
Max Rebate - PFFS	0.001	0.000	-0.000	0.094	0.018	-0.014*	-0.042	0.028
	(0.001)	(0.000)	(0.003)	(0.100)	(0.017)	(0.007)	(0.040)	(0.034)
Own IV Missing	-0.319*	0.008	0.088	-22.376	2.578	-1.091	13.860**	24.859***
	(0.163)	(0.051)	(0.222)	(17.961)	(2.969)	(0.948)	(6.435)	(8.143)
Rival Mean Total Premium	0.002**	-0.001	0.002	-0.221**	0.018	-0.022**	-0.034	-0.028
	(0.001)	(0.001)	(0.001)	(0.087)	(0.016)	(0.009)	(0.024)	(0.027)
Rival Mean Drug	-0.001**	-0.000	0.001	-0.030	-0.003	-0.007	0.002	0.115***
	(0.001)	(0.000)	(0.002)	(0.043)	(0.010)	(0.005)	(0.007)	(0.031)
Rival Mean Med. OOPC - HMO	0.005***	0.000	-0.001	-0.263***	0.057	-0.038*	0.016	0.080**
	(0.001)	(0.001)	(0.002)	(0.086)	(0.037)	(0.022)	(0.057)	(0.031)
Rival Mean Med. OOPC - LPPO	0.003**	0.000	-0.001	-0.111	-0.111***	0.151***	0.021	0.078**
	(0.002)	(0.001)	(0.002)	(0.088)	(0.035)	(0.028)	(0.058)	(0.032)
Rival Mean Med. OOPC - PFFS	0.005***	0.000	0.004	-0.306	-0.154***	-0.057**	0.630**	0.166**
	(0.002)	(0.001)	(0.004)	(0.225)	(0.055)	(0.023)	(0.272)	(0.071)
Rival Mean Rebate - HMO	0.001	-0.000	0.002**	-0.036	0.000	-0.008	0.013	-0.014
	(0.001)	(0.000)	(0.001)	(0.052)	(0.032)	(0.010)	(0.017)	(0.026)
Rival Mean Rebate LPPO	0.003***	-0.001	0.002**	-0.077	0.079***	-0.104***	0.037	0.003
	(0.001)	(0.001)	(0.001)	(0.072)	(0.027)	(0.028)	(0.026)	(0.028)
Rival Mean Rebate PFFS	0.005***	-0.000	-0.004	0.345	0.050	-0.036*	0.249	0.018
	(0.002)	(0.001)	(0.007)	(0.397)	(0.033)	(0.018)	(0.238)	(0.055)
Rival IV Missing	0.665***	-0.082	0.257	-34.014***	1.216	-4.692	5.535	14.744***
	(0.226)	(0.130)	(0.205)	(11.166)	(4.699)	(3.243)	(7.136)	(4.797)
Mean Plan Age	-0.267***	-0.101***	-0.264***	-4.872**	1.133***	-0.154	-2.004***	-0.038
	(0.054)	(0.023)	(0.048)	(2.238)	(0.352)	(0.270)	(0.502)	(0.286)
Mean Contract Age	-0.077***	0.004**	0.018***	0.690***	-0.206*	-0.015	0.207***	-0.011
	(0.017)	(0.002)	(0.006)	(0.249)	(0.109)	(0.029)	(0.068)	(0.082)
Drug Coverage - HMO	1.105***	-0.033	-0.524**	37.921***	-1.315	-1.807**	1.052	-15.865***
	(0.199)	(0.045)	(0.264)	(7.086)	(2.401)	(0.777)	(2.446)	(6.090)
Drug Coverage - LPPO	-0.188*	2.081***	-0.685**	30.814***	-2.362*	0.669	0.456	-18.586*
	(0.110)	(0.306)	(0.295)	(6.523)	(1.258)	(3.460)	(2.884)	(9.722)
Drug Coverage - PFFS	-0.125	-0.052	0.341	37.289***	-1.670	-1.479**	-0.732	-46.060***
	(0.077)	(0.041)	(0.516)	(7.215)	(1.074)	(0.686)	(2.291)	(5.746)
Plan Age	0.285***	0.091***	0.233***	0.403	0.035	-0.416	0.690	-0.348
	(0.047)	(0.020)	(0.051)	(1.703)	(0.355)	(0.268)	(0.447)	(0.371)
Contract Age	-0.316*	-0.046	0.268*	-41.185*	-0.848	-0.007	-7.602	-14.653***
	(0.170)	(0.040)	(0.160)	(21.723)	(0.832)	(0.349)	(10.942)	(3.759)
Observations	144,246	144,246	144,246	144,246	144,246	144,246	144,246	144,246
R-squared	0.254	0.237	0.085	0.164	0.074	0.137	0.150	0.945

Notes: The regression also includes fixed effects for contract-state and state-year. Columns 1 through 8 report the first stage regressions of the model in column 6 of Table 5. The standard errors are clustered at the contract level *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Gammas Estimates

VARIABLES	(1) 2008	(2) 2009	(3) 2010	(4) 2011	(5) 2008	(6) 2009	(7) 2010	(8) 2011
	Premium				Rebate			
HMO	0.609***	0.538***	0.556***	0.592***	0.608***	0.495***	0.545***	0.574***
	(0.0211)	(0.0153)	(0.0130)	(0.0131)	(0.00347)	(0.00239)	(0.00263)	(0.00237)
Observations	6,419	8,257	7,968	7,989	6,419	8,257	7,968	7,989
	Premium				Rebate			
LPPO	0.793***	0.648***	0.612***	0.677***	0.667***	0.534***	0.556***	0.601***
	(0.0138)	(0.0139)	(0.00634)	(0.00734)	(0.00780)	(0.00641)	(0.00662)	(0.00542)
Observations	2,648	3,739	4,676	5,648	2,648	3,739	4,676	5,648
	Premium				Rebate			
PFFS	0.749***	0.501***	0.368***	0.405***	0.669***	0.490***	0.555***	0.571***
	(0.00243)	(0.00247)	(0.00217)	(0.00542)	(0.00128)	(0.00159)	(0.00295)	(0.00361)
Observations	31,370	35,860	22,465	7,223	31,370	35,860	22,465	7,223

Notes: The coefficients for γ_1 and γ_2 are estimated separately by MCO type and year. Columns 1 through 4 report the estimates for the γ_1. Columns 5 through 8 report the estimates for the γ_2. The standard errors are heteroscedasticity adjusted *** p<0.01, ** p<0.05, * p<0.1.