# Common Ownership and Risk Selection in Medicare Part D

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**Most recent draft**

**Abstract**

This paper shows how common ownership among Medicare Part D insurers affects premium setting and interacts with risk selection. Using the 13F filing, we document substantial overlap in insurers' institutional owners. Reduced form evidence shows that greater exposure to common ownership is associated with higher premiums. We then estimate a structural model of demand and supply for prescription drug plans (PDP) that quantifies the effects of common ownership and risk selection. Non-nested tests and conduct parameter estimates favor common ownership conduct over own profit maximization. We find that common ownership magnifies the effect of risk selection on premiums, and removing both would reduce average premiums by 20 percent and increase plan enrollment by 14.7 percentage points, improving allocative efficiency.

***Keywords***: Medicare Part D, Health Insurance, Common ownership, Risk Selection, Antitrust

***JEL Codes***: I11, I13, L13, L21, L41

# 1 Introduction

Institutional investors, such as BlackRock, Vanguard, and State Street, have been increasing their ownership across U.S. public firms. They doubled their share in the S&P 500 firms from 40% in the 1990s to 80% in the 2010s (Backus et al., 2021b). Their rise has fueled concern that firms may maximize shareholder value by softening competition between rivals in which these shareholders also hold stakes, as formalized by the common ownership hypothesis (Rotemberg (1984) and O'brien and Salop (1999)). Recent empirical studies have explored these forces in various industries (Azar et al., 2018; Park and Seo, 2019; Backus et al., 2021b), yet the evidence in healthcare remains limited. Filling this gap is imperative given that the U.S. spends about 18% of GDP on health care—well above other OECD countries (Anderson et al., 2019; Gunja et al., 2023)—and that spending has grown faster than in peer nations, reaching $4.5 trillion in 2022 (Hartman et al., 2024). Rising costs have heightened concerns about market power and pricing in the U.S. healthcare sector. This paper sheds light on this discussion by examining common ownership among major insurers (also called the plan sponsor) in the Medicare Part D market and quantifying its effects on insurer pricing and beneficiary enrollment.

We begin by documenting the prevalence and trends of common ownership within the Medicare Part D market. Using plan-level Landscape and Enrollment data from 2013 to 2020, sourced from the Centers for Medicare & Medicaid Services (CMS), we connect each insurer to its institutional owners using 13F filings from the Securities and Exchange Commission (SEC). The top 5 shareholders of each insurer are mostly large institutional investors such as Blackrock, Vanguard, State Street, Fidelity, and Capital Group. Specifically, in 2013 and 2017, Vanguard and BlackRock belonged to the top 5 owners of all top 5 insurers in the Medicare Part D market.

To quantify common ownership incentives, we construct a "profit weight", $\kappa_{fg}$, which reflects how much an insurer accounts for rivals' profits due to shared institutional ownership (Rotemberg, 1984; Bresnahan and Salop, 1986; O'brien and Salop, 1999; Backus et al., 2021b). Specifically, the measure implies insurer $f$ values \$1 of rival $g$'s profit as \$$\kappa_{fg}$ of its own when setting premiums. Since this weight varies within insurers across regions and years, we estimate reduced form regressions with insurer, market, and year fixed effects and find that plans offered by insurers with stronger common ownership incentives are associated with higher Prescription Drug Plan (PDP) premiums. This reduced-form evidence motivates a structural model that links common ownership to insurers' conduct and its welfare consequences.

A distinctive feature of Medicare Part D is that competition unfolds in a market shaped by risk selection. CMS pays each plan a prospective, risk adjusted "direct subsidy," calculated from beneficiaries' diagnoses and demographics in the previous year. Although year end risk corridor reconciliation claws back extreme gains or losses, plans still retain a share of the difference between the subsidy and realized drug expenditure, preserving incentives to attract lower risk beneficiaries. Insurers tailor plan characteristics, such as formulary design, tier structure, and deductibles, within regulatory limits ("standard benefit") to appeal to cost effective enrollees (Carey, 2017; Lavetti and Simon, 2018). Consistent with these risk selection incentives, studies found that higher risk beneficiaries (higher spending) gravitate toward more generous, high premium plans, while lower cost beneficiaries choose leaner, low premium options (Polyakova, 2016).

To integrate these features, we estimate a structural model of differentiated demand for stand-alone PDPs and premium setting supply. In particular, our supply side model allows insurers to internalize rivals' profits based on common ownership measured by profit weights, while considering the selection of low cost enrollees. Our model essentially assumes that insurers determine their plan characteristics that will attract low cost enrollees before competing in premiums in a Nash-Bertrand setting. Further. we assess insurer conduct using the non-nested Rivers-Vuong (RV) test, implemented following Duarte et al. (2023), and estimate the conduct parameter akin to Kennedy et al. (2017); Miller and Weinberg (2017). The non-nested test prefers common-ownership conduct over own-profit maximization, and the conduct parameter implies behavior as if they value rival profits when setting premiums. Both methods suggest that common ownership increases the market power of insurers in the Medicare Part D market.

We perform counterfactual experiments to quantify the implications of common ownership for premiums, welfare and enrollment in Medicare Part D. We show that removing common ownership reduces average PDP premiums by 20 percents and increases enrollment by 14.7 percentage points, enhancing allocative efficiency: consumer surplus rises by 16.4 percent, insurer surplus falls by 26.5 percent, and total surplus increases by 2.26 percent. Further, under no risk selection, the premium reductions from removing common ownership is even larger at 24 percents. The rise in total surplus by removing common ownership is greater when risk selection is absent. These differences suggest that risk selection constrains the internalization incentive of common ownership: when insurers maximize profit by selecting the low cost consumers, they lower their premiums. Market power effect of common ownership can have a weaker adverse effect on social surplus in selection markets (Mahoney and Weyl, 2017). The results underscore the interplay between common ownership and risk selection.

This paper contributes to three strands of literature in economics. The first is the Medicare Part D literature that links market structure to pricing and welfare. Structural analyses such as Lucarelli et al. (2012) and Miller and Yeo (2019) highlight how reduced plan differentiation or introduction of a public option can alter premiums and consumer surplus, while reduced-form evidence in Chorniy et al. (2020) and Hill and Wagner (2021) shows that horizontal mergers increase premiums. A common feature of the existing literature work is that insurers are assumed to price independently. To our knowledge, we provide the first evidence that common ownership shapes pricing and enrollment in Medicare Part D without consolidation. Our results reveal that the Medicare Part D market is less competitive than suggested by concentration measures such as the Herfindahl–Hirschman Index (HHI). We also find that, in addition to market concentration, the composition of insurers is another dimension of market structure that matters to insurer pricing. Specifically, the presence of nonprofit or private (not listed) insurers, which are insulated from index-fund ownership, provides a countervailing force against common owner-induced coordination in pricing.

The second is the recent literature on the competitive effects of common ownership. Prior studies focus on consumer goods and services such as airlines, banking, and cereal (Azar et al., 2018; Kennedy et al., 2017; Azar et al., 2022; Backus et al., 2021a), with few applications in healthcare (Liu and Yao, 2023; Newham et al., 2025). Since previous studies show mixed effects of common ownership on pricing (Azar et al., 2018; Backus et al., 2021a; Kennedy et al., 2017), thus it is not straightforward to infer the competitive effects of common ownership in an unexplored market. We add to this literature by extending the understanding of how common ownership affects competition in health insurance, a novel setting with policy and public health relevance. Further, since health insurance exhibits risk selection, we extend the existing structural analysis of common ownership by taking risk selection into account. We show how they interplay with each other, i.e. the cost-reducing incentive of risk selection constrains the upward pricing pressure from common ownership.

The third is the growing literature that examines the interaction of market power and selection (Starc, 2014; Mahoney and Weyl, 2017). That literature shows that selection can reduce markup in settings with imperfect competition because insurers want to select low cost consumers at the margin. Thus, risk selection reduces market power. We extend this literature to a setting of imperfect competition with price coordination. We show that risk selection reduces market power exerted by insurers owned by the same investors. When common ownership is prevalent in an insurance market, policies used to curb selection, such as risk adjustment, can constrain markup.

The remainder of the paper proceeds as follows. Section 2 reviews institutional details of Medicare Part D. Section 3 describes the data and measurement, including the construction of profit weights along with reduced-form evidence. Section 4 develops and estimates the structural model with conduct and cream skimming and reports the counterfactuals in Section 5.3. Section 6 concludes.

# 2 Background

## 2.1 Plan Types and Benefit Design

Medicare Part D was created by the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) and implemented in 2006. It provides prescription drug coverage to Medicare beneficiaries through private insurers that contract with the Centers for Medicare & Medicaid Services (CMS). Part D plans come in two forms. Stand-alone Prescription Drug Plans (PDPs) cover only prescription drugs and supplement traditional fee for service Medicare Parts A and B. Medicare Advantage prescription drug plans (MA-PDs) bundle Parts A, B, and D in a single managed care product.[1] In this paper, we restrict our analysis to the stand-alone PDP market. Accordingly, We treat MA-PDs and other sources of drug coverage, e.g. employer sponsored retiree plans or Veterans Affairs benefits, as outside options in beneficiaries' choice sets.

Although plan designs differ across insurers and over time, all PDPs must satisfy a minimum standard benefit defined by CMS. CMS specifies a four phase cost sharing structure that every plan must match or exceed, which are an annual deductible, an initial coverage phase, a coverage gap phase, and a catastrophic coverage phase. The deductible is the amount an enrollee must pay out-of-pocket (OOP) before the PDP begins to cover. After the deductible is met, the beneficiary typically pays 25% of drug spending as copayments or coinsurance during the initial coverage phase. When total drug spending reaches the coverage gap threshold, the beneficiary faces a larger share, i.e. more than 25%, of their OOP drug costs before reaching the catastrophic threshold, after which cost sharing falls to 5%.[2] In addition to this cost sharing schedule, each PDP must submit a formulary satisfying standards by CMS.[3] A plan that offers this standard level of coverage is referred to as a basic plan.

Beyond this minimum standard, insurers can offer enhanced PDPs that may provide a wider formula of covered drugs, lower deductibles, or additional protection in the coverage gap. Formularies are typically organized into tiers (for instance, preferred/non-preferred generics, preferred/non-preferred brands, and specialty drugs). Typically, the lower the tier, the lower the cost-sharing,

[1]Beneficiaries enrolled in MA plans without prescription drug coverage can also choose to enroll in a PDP.

[2]As of 2020, the coverage gap has been essentially closed, and beneficiaries pay 25% of the OOP drug costs. The complete closure of the coverage gap will be effective in 2025 as part of the Inflation Reduction Act (IRA).

[3]Part D formularies must provide an "adequate" coverage of drugs, which is evaluated after insurers submit their formularies. Specifically, Medicare Prescription Drug Benefit Manual states "Part D formularies must include drug categories and classes that cover disease states, consistent with Part D program requirements."

and the higher the tier, the higher the cost-sharing. Variation in the generosity of cost sharing and formulary design in basic and enhanced PDPs generates substantial heterogeneity in financial protection and out-of-pocket spending risk for beneficiaries.

## 2.2 Premiums and Subsidies

Under this benefit design, Part D plan revenue consists primarily of two sources: enrollee premiums and subsidies (payments) from CMS. PDP premiums are not set directly as posted prices by insurers. Instead, they are determined through an annual bidding process. For each PDP an insurer offers in a given market, the insurer submits a standardized bid equal to the premium it would charge to beneficiaries with average health risk.[4] The premium that enrollees actually pay is then calculated as the difference between the plan's bid and the national average bid, plus the base premium, which is again a fixed share of the national average bid.

In addition to premiums, PDPs receive several types of subsidies. The first is the risk adjustment payment, often called the direct subsidy. CMS pays the gap between a plan's risk-adjusted bid and the premium paid by the enrollee, where the risk is captured by the RxHCC score derived from the enrollee's diagnostic history and demographics. Although this system is intended to offset insurers' incentives for risk selection, the score is imperfect and does not fully remove incentives to attract more profitable enrollees, i.e. those whose drug spending is low relative to their risk score. In practice, the risk assessment model (RxHCC) can become outdated as technology and drug markets change, and the score does not capture how individuals adjust their drug use in response to changes in cost sharing (Carey, 2017; Einav et al., 2016).

The second type of the subsidy is the reinsurance payment for high cost enrollees. Under the standard Part D benefit, Medicare subsidizes 80% of drug spending for those who enter the catastrophic phase, while enrollees pay 5% and plans pay the rest. Similar to the risk adjustment payment, Reinsurance payments are also paid prospectively with reconciliation after the year, so

[4] In the Part D risk-adjustment system described below, average health risk corresponds to an enrollee with a risk score normalized to one.

they act as a cost based subsidy targeted to the highest cost enrollees and complement the risk adjustment. From 2007 to 2017, among non-LIS beneficiaries, the share of a plan's liability paid by Medicare reinsurance increased from 5% to 23%, while the share paid by insurer fell from 53% to 29%. Among LIS beneficiaries, the reinsurance share rose from 21% to 40% over this period, indicating it became an increasingly large component of total Part D spending (Medicare Payment Advisory Commission, 2020).

The third type of the subsidy is the low income subsidy (LIS), which provides additional support with premiums and cost sharing for enrollees with low income. For LIS enrollees, Medicare pays the basic plan premium up to a regional benchmark amount and reimburses most of the enrollee's cost sharing. Decarolis (2015) and Miller (2015) find that insurers with a large share of LIS enrollees tend to set their basic premiums close to the maximum subsidy that Medicare will pay on behalf of these enrollees, suggesting that plans strategically respond to the LIS payment to maximize their profit and hints that the risk score for LIS enrollees may be overestimated (Carey, 2017).

# 3 Data and Descriptive Evidence

We construct our dataset at the plan by market level for the period 2013-2020 using three primary data sources. CMS monthly enrollment reports by plan, PDP penetration reports, and annual landscape files provide plan characteristics, plan level enrollment, and the number of Part D eligible beneficiaries. For each year, we use the December enrollment files, which reflect the beneficiaries' plan choices after the annual open enrollment period (October 15 to December 7).[5] To identify the shareholdings of each institutional investor, we scrape 13F-HR filings from the SEC database (EDGAR) and parse them following Backus et al. (2021b). Finally, we obtain the number of outstanding shares for each insurer from the Center for Research in Securities Prices (CRSP) through the Wharton Research Data Services (WRDS).

[5]We exclude employer-sponsored or group plans, often called 800-series plans, as they are not accessible to regular Part D enrollees and their plan characteristics are not reported in the landscape files.

We define a market as a PDP region–year, resulting in 272 markets (34 regions over 8 years). A PDP region is a geographic service area defined by CMS for Part D plans, typically consisting of one or more states.[6] As beneficiaries can only enroll in plans within their own region, plans compete solely for enrollees in their PDP region, giving us a natural geographic market for analysis.

## 3.1 Plan Characteristics and Premiums

Table 1 reports summary statistics for our sample. Panel A presents the market-level statistics. On average across markets, there are about 1.7 million Part D eligible beneficiaries and 0.6 million PDP enrollees in a market, so roughly one third of Part D eligible consumers enroll in PDPs. The average market in our sample offers 26 plans from 10 insurers. For comparison, between 2007 and 2010, 49 plans were offered from 16 insurers on average (Decarolis et al., 2020). The PDP market during our sample period become more concentrated and offers fewer options, which increases the scope for common ownership to influence the part D market.

Panel B reports the plan-level statistics. The average market share is 1.34% with 219 enrollees, where the market share is defined as the number of enrollees in the plan divided by the number of Medicare eligible beneficiaries in the market. The annual premium is approximately $614 on average, with large spread from $125 to $2,365, and the average deductible is $221. Following Decarolis et al. (2020), we construct a measure of plan vintage to capture consumer inertia, defined as the number of years that a PDP has been offered in a market. On average, plans in our sample have been offered in the same market for about 9 years. Plan quality is measured by the CMS star ratings on a 0 to 5 scale, and has an average rating of 3.07.

Around 54% of the plans in our sample are enhanced plans that provide supplemental benefits above the CMS standard. In addition, 26% of plans offer extra coverage in the coverage gap and 28% include at least one tier of drugs without a deductible. We also use the indicator to flag plans with premiums below the regional benchmark that are subject to random assignment of LIS enrollees.

[6]We exclude 5 territories from 39 PDP regions, which leaves 34 PDP regions. Details on the PDP regions are provided in Appendix A.

Table 1: Summary Statistics

| | Mean | Std. Deviation | Min | Max | N |
|---|---|---|---|---|---|
| | *Panel A. Market level* | | | | |
| Market eligibles (in millions) | 1.67 | 1.27 | .076 | 6.46 | 272 |
| Market enrollments (in millions) | 0.57 | 0.40 | .019 | 2.06 | 272 |
| Market PDP rate (in %) | 34.7 | 8.20 | 8.04 | 53.7 | 272 |
| No. of PDP plans | 25.9 | 4.07 | 16 | 36 | 272 |
| No. of insurers | 10.1 | 2.18 | 6 | 16 | 272 |
| | *Panel B. Plan level* | | | | |
| Enrollments (in 100) | 219 | 401 | 0.13 | 5132 | 7040 |
| Shares (in %) | 1.34 | 1.94 | 0.002 | 18.9 | 7040 |
| Premiums (in $) | 614 | 365 | 125 | 2365 | 7040 |
| Deductible | 221 | 180 | 0 | 435 | 7040 |
| Vintage | 9.31 | 3.62 | 0 | 14 | 7040 |
| Star Rating | 3.07 | 0.96 | 0 | 5 | 7040 |
| Enhanced plan | 0.54 | 0.50 | 0 | 1 | 7040 |
| Include No Deductible Tiers | 0.28 | 0.45 | 0 | 1 | 7040 |
| Extra Coverage in the Gap | 0.26 | 0.44 | 0 | 1 | 7040 |
| Below Benchmark | 0.28 | 0.45 | 0 | 1 | 7040 |
| National PDP | 0.78 | 0.41 | 0 | 1 | 7040 |
| Bids (in $) | 981 | 405 | 332 | 2640 | 7040 |
| LIS (in $) | 556 | 528 | 0 | 2573 | 7040 |
| Reinsurance (in $) | 950 | 576 | 43 | 6969 | 7040 |

*Note:* Panel A shows the summary statistics at market level (CMS region×Years) and Panel B shows the plan level summary statistics. Premiums on both panel A and B are in annual premiums. *Source:* CMS Part D Landscape and monthly enrollments files.

27% of the plans in our sample meet this condition. Lastly, 78% of plans are offered nationally in all 34 PDP regions.[7]

For PDP bids and payments, the average plan bid is $981. Premiums from enrollees cover roughly 63% of the bid for an average risk enrollee, and the remaining $367 is funded by the risk adjustment payment from CMS. Plans also receive substantial subsidies through the LIS and

[7]Although the plan formularies may be identical across regions for a given national plan, premiums are determined on a regional basis. Firms submit separate bids in each CMS region, and plan identifiers are region-specific.

reinsurance payments. On average, a plan receives $556 per enrollee in LIS payments and $950 per enrollee in reinsurance, amounts that are comparable in size to the premium and the bid. These programs, therefore, account for a large share of total PDP revenue. Reinsurance payments, in particular, vary widely between plans. Since reinsurance payments increase with the share of enrollees who reach the catastrophic phase, this dispersion is informative about differences in enrollees' risk across plans. In the supply model, we use this variation in reinsurance as a summary measure of a plan's risk selection.

## 3.2 Ownership

Table 2 lists the five largest PDP insurers in each year by the number of enrollees and reports their share of the total PDP enrollment. A small number of insurers account for most of the PDP enrollment in every year of our sample. Those are Aetna, Cigna, CVS, Humana, UnitedHealth, WellCare, and, starting in 2020, Centene through its acquisition of WellCare. They cover 81% of all PDP enrollment in 2013, increasing to 90% in 2018 and 2019 before slightly falling to 87% in 2020. All of these firms are publicly traded, and their equity is widely held by institutional investors. Thus, any effect of common ownership on how these insurers set premiums is likely to matter for a large majority of Part D beneficiaries.

From the 13F filings and the CRSP data on outstanding shares, we construct the investor by insurer ownership shares. Positions in preferred stock and other derivatives, such as options or convertible bonds, are excluded. To account for ownership through subsidiaries of institutional investors, we consolidate subsidiary filings into the parent CIK[8]

Table 3 shows the five largest institutional investors in insurers in Table 2 for 2013, 2017, and 2020. Ownership of these insurers is concentrated in a few large investors. BlackRock, Vanguard, State Street, Fidelity, and Capital Group repeatedly appear as the top shareholders across the insurers and years. For example, BlackRock and Vanguard are two of the largest shareholders for all of the insurers above for all years, and Capital Group is a major owner of several of these firms, including

[8]The CIK number is a unique identifier used by the SEC to identify corporations, funds, and individuals.

Table 2: Top 5 Insurers' Share of PDP Enrollment, 2013–2020

| 2013 | | 2014 | | 2015 | | 2016 | |
|---|---|---|---|---|---|---|---|
| UnitedHealth | 31.9% | UnitedHealth | 26.6% | UnitedHealth | 25.1% | Humana | 24.9% |
| Humana | 21.4% | Humana | 20.6% | Humana | 22.8% | UnitedHealth | 24.6% |
| Aetna | 14.3% | CVS | 15.9% | CVS | 17.8% | CVS | 22.7% |
| Cigna | 7.8% | Aetna | 8.1% | Cigna | 7.5% | Aetna | 10.2% |
| Wellcare | 5.4% | Wellcare | 7.5% | Aetna | 7.2% | Wellcare | 5.2% |
| Total | 80.8% | Total | 78.7% | Total | 80.5% | Total | 87.7% |

| 2017 | | 2018 | | 2019 | | 2020 | |
|---|---|---|---|---|---|---|---|
| Humana | 25.9% | CVS | 23.3% | CVS | 22.6% | Centene | 22.0% |
| UnitedHealth | 23.7% | Humana | 23.2% | Humana | 20.2% | CVS | 20.0% |
| CVS | 22.7% | UnitedHealth | 21.5% | UnitedHealth | 20.2% | UnitedHealth | 18.9% |
| Aetna | 9.8% | Wellcare | 15.4% | Wellcare | 19.9% | Humana | 18.3% |
| Wellcare | 5.8% | Cigna | 7.1% | Cigna | 7.2% | Cigna | 7.6% |
| Total | 87.8% | Total | 90.5% | Total | 90.1% | Total | 86.7% |

*Note:* This table reports, for each year, the five largest insurers in stand-alone prescription drug plan (PDP) enrollment and their share out of total PDP enrollment. Entries in the second column of each subtable are percentages of total national PDP enrollment in that year. The row 'Total' gives the combined share of these five insurers. Enrollment in 800-series plans is excluded. *Source:* Authors' calculations from CMS Medicare Part D enrollment data.

Humana and UnitedHealth. The ownership of these investors also increased over time. In 2013, their typical blocks are about 5 to 7% of the outstanding shares. By 2017 and 2020, stakes of 7% to 9% are common. This increasing overlapping ownership motivates our focus on the profit weights that we introduce in the next subsection.

## 3.3 Measuring Common Ownership

We measure common ownership through a profit weight that links investors' portfolios to firms' pricing incentives. The central idea is that managers maximize their investors' payoffs, and investors who hold shares in several competing firms care about the value of their overall portfolio rather than the profits of any single firm. A series of studies (Rotemberg, 1984; Bresnahan and Salop, 1986; O'brien and Salop, 1999) develops this idea formally and provides the theoretical foundation

Table 3: Top 5 Owners of Major Insurers, 2013-2020

**Aetna**

| 2013 | | 2017 | | 2020 |
|---|---|---|---|---|
| Capital Group | 6.81% | Capital Group | 7.45% | Acquired by WellCare in 2018 |
| Blackrock | 6.73% | Blackrock | 7.40% | |
| State Street | 6.24% | Vanguard | 6.85% | |
| Wellington Management | 5.10% | State Street | 6.08% | |
| Vanguard | 4.70% | Price T Rowe Associates | 5.06% | |

**Wellcare**

| 2013 | | 2017 | | 2020 |
|---|---|---|---|---|
| Blackrock | 8.57% | Vanguard | 10.00% | Acquired by Centene in 2020 |
| Wellington Management | 8.22% | Blackrock | 9.60% | |
| Price T Rowe Associates | 7.01% | Capital Group | 7.93% | |
| Vanguard | 5.72% | Price T Rowe Associates | 4.58% | |
| State Street | 3.59% | Wellington Management | 4.48% | |

**Cigna**

| 2013 | | 2017 | | 2020 | |
|---|---|---|---|---|---|
| Blackrock | 5.57% | Price T Rowe Associates | 7.20% | Price T Rowe Associates | 8.27% |
| Vanguard | 4.87% | Vanguard | 7.01% | Blackrock | 7.74% |
| State Street | 4.48% | Blackrock | 6.96% | Vanguard | 7.70% |
| Franklin Resources | 4.24% | Dodge Cox | 4.35% | FMR | 5.41% |
| Artisan Partners Limited | 4.16% | State Street | 4.22% | Capital Group | 5.34% |

**CVS**

| 2013 | | 2017 | | 2020 | |
|---|---|---|---|---|---|
| Blackrock | 5.79% | Vanguard | 7.76% | Vanguard | 8.05% |
| Vanguard | 4.75% | Blackrock | 6.61% | Blackrock | 7.07% |
| FMR | 4.60% | State Street | 4.24% | State Street | 4.16% |
| State Street | 4.39% | FMR | 3.39% | Capital Group | 3.99% |
| Wellington Management | 4.19% | Wellington Management | 2.23% | FMR | 2.02% |

**Humana**

| 2013 | | 2017 | | 2020 | |
|---|---|---|---|---|---|
| Capital Group | 14.08% | Capital Group | 11.34% | Blackrock | 9.04% |
| Blackrock | 6.71% | Blackrock | 8.39% | Capital Group | 8.66% |
| JPmorgan Chase | 6.14% | Vanguard | 6.89% | Vanguard | 7.68% |
| Vanguard | 4.71% | FMR | 6.44% | Price T Rowe Associates | 7.55% |
| Wellington Management | 4.36% | Price T Rowe Associates | 4.60% | FMR | 7.00% |

**Unitedhealth**

| 2013 | | 2017 | | 2020 | |
|---|---|---|---|---|---|
| Capital Group | 7.47% | Capital Group | 7.15% | Vanguard | 8.34% |
| Blackrock | 5.70% | Blackrock | 7.07% | Capital Group | 7.90% |
| FMR | 5.09% | Vanguard | 6.89% | Blackrock | 7.55% |
| Wellington Management | 4.95% | FMR | 5.87% | FMR | 5.54% |
| State Street | 4.71% | State Street | 4.70% | State Street | 4.66% |

*Note:* This table documents the top 5 investors of the firms reported in the table 2. *Source:* Authors' computation using scrapped 13F fillings from SEC Edgar.

for the profit weight. We follow the standard assumptions in this literature. First, each shareholder's payoff is a weighted average of the firms' profits in her portfolio. Second, managers maximize a weighted average of shareholder payoffs. Third, the weight on a shareholder is proportional to her shareholdings. Under these assumptions, firm $f$ behaves as if it maximizes an objective function that combines its own profit with the profits of its rivals. In a market with firm $f$ and its rivals $g$, this objective can be written as:

$$Q_f = \pi_f + \sum_g \kappa_{fg}\pi_g,$$

where $\pi_f$ denotes the profit of firm $f$ in a given market and $\kappa_{fg}$ is the profit weight that summarizes how much firm $f$ internalizes the profit of rival $g$. Then, the profit weight between firm $f$ and $g$, $\kappa_{fg}$, is calculated from $\beta_{fs}$ and $\beta_{gs}$, which are the shareholdings of the owner $s$ in firm $f$ and $g$ as:

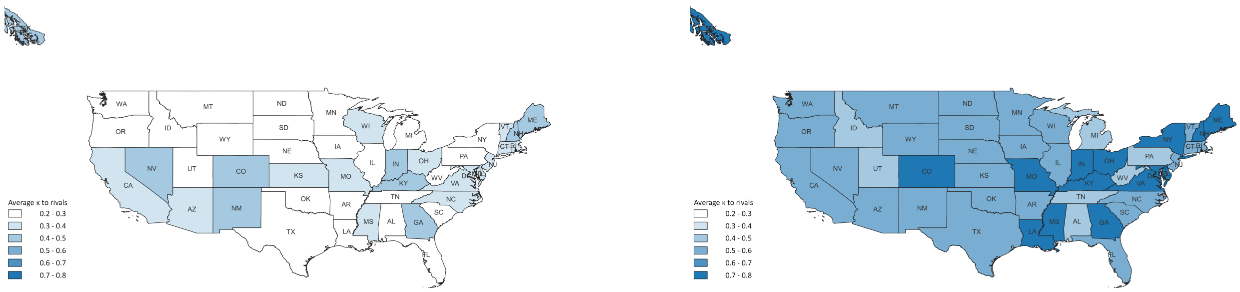
$$\kappa_{fg} = \frac{\sum_{\forall s} \beta_{fs} \cdot \beta_{gs}}{\sum_{\forall s} \beta_{fs}^2},$$

The numerator is large when investors who are important owners of firm $f$ also hold sizeable stakes in firm $g$. The denominator normalizes this term by the overall concentration of ownership.

Two extreme examples make the interpretation of this weight clear. If no shareholder holds both firms in common, then $\beta_{fs} \cdot \beta_{gs} = 0$ for every $s$ and $\kappa_{fg} = 0$. The firm $f$ then behaves as if it only maximizes its own profit. On the other end, if two insurers merge and become a single firm so that $\beta_{fs} = \beta_{gs}$ for all investors $s$, then $\kappa_{fg} = 1$. In that case, the manager of the merged firm cares about each dollar of profit at $g$ exactly as much as at $f$, as in a standard merger analysis.[9] Thus, $\kappa_{fg} \in (0, 1)$ is analogous to a partial merger induced by overlapping institutional owners.

Figure 1 depicts the average profit weights to rival $\kappa$ by each CMS region in 2013 and 2017. The average of the profit weight to rival increases from 2013 to 2017 in most of the CMS regions. Specifically, the rises in Louisiana and New York are relatively larger than the others. We further present the trends of $\kappa$ in each CMS region across years in Figure 2. It illustrates that, for most CMS regions, $\kappa$ increases until 2017 and then starts to decline until the end of our sample period.

[9] In some cases $\kappa_{fg}$ can exceed one. This is interpreted as tunneling. See Backus et al. (2021b) for details.




(a) Average $\kappa$ to rivals in 2013

(b) Average $\kappa$ to rivals in 2017

Figure 1: Changes in profit weights to rivals across U.S.

*Note :* This figure depicts changes in average profit weight to rival, $\kappa_{ij,i\neq j}$, from 2013 to 2017. *Source :* Authors' computation

These figures show that there are variations in $\kappa$ across CMS regions and over time, which is useful for identifying the effects of common ownership on market outcomes.

## 3.4 Reduced-Form Analysis

We begin our analysis by establishing the reduced-form relationship between common ownership incentives and market outcomes, i.e. focusing on the PDP premium and market shares. Building upon the insights provided by O'Brien (2017), we consider the following relationships:

$$\ln p_{jmt} = \lambda C_{fm} + x_{jmt}\theta + \alpha_t + \nu_m + \xi_f + \epsilon_{jmt},$$

$$\ln s_{jmt} = \lambda C_{fm} + x_{jmt}\theta + \alpha_t + \nu_m + \xi_f + \epsilon_{jmt}.$$

For plan $j$ offered by insurer $f$, we use $C_{fm} = \sum_{g\in G_m} \kappa_{fg} \cdot \kappa_{gf}$ of insurer $f$ to measure common ownership incentive. It is the sum of products of weights that insurer $f$ assigns to its rivals $g$ in market $m$ and the weight that the rivals assign to $f$. Since Backus et al. (2021b) show the profit

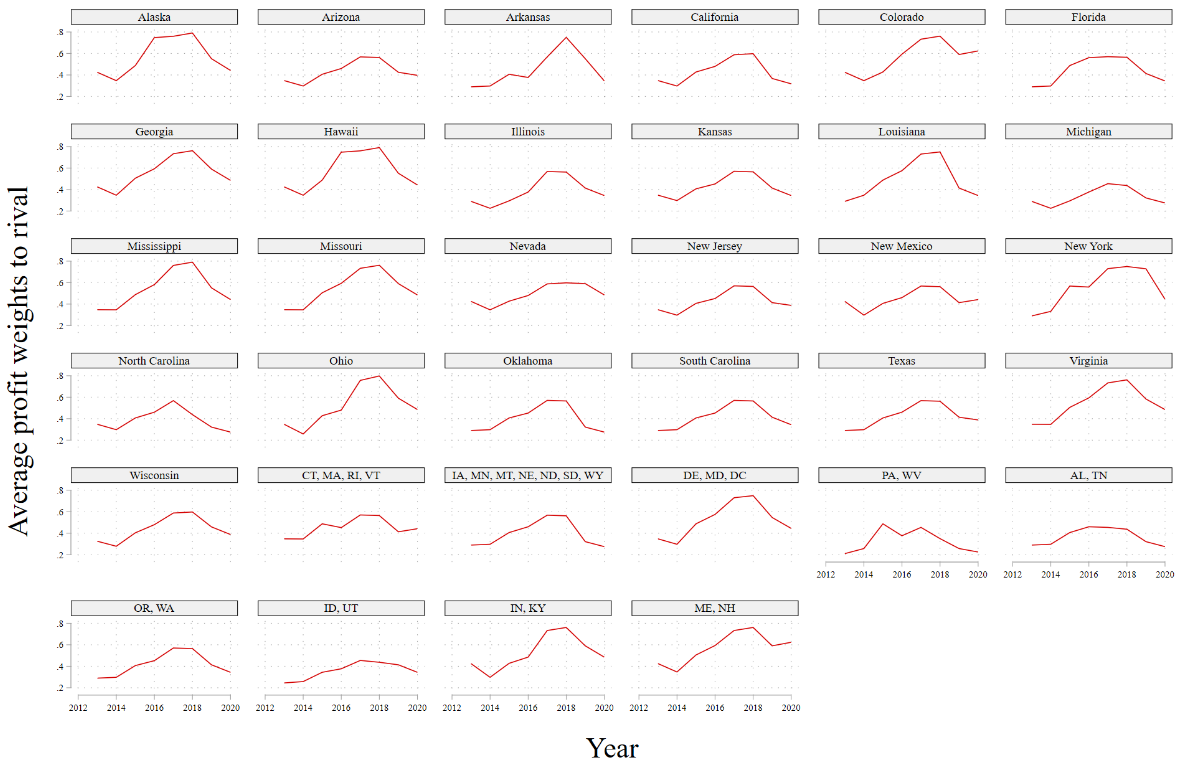



Figure 2: Average $\kappa$ to rivals over time by markets

*Note :* This figure presents a trend of average profit weight to rival, $\kappa_{ij,i\neq j}$, across years by CMS region. *Source :* Authors' computation

weight can be decomposed into two parts:

$$\kappa_{fg} = \underbrace{cos(\beta_f, \beta_g)}_{\text{overlapping ownership}} \cdot \underbrace{\sqrt{\frac{IHHI_g}{IHHI_f}}}_{\text{relative IHHI}},$$

where $cos(\beta_f, \beta_g)$ is a cosine similarity measure of investors in insurer $f$ and $g$, and $IHHI_f$ is a concentration measure of investors in insurer $f$, the measure $C_{fm}$ can be interpreted as the degree of similarity in investors between insurers (sum of squared cosine measures). We expect the coefficient of $C_{fm}$ to be positive and negative if common ownership incentives influence the PDP premium and market share, respectively.

Table 4 reports the regression results. In Columns (1), (2), and (3), we present the coefficients of

Table 4: Reduced-Form Regression Results

| VARIABLES | (1) log(Premium) | (2) log(Premium) | (3) log(Bid) | (4) log(Bid) | (5) log(Share) | (6) log(Share) |
|---|---|---|---|---|---|---|
| Common Ownership | | | | | | |
| $C_{fm}$ | 0.150 | | 0.083 | | -0.100 | |
| | (0.013) | | (0.008) | | (0.025) | |
| $\bar{C}_{fm}$ | | 0.727 | | 0.173 | | 0.136 |
| | | (0.086) | | (0.059) | | (0.256) |
| Control Variables | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Region FE | Y | Y | Y | Y | Y | Y |
| Parent group FE | Y | Y | Y | Y | Y | Y |
| Observations | 7,045 | 7,045 | 7,045 | 7,045 | 7,045 | 7,045 |
| R-squared | 0.658 | 0.654 | 0.738 | 0.735 | 0.700 | 0.700 |

*Note:* This table reports estimates from the baseline regression. Full results including control variables are shown in Table 10 in the appendix. Standard errors are clustered at the CMS region level and shown in parenthesis.

$C_{fm}$ for the log of the plan's premium, bid, and market share as dependent variables, respectively. In accordance with theoretical predictions, our findings indicate that common ownership incentives exert upward pressure on a plan's premium and bid. Specifically, our results suggest that if listed insurers in a market were solely owned by one investor, in contrast to the scenario where there are no common owners, the insurers would bid approximately 8% higher. Importantly, our results suggest that common ownership incentives exert a more positive impact on premium consumers pay than bid by the insurers. Consistently, we observe that the market share of a PDP decreases in response to an increase in the premium when its offering insurer has a higher common ownership incentive.

# 4 Model

In this section, we develop a structural model to examine how common ownership affects premiums and in turn influences enrollment decisions for PDPs and social welfare. We model beneficiaries' demand for PDPs following the framework of Berry (1994) and Berry et al. (1995)

and specify a supply side model that recovers insurer marginal costs and embeds common ownership and risk selection.

## 4.1 Demand

Each year $t$, consumer $i$ in CMS region $m$ chooses between enrolling in PDP $j$ among the set of available plans $J_{mt}$ or choosing the outside option $j = 0$. The outside option includes not enrolling in any plan or enrolling in a non-PDP plan, for example, a MA-PD, an employer-sponsored plan, or veteran drug coverage. The indirect utility of consumer $i$ is written as:

$$u_{ijmt} = x_{jmt}\beta_i - \alpha_i p_{jmt} + \xi_{jmt} + \varepsilon_{ijmt} \tag{1}$$

where $x_{jmt}$ is a vector of observable plan characteristics including annual deductible, vintage, star ratings, an indicator for whether the PDP is enhanced, an indicator for whether the PDP has a tier exempts from the deductible, an indicator for whether the PDP has extra gap coverage, an indicator for whether the PDP is below benchmark (i.e. subject to the Low-Income Subsidy assignment) and an indicator for whether the PDP is offered nationwide. $p_{jmt}$ is PDP $j$'s premium. Year, CMS region and insurer fixed effects (FEs) are also included. $\xi_{jmt}$ is the unobserved characteristics of plan $j$. Lastly, $\epsilon_{ijmt}$ is an individual $i$'s preference shock for each plan. We assume that $\epsilon_{ijmt}$ is iid with a Type 1 extreme value distribution.

In a spirit of Decarolis et al. (2020), we allow the coefficient of premium, $\alpha_i$, and the indicator for extra gap coverage, $\beta_i$, to be random. Specifically, we assume that $\alpha_i$ follows log-normal distribution such that:

$$\ln \alpha_i = \alpha + \sigma_\alpha v_i,$$

while defining $\beta_i$ follows the normal distribution. We approximate the integral over the random coefficients using a Gauss Hermite product rule when computing model implied choice probabilities and elasticities, following Conlon and Gortmaker (2020).

## 4.2 Supply

Insurers receive revenue from two sources. First, it is the direct subsidy from CMS, which is computed by each PDP's bid adjusted for risk factors of enrollees less the premium, $r_j b_j - p_j$, where $r_j$ is the PDP's average enrollee risk score and $b_j$ is the bid. Second, it is the combination of reinsurance subsidies, risk corridor payments and low-income subsidies (LIS).[10] We decompose reinsurance, $RI_j$, into an "expected" component driven by observed risk scores and a residual capturing selection beyond the risk score:

$$RI_j = \widehat{RI}_j + a_j,$$

where $\widehat{RI}_j = \gamma_0 + \gamma_1 r_j$.[11] A negative residual, $a_j < 0$, signals that a plan's enrollees incur lower costs than predicted by their risk scores—implying risk selection by the PDP. Since CMS does not disclose plan-level risk-corridor reconciliations and corridor shares simply scale gains and losses, we exclude them but doing so leaves marginal incentives, hence our estimates, unaffected. Further, we treat the LIS as an exogenous transfer.

Bringing all payments together, insurer $f$'s profit in each market is

$$\pi_f = \sum_{j \in J_f} \Big( p_j + \underbrace{(r_j b_j - p_j)}_{\text{Direct subsidy}} + \underbrace{\widehat{RI}_j + LIS_j}_{\text{Other subsidies}} - r_j mc_j + \psi\, a_j \Big)\, s_j(b_j, X_j, \xi_j)\, M, \tag{2}$$

where $M$ is market size. Marginal cost per enrollee $mc_j$ depends on a vector of observed cost shifters, $W$, and unobserved cost shock, $\omega_j$. Risk selection—PDPs' efforts to attract beneficiaries whose costs fall below what the risk-adjustment formula predicts—has been documented repeatedly in Medicare Part D (Einav et al., 2016; Lavetti and Simon, 2018). We incorporate it into the supply model by using the residual $a_j$, specifically $\psi < 0$ measures the marginal revenue gain from this

[10] Medicare Payment Advisory Commission. 2015. Sharing Risk in Medicare Part D. Report to the Congress, June. Washington, DC: Medicare Payment Advisory Commission.

[11] Flexible functional form for $\widehat{RI}_j(r_j)$ yield qualitatively identical result (see Appendix).

risk selection on average by reducing expected cost.

Given eq. (2), insurer $f$ chooses $\{b_j\}_{j\in J_f}$ to maximize

$$Q_f = \sum_{j\in J_f} \left( r_j b_j + \widehat{RI}_j + LIS_j - r_j mc_j + \psi a_j \right) s_j M + \sum_g \kappa_{fg}\, \pi_g(r_g, b_g, c_g), \tag{3}$$

where $\kappa_{fg}$ measures the degree to which insurer $f$ internalizes rival $g$'s profits (e.g. $\kappa_{fg} = 0$ corresponds to Nash–Bertrand competition; $\kappa_{fg} = 1$ to collusion).

Premiums are then set mechanically as the difference between each plan's bid and the CMS base premium, which equals $\zeta$ times the enrollee-weighted average bid $\bar{b}$ across all PDPs and MA–PDs in the year (Medicare Payment Advisory Commission, 2022):

$$p_j = \max\{0,\ b_j - (1-\zeta)\bar{b}\}. \tag{4}$$

We recover $\zeta$ from observed base premium and average bid each year and assume each insurer takes $\bar{b}$ as given. Taking first-order conditions with respect to $b_j$ for each $j \in J_f$ and stacking across PDPs yields the supply-side equation:

$$\begin{aligned} mc_j &= b_j + r_j^{-1} \left[ \left(\boldsymbol{\Omega}_t(\kappa) \circ \boldsymbol{\Delta}\right)^{-1} (\mathbf{r} \circ \mathbf{s}) + (\widehat{RI}_j + LIS_j + \psi a_j) \right]_j \\ &= f(W_j) + \omega_j, \end{aligned} \tag{5}$$

where $\boldsymbol{\Omega}_t(\kappa)$ is the $J \times J$ ownership matrix in market $t$, such that

$$\Omega_t = \begin{cases} 1 & \text{if } (j,k) \in J_f \text{ for any } f, \\ \kappa_{fg} & \text{if } j \in J_f,\ k \in J_g \text{ for any } (f,g), \\ 0 & \text{otherwise.} \end{cases}$$

$\boldsymbol{\Delta}$ is the Jacobian of market shares with respect to premiums, $\circ$ denotes the Hadamard (element-wise) product, and $s$ and $r$ are the vectors of shares and risk scores in the market.

The first-order conditions suggest that common ownership raises bids because of its positive impact on the markup term. In addition, PDPs with low-cost enrollees $a_j < 0$ enjoy higher profit that reduces the upward pressure on bids. Interestingly, there is a potential interplay between common ownership and risk selection because when PDPs that have low-cost enrollees will bring down the bids of all PDPs belonging to the common owner.

## 4.3 Instruments

Endogeneity arises on both sides of the model. On the demand side, premiums are correlated with unobserved product characteristics, such as formulary details. We instrument premiums using the differentiation instruments of Gandhi and Houde (2019) and treat plan characteristics as exogenous, consistent with evidence that these features are stable to bid changes (Polyakova, 2016; Decarolis et al., 2020). The instruments, denoted *diff*, measure the distance between a PDP and its rivals in plan characteristic space, capturing the "closeness of competition." As they correlate with price but not with the unobserved characteristics, they provide valid exclusion restrictions. We employ a quadratic specification:

$$z_{jm}^{\text{Diff}} = \left\{ x_{jm}, \sum_k \left( d_{jkm}^x \right)^2, \sum_k \left( d_{jkm}^{\hat{p}} \right)^2, \sum_k d_{jkm}^{\hat{p}} \times d_{jkm}^x \right\},$$

where $d_{jkm}^x$ and $d_{jkm}^{\hat{p}}$ denote the distances in characteristics and predicted premiums within market $m$, respectively. We obtain $\hat{p}$ from a random-forest regression of observed premiums on exogenous characteristics and their differentiation measures, following Backus et al. (2021a). We also add standard BLP-type product count instruments (*Nprod*) measuring the number of PDPs offered by the insurer, its competitors, and the number of nonprofit insurers in the market.

On the supply side, markups are endogenous because unobserved costs affect bids and hence premiums, which in turn enter the markup equation through their influence on demand derivatives and market shares. Rearranging Equation (5) makes the source of endogeneity transparent:

$$r_j b_j = r_j f(W_j) - \left(\widehat{RI}_j + LIS_j + \psi a_j\right) - \eta_{jt}(\kappa) + r_j \omega_j,$$

where $\eta_{jt}(\kappa)$ is risk-adjusted markup:

$$\eta_{jt}(\kappa) \equiv \left[\left(\Omega_t(\kappa) \circ \Delta_t\right)^{-1}\left((\mathbf{r_t} \circ \mathbf{s_t})\right)\right]_j,$$

Because $\Delta_t$ and $s_t$ in $\eta_{jt}(\kappa)$ depend on premiums (hence bids), any unobserved cost shock $\omega_j$ implicitly feeds back into $\eta_{jt}(\kappa)$, making $\mathbb{E}[\eta_{jt}(\kappa)\,\omega_j] \neq 0$. Valid instruments must therefore explain $\eta_{jt}(\kappa)$ while remaining orthogonal to $\omega_j$.

We treat $a_{jt}$ as predetermined relative to $\omega_{jt}$ based on timing. Plan characteristics that induce $a_{jt}$ are fixed before bids are submitted, whereas cost shocks realize afterward. Consequently, these characteristics are also exogenous in demand. Conditional on $W_{jt}$ and fixed effects, we construct three sets of instruments. First and second instruments are *diff* and *Nprod* as BLP-type instruments are valid sets of exclusion restriction (Backus et al., 2021a). Third instrument is a set of indicators for PDPs tied to major mergers: (i) an indicator for PDPs provided by WellCare in 2018–2019 after acquiring Aetna's Part D business, and (ii) an indicator for PDPs provided by Cigna from 2018 after acquiring Express Scripts. In both cases, networks and operational integration occurred only after 2020, implying these indicators shift $\Omega_t(\kappa)$ and hence markups during the transition period without contemporaneous cost changes.[12]

Table 5: Demand Estimates

| VARIABLES | (1)<br>Logit (2SLS) | (2)<br>BLP<br>2013 – 2019 | (3)<br><br>2013 – 2020 |
|---|---|---|---|
| Premium | | | |
| Mean | −2.013 | 1.629 | 1.706 |
| | (.061) | (.304) | (.243) |
| Std. deviation | | .959 | 1.048 |
| | | (.103) | (.082) |
| Std. deviation, inside | | .500 | .900 |
| | | (2.897) | (1.521) |
| Extra coverage | | | |
| Mean | −.049 | .027 | −.329 |
| | (.041) | (.200) | (.203) |
| Std. deviation | | .076 | .916 |
| | | (3.189) | (.287) |
| Deductible | −2.895 | −3.399 | −3.526 |
| | (.128) | (.090) | (.089) |
| Vintage | .273 | .278 | .268 |
| | (.012) | (.007) | (.007) |
| Star rating | .090 | .103 | .088 |
| | (.028) | (.015) | (.014) |
| Type (Enhanced) | −.006 | −.192 | −.191 |
| | (.040) | (.033) | (.034) |
| No Deductible Tier | .381 | .281 | .315 |
| | (.031) | (.025) | (.024) |
| Below benchmark | 1.509 | 1.302 | 1.281 |
| | (.031) | (.037) | (.036) |
| National PDP | .126 | .115 | .176 |
| | (.063) | (.034) | (.038) |
| Observations | 7040 | 6092 | 7040 |
| Year FEs | Y | Y | Y |
| CMS Region FEs | Y | Y | Y |
| Parent Group FEs | Y | Y | Y |
| Median Own Elasticity | −0.962 | −1.463 | −1.462 |
| Median Agg. Elasticity | −.598 | −.719 | −.664 |
| Median Outside diversion | .673 | .523 | .480 |

*Note:* This table reports the demand estimates of eq. (1). Numbers in parentheses are the standard errors.

# 5 Results

## 5.1 Parameter Estimates

Table 5 presents demand estimates across different model specifications. Column (1) reports results from a non-random coefficients model estimated via 2SLS, while Columns (2) and (3) show estimates from random coefficients models. Column (2) excludes data from 2020 to assess the sensitivity of estimates to the COVID-19 period. As estimates remain largely unchanged, we adopt the full-sample estimates in Column (3) as our baseline.

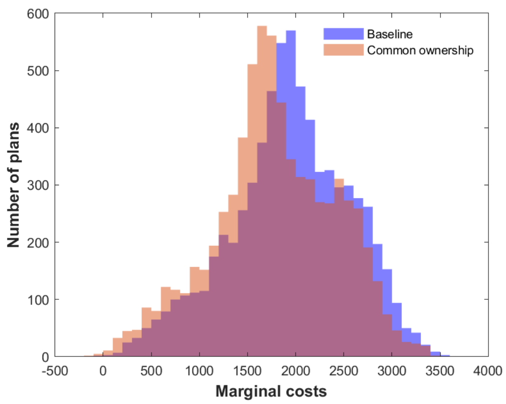
Under the baseline specification, the mean premium coefficient is 1.71, with a random coefficient of 1.05, indicating substantial heterogeneity in price sensitivity. The median own-price elasticity is -1.46, and the median aggregate elasticity is -0.66, implying that a 1% uniform increase in premiums would lower total PDP enrollment in a market by 0.66%. This aggregate elasticity suggests that there is a limited substitution towards the outside options. Relative to Decarolis et al. (2020), who report mean price coefficients of 2.46–3.25 with limited heterogeneity for 2007–2010, our estimates find a lower average price sensitivity but a greater heterogeneity across consumers in 2013 to 2020.

Consumers also do not prefer higher deductibles. Specifically, the implied willingness to pay for a one-dollar reduction in deductible is \$0.64 ($-3.53/5.53$), close to the \$0.68 found in Decarolis et al. (2020). Given an average deductible of \$347 among non-zero deductible plans, the WTP for full deductible removal is \$222 ($-347 \times -3.53/5.53$), slightly above \$198 estimate for the median-risk group in Decarolis et al. (2020)-consistent with rising odds of spending through deductibles (Sayed et al., 2023). A back-of-the-envelope check, following Decarolis et al. (2020), suggests an expected monetized value of \$208 ($0.8 \times [\$347 - 0.25 \times \$347]$), aligning closely with our result.

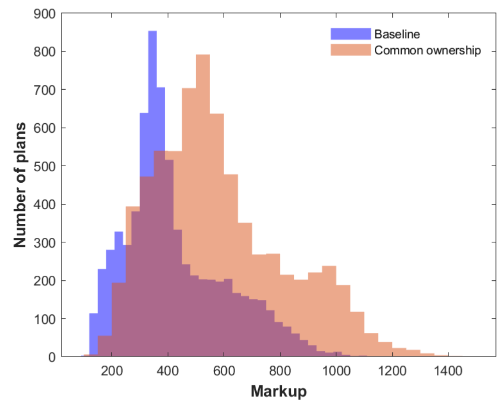
Further, non-price attributes significantly shape demand of PDPs. Consumers favor plans with a longer market presence, higher star ratings, deductible-exempt drug tiers, subject to the random assignment of LIS beneficiaries and national availability. Preferences for extra gap coverage are

[12] https://www.justice.gov/opa/pr/justice-department-requires-cvs-and-aetna-divest-aetna-s-medicare-individual-part-d; https://wellcare.com/Utah/Aetna-Transition

Figure 3: Distribution of estimated marginal costs and profits




(a) Marginal costs




(b) Markup

*Note :* This figure depicts the estimated $mc$ and $\eta$ of the model (5) under each firm conduct.

heterogeneous and do not significantly affect utility on average. In contrast, plans with an "enhanced" design are less preferred, likely due to their greater cost-sharing burden discussed later in this section.

Figure 3 shows the distributions of estimated risk-adjusted markups, $\eta_{jt}(\kappa)$, and marginal costs, $mc_{jt}$, under alternative ownership assumptions. Assuming no common ownership, average marginal cost is \$1,940; under common ownership, it falls to \$1,785-both plausible based on the \$1,000–\$1,800 range reported in Decarolis et al. (2020).

Table 6 reports hedonic regression estimates of marginal costs on plan characteristics, $W_j$. PDPs offer extra gap coverage, subject to LIS allocation and are available nationally exhibit higher marginal costs. This pattern reflects higher drug spending among LIS enrollees—roughly twice that of non-LIS enrollees, despite out-of-pocket payments representing only 20% of total spending (Sayed et al., 2023). In contrast, plans with a longer market presence, a higher star rating, an enhanced benefit design and deductible-exempt tiers are associated with lower marginal costs. The lower cost of enhanced plans may reflect higher cost sharing relative to basic plans, reducing insurer liability (Kaiser Family Foundation, 2015). Overall, the results are consistent with economic intuition: features linked to higher utilization raise costs, while features related to higher cost sharing

Table 6: Supply Estimates

| VARIABLES | (1)<br>$MC_{DB}$ | (2)<br>$MC_{CO}$ |
|---|---|---|
| Extra coverage | .299 | .276 |
| | (.007) | (.008) |
| Deductible | −.760 | −.736 |
| | (.030) | (.033) |
| Vintage | −.036 | −.040 |
| | (.002) | (.003) |
| Star rate | −.067 | −.070 |
| | (.005) | (.005) |
| Type (Enhanced) | −.684 | −.705 |
| | (.013) | (.016) |
| No Deductible Tier | −.298 | −.297 |
| | (.010) | (.010) |
| Below benchmark | .432 | .464 |
| | (.010) | (.010) |
| National PDP | .203 | .224 |
| | (.015) | (.019) |
| $\psi$ | −.199 | −.203 |
| | (.030) | (.030) |
| Year FEs | Y | Y |
| CMS Region FEs | Y | Y |
| Parent Group FEs | Y | Y |
| Mean dependent (Implied MC, $000s) | 1.940 | 1.785 |
| Adj. $R^2$ | .693 | .704 |
| Adj. $R^2$ (within) | .621 | .641 |
| Observations | 7040 | 7040 |

*Note:* This table reports the parameter estimates for the supply model. $MC_{DB}$ represents the marginal costs under standard differentiated Bertrand competition, while $MC_{CO}$ indicates the marginal costs under common ownership. Numbers in parentheses indicate the standard errors

or usage of management tools (e.g., prior authorization) reduce them.

Interestingly, the parameter $\psi$, which captures the marginal revenue gain from risk selection, remains consistently around -0.2 for both conduct assumptions. This suggests that every dollar reduction in reinsurance payments translates into a $0.20 increase in insurer profits.

## 5.2 Non-nested test and internalization parameter

Two empirical strategies are commonly used to examine firm conduct in differentiated product markets: testing a finite set of candidate models and estimating a conduct parameter. Model testing is less demanding of instruments and more robust to weak identification, but may be inconclusive if neither model can be falsified. Parameter estimation yields a direct quantitative measure of conduct but is more sensitive to misspecification and requires stronger instruments (Magnolfi and Sullivan, 2022). We implement both approaches to evaluate whether common-ownership pricing better explains the data than own-profit maximization, and to quantify the implied degree of internalization.

We first apply the non-nested RV test (Rivers and Vuong, 2002) to compare the fit between the common-ownership and own-profit–maximization models. For conduct model $m$, we use GMM objective as a measure for lack of fit as

$$Q_m = g_m' \mathcal{W} g_m$$

where $g_m = \mathbb{E}\left[z_j \omega_j\right]$ is the supply-side moment and $\mathcal{W}$ is the optimal weighting matrix. The supply-side first-order condition (5) implies

$$mc_j = b_j - \mu_j = f(W) + \omega_j$$

where the risk-adjusted markup net of subsidies and selection effects is defined as:

$$\mu_j = r_j^{-1}\left[\eta_j(\kappa) - \left(\widehat{RI}_j + LIS_j + \psi a_j\right)\right]$$

Following Duarte et al. (2023), we construct $\omega_j$ by subtracting the risk-normalized markup net of subsidies and selection effects, $\mu_j$, from the bid, $b_j$, after residualizing both variables and the instruments on $W$.

The RV test evaluates the null hypothesis that both models provide an equally good fit:

$$H_0 : \quad Q_1 = Q_2$$

with two-sided alternatives $H_1 : Q_1 < Q_2$ and $H_2 : Q_2 < Q_1$. The test statistic is:

$$T^{RV} = \frac{\sqrt{n}(Q_1 - Q_2)}{\sigma_{RV}} \sim N(0, 1)$$

Backus et al. (2021a) emphasize the importance of specifying conditional moments, $\mathbb{E}[\omega_j|Z] = \mathbb{E}[\omega_{jt} \cdot A(Z)] = 0$, through a flexible weighting function $A(Z)$ to account for non-linearities. Appendix B shows that using flexible function does not change our result qualitatively. We estimate the asymptotic variance, $\sigma^2_{RV}$, with the delta-method estimator derived in Duarte et al. (2023, Appendix C), which adjusts for both the first-stage demand estimation and clustering.

In addition to model selection, we estimate the conduct parameter, $\tau$, which measures the extent to which firms internalize the profits of (commonly owned) rivals (Miller and Weinberg, 2017; Kennedy et al., 2017; Park and Seo, 2019). We adjust Equation 3 in Section 4.2 similar to Kennedy et al. (2017) by multiplying the conduct parameter, $\tau$, to the common ownership incentive term:

$$Q_f = \sum_{j \in J_f} \left( r_j b_j + \widehat{RI}_j + LIS_j - r_j mc_j + \psi a_j \right) s_j M + \tau \cdot \sum_g \kappa_{fg} \pi_g(r_g, b_g, c_g),$$

where $\tau$ is estimated through GMM along with $\psi$.

Table 7 presents the results of the RV test and conduct parameter estimates. Following Duarte et al. (2023), we treat each source of variation separately, form a model confidence set for each instrument set, and aggregate only across nonconflicting sets supported by strong instruments. The F-statistics reported beneath the RV test are effective F-statistics, which assess instrument strength and detect potential test degeneracy within the RV framework.

Three of the instruments - differentiation, merger, and pooled ($Diff$, $1[Wellcare, Cigna]$, and Pooled) - consistently favor the common-ownership model over own-profit maximization, with

Table 7: Non-Nested Tests

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Model 2 : Common ownership | | | |
| | Diff | NProd | 1[Wellcare, Cigna] | Pooled IVs |
| $T_{RV}$ | | | | |
| Model 1 | | | | |
| Own profit maximization | 7.96 | 0.27 | 7.23 | 7.95 |
| F-statistics | | | | |
| | 51.12 | $1.68^{\dagger}$ | 58.24 | 47.14 |
| Internalization parameter ($\tau$) | 1.61 | 1.38 | 2.21 | 1.57 |
| | (0.14) | (1.14) | (0.06) | (0.15) |

*Note:* This table reports the test results using the procedures suggested by Duarte et al. (2023). Standard errors, reported in parentheses, are computed using the delta method. F-statistics with † are below the critical value for best case power above 0.95

$T_{RV} > 7$ in each case. Their effective F-statistics exceed the critical values for worst-case size ($r_s = 0.075$) and best-case power ($r_p = 0.95$) with 95% confidence, ruling out weak-instrument degeneracy as the driver of model selection. In contrast, the $NProd$ set fails the effective-F test and is inconclusive. Since the $Diff$, merger timing, and pooled columns all select the common-ownership model and $NProd$ does not contradict these selections, we interpret that our test prefers the common ownership model to the own-profit maximization model.

The conduct parameter is estimated precisely at $\tau = 1.61$ (s.e. 0.14) with $Diff$, $\tau = 2.21$ (0.06) with merger timing, and $\tau = 1.57$ (0.15) with pooled. In contrast, $NProd$ yields an imprecise estimate of $\tau = 1.38$ (1.14). Estimates of $\tau > 1$ suggest that firms internalize common-ownership incentives for setting their bids and hence premiums. Further, we measure common-ownership incentives under the proportional control assumption (i.e., one share–one vote), weighting investors by shares. The estimated conduct parameter $\tau > 1$ suggests a stronger-than-proportional internalization, so our price, enrollment, and welfare effects in the following counterfactual experiments should be viewed as conservative lower bounds. We leave further research to examine how the proportional control assumption affects the interplay between common ownership and risk selection.[13]

## 5.3 Counterfactuals

In this section, we examine the effects of common ownership in Medicare Part D market, as well as its interplay with risk selection. We consider four counterfactual scenarios, each defined by a pair of parameters $(\kappa, \psi)$. In the baseline scenario, $S_1$, we observe $(\kappa, \psi) = (\kappa_{fg}, \hat{\psi})$ from data. Scenario $S_2$ removes risk selection while preserving common ownership incentives, with $(\kappa, \psi) = (\kappa_{fg}, 0)$. Scenario $S_3$ removes only common ownership, with $(\kappa, \psi) = (0, \hat{\psi})$. Scenario $S_4$ eliminates both with setting $(\kappa, \psi) = (0, 0)$. For each case, we simulate equilibrium outcomes by solving plan bids under the corresponding $(\kappa, \psi)$, accounting for the endogeneity of subsidies to the average bid. We use a nested fixed-point algorithm: the outer loop fixes the average bid $\bar{b}$; the inner loop solves plan bids using Equation (5); and we update $\bar{b}$ until it equals the enrollment-weighted average of the resulting bids. Further details are provided in Appendix C

Table 8 presents the outcomes across the four counterfactual scenarios. Removing common ownership ($S_3$) leads to substantial reduction in annual premium consumers face: average premiums fall by $125.49 (-20.45%), and bids drop by $199.51 (-20.34%), consistent with reduced market power. From the reduced premium, consumer surplus increases by $97.69 million (+16.40%), while insurer surplus declines by $77.61 million (-26.53%), resulting in a net gain in social surplus of $20.08 million (+2.26%). Enrollment in PDPs increases by 14.69 percentage points (+42.31%), showing that lower prices draw additional beneficiaries into the market.

Figure 4 visualizes these effects. Figure 4a tracks counterfactual annual premium trends from 2013 to 2020. While observed premiums remain relatively stable, counterfactual premiums decline

[13] Without assuming a proportional control assumption, $\kappa_{fg}$ takes a form presented in Rotemberg (1984); Bresnahan and Salop (1986); O'brien and Salop (1999):

$$\kappa_{fg} = \frac{\sum_{\forall s} \gamma_{fs} \cdot \beta_{gs}}{\sum_{\forall s} \gamma_{fs} \beta_{fs}}$$

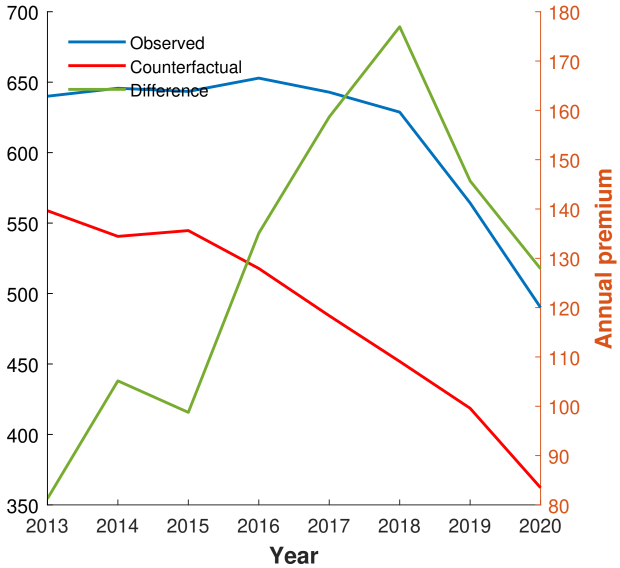
where $\gamma_{fs}$ is a weight that a manager in firm $f$ levying on investor $s$'s shareholdings.

Table 8: Counterfactual Results

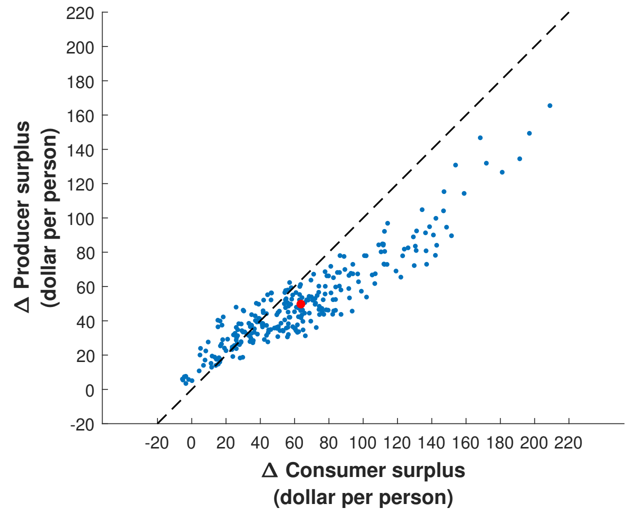
| | (1) $S_1$: Base | (2) $S_2$: No RS | (3) $S_3$: No CO | (4) $S_4$: Neither |
|---|---|---|---|---|
| Premium (annual, in \$) | | | | |
| Mean | 613.78 | 660.9 | 488.29 | 496.57 |
| Difference | | 47.12 | −125.49 | −117.21 |
| | | (7.68%) | (−20.45%) | (−19.10%) |
| Standard deviation | 365.19 | 383.92 | 368.17 | 364.10 |
| Bid (annual, in \$) | | | | |
| Mean | 980.94 | 1003.50 | 781.43 | 786.00 |
| Difference | | 22.56 | −199.51 | −194.94 |
| | | (2.30%) | (−20.34%) | (−19.87%) |
| Standard deviation | 404.53 | 422.80 | 421.26 | 419.43 |
| Insurer surplus (annual, in \$*mil*) | | | | |
| Mean | 292.58 | 282.18 | 214.97 | 215.19 |
| Difference | | −10.40 | −77.61 | −77.39 |
| | | (−3.55%) | (−26.53%) | (−26.45%) |
| Standard deviation | 214.28 | 212.52 | 160.21 | 162.10 |
| Consumer surplus (annual, in \$*mil*) | | | | |
| Mean | 595.74 | 592.65 | 693.43 | 694.13 |
| Difference | | −3.09 | 97.69 | 98.39 |
| | | (−.52%) | (16.40%) | (16.52%) |
| Standard deviation | 427.78 | 443.63 | 495.60 | 518.33 |
| PDP enrollment rate | | | | |
| Mean | 34.72% | 37.93% | 49.41% | 49.25% |
| Difference | | 3.21%*p* | 14.69%*p* | 14.54%*p* |
| | | (9.25%) | (42.31%) | (41.87%) |
| Standard deviation | .08 | .11 | .15 | .15 |

*Note:* This table reports the results of a counterfactual simulation. The Baseline scenario ($S_1$) reflects the observed level of common ownership and risk selection. The counterfactual scenarios remove risk selection ($S_2$), common ownership ($S_3$), and both. See text for details. Numbers in parentheses indicate percentage changes relative to the baseline. RS: Risk Selection; CO: Common Ownership

steadily, with the gap between them widens sharply after 2015 and peaks in 2018. Figure 4b shows market-level changes in consumer and producer surplus. Majority of markets lie below the 45-




(a) Trend of Counterfactual Premiums




(b) Change in Producer and Consumer Surplus Across Markets

Figure 4: Effects of Removing Common Ownership on Surplus and Premiums

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*Note :* This figure illustrates the effects of removing common ownership on market outcomes. Panel (a) compares observed and counterfactual annual premiums from 2013 to 2020. The green line, measured on the right axis, shows the premium difference between the two scenarios. Panel (b) plots market-level changes in consumer and producer surplus per person, with each dot representing a market. Points below the 45-degree line indicate gains for consumers are larger than absolute value of loss for producers. The red dot denotes the average change in each surplus across all markets.

degree line, indicating that consumer gains exceed producer losses overall. The red dot marks the average changes, confirming a redistribution of surplus towards consumers and a gain in allocative efficiency.

Turning to risk selection, we shut it down by setting $\psi = 0$ and compare $S_1$ and $S_2$. Since insurers cannot target lower-cost enrollees, the average premium increases from \$614 to \$661 (+7.7%). This result is consistent with previous findings (see Mahoney and Weyl (2017); Miller and Yeo (2019)): insurers can profit from favorable risk selection by pricing more aggressively to attract low-cost beneficiaries and thereby earning selection rents. When this channel is removed, the selection term $\psi a_j$ drops out of the supply-side first-order condition (eq. (3)); the markups rise to cover expected costs and lifting premiums. Since the premium is set at the elastic portion of demand, an increase in premium leads to a reduction in insurer surplus by 3.6% and a reduction in consumer surplus slightly by 0.5%.

To understand the interplay between common ownership and risk selection, we compare the outcomes in $S_2$ and $S_4$. In the absence of risk selection, removing common ownership leads to reduction in average premiums by $164.33 (-24.86%), and reduction in bids by $217.5 (-21.67%). From the reduced premium, consumer surplus increases by $101.48 million (+17.12%), while insurer surplus declines by $66.99 million (-23.74%), resulting in a net gain in social surplus of $34.49 million (+3.94%). Enrollment in PDPs increases by 11.32 percentage points (+29.84%).

Common ownership causes firms to partially maximize joint profits, which softens price competition. Interestingly, risk selection offsets a part of the internalization incentive among insurers owned by the same investors. Specifically, in our counterfactual experiments, a quarter of premium decrease (and 8% of bid decrease) from removing common ownership is offset by risk selection. With a smaller decrease in premium, removing common ownership has a weaker position effect on social surplus when risk selection is present.

# 6 Conclusion

This paper documents that institutional investors hold non-trivial ownership stakes across major Medicare Part D insurers, and provides reduced form evidence that PDPs offered by insurers with a higher level of common ownership with rival insurers are higher in premium and lower in market share. Embedding ownership links in a structural model of differentiated demand and supply, we find that insurers internalize rivals' profits when setting premiums. Counterfactual experiments find economically significant effects: eliminating common ownership reduces average premiums by about 20% and increases Part D enrollment by 14.7 percentage points (≈42% gain in coverage). Overall, there is a gain in allocative efficiency: a net increase in social surplus of 2.26%. Further, we find that risk selection constraints the internalization incentive of common ownership. The upward pricing pressure on premiums due to common ownership is reduced by about a quarter when risk selection is present. Removing common ownership has a weaker positive effect on social surplus when risk selection is present.

Our results have several policy implications. First, antitrust authorities may assess competition in Medicare Part D by looking into common ownership among institutional investors in addition to consolidation. Insurers' conduct can be affected by common ownership without any consolidation. Also, the presence of nonprofit or private (not listed) sponsors may provide a countervailing force against common owner-induced coordination. Second, the policy effect of reducing common ownership, e.g. limiting overlapping institutional holdings, on premiums could depend on the extent of risk selection. It suggests that curbing common ownership could have different impacts on premiums across Medicare Part D, Medicare Advantage, ACA exchanges, and other insurance markets. It calls for further research on how common ownership affects the market outcomes of other health insurance markets.

Beyond these competitive effects, the increased Part D enrollment due to a lower common ownership also carries implications for health policy. Greater participation increases prescription drug use and reduces out-of-pocket spending (Park and Martin, 2017), which in turn lowers hospitalization rates (Afendulis et al., 2011), improves mental health (Ayyagari and Shane, 2015), and reduces cardiovascular mortality (Huh and Reif, 2017; Dunn and Shapiro, 2019). Thus, curbing common ownership may yield welfare gains not only through lower premiums but also through improved health outcomes.

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# Appendices

## A Medicare Part D markets (PDP regions)

Table 9: CMS regions

| Market ID | States | No. of states |
|---|---|---|
| 1. | Connecticut, Massachusetts, Rhode Island, Vermont | 4 |
| 2. | Wyoming, North/South Dakota, Nebraska, Montana, Iowa, Minnesota | 7 |
| 3. | Delaware, Maryland, Washington D.C | 3 |
| 4. | Pennsylvania, West Virginia | 2 |
| 5. | Alabama, Tennessee | 2 |
| 6. | Oregon, Washington | 2 |
| 7. | Utah, Idaho | 2 |
| 8. | Indiana, Kentucky | 2 |
| 9. | New Hampshire, Maine | 2 |
| 10. ~ 34. | Remaining 25 states form a market by itself | 25 |
| Total | 34 markets | 51 states |

*Note:* 5 territories (Puerto Rico, Virgin Islands, Northern Mariana Islands, Guam, American Samoa) are excluded from the data set.

## B Robustness Check

## C Algorithm for Counterfactual Plan Bids and Premiums

This section describes how we compute the equilibrium in each counterfactual scenario. As described in Section 4.2, the monthly premium for a plan is determined by the plan's bid and the enrollee weighted average bid in that year. CMS reports, for each year, the average bid along with the base premium, defined as a fraction $\zeta_t$ of the average bid. Then the plan premium is calculated as the difference between its bid and the average bid, added to the base premium as described in

Equation (4):

$$p_j = \max\{0,\ b_j - (1-\zeta)\bar{b}\}$$

For each year $t$, we recover $\zeta$ by dividing the base premium by the average bid and treat $\zeta$ as constant in a given year in all counterfactual simulations. Because the enrollee-weighted average bid is, by regulation, constructed using both PDPs and MA-PDs, and we do not model MA-PD demand, we hold MA-PD enrollment and bids fixed at their observed levels. MA-PDs affect the simulations only through their contribution to the average bid and, in turn, to the base premium.

We solve for counterfactual equilibrium using a nested fixed-point algorithm similar to Decarolis et al. (2020). For each year, the outer loop starts by guessing the average bid, denoted $\bar{b}_t$. Then, conditional on this $\bar{b}_t$, the inner loop solves for the equilibrium that satisfies the first-order condition in Equation (5), appropriately modified for each counterfactual scenario. Using the resulting equilibrium bids, we calculate the average bid by weighting counterfactual enrollment each year, and iterate the process until we find that the average bid equals the equilibrium average bid. We search for $\bar{b}_t$ using the bisection method, allowing the search interval to expand whenever the equilibrium average bid does not cross the candidate value within the initial range. We also tested with a grid search; however, the bisection was faster and delivered more stable performance in locating fixed points across years and counterfactual scenarios.

# D Additional Results

Table 10: Full regression result - plan level

| VARIABLES | (1) log(Price) | (2) log(Price) | (3) log(Bid) | (4) log(Bid) | (5) log(Share) | (6) log(Share) |
|---|---|---|---|---|---|---|
| Common Ownership | | | | | | |
| $C_{fm}$ | 0.150*** | | 0.083*** | | -0.100*** | |
| | (0.013) | | (0.008) | | (0.025) | |
| $\bar{C}_{fm}$ | | 0.727*** | | 0.173*** | | 0.136 |
| | | (0.086) | | (0.059) | | (0.256) |
| Control Variables | | | | | | |
| Star rating | -0.029*** | -0.040*** | -0.015*** | -0.025*** | 0.135*** | 0.150*** |
| | (0.007) | (0.007) | (0.004) | (0.004) | (0.017) | (0.018) |
| Type (Enhanced) | -0.208*** | -0.205*** | -0.120*** | -0.115*** | 0.028 | 0.019 |
| | (0.021) | (0.022) | (0.013) | (0.014) | (0.055) | (0.055) |
| Below benchmark | -0.398*** | -0.397*** | -0.219*** | -0.218*** | 1.824*** | 1.822*** |
| | (0.016) | (0.017) | (0.010) | (0.010) | (0.050) | (0.050) |
| National PDP | -0.008 | -0.016 | -0.032*** | -0.036*** | 0.176*** | 0.179*** |
| | (0.013) | (0.013) | (0.009) | (0.010) | (0.047) | (0.047) |
| No Deductible Tier | -0.208*** | -0.210*** | -0.121*** | -0.123*** | 0.608*** | 0.613*** |
| | (0.011) | (0.011) | (0.007) | (0.007) | (0.044) | (0.044) |
| Deductible | -1.219*** | -1.218*** | -0.783*** | -0.778*** | -1.795*** | -1.808*** |
| | (0.039) | (0.038) | (0.025) | (0.026) | (0.118) | (0.119) |
| Extra coverage | 0.416*** | 0.414*** | 0.251*** | 0.249*** | -0.688*** | -0.683*** |
| | (0.008) | (0.008) | (0.006) | (0.006) | (0.027) | (0.027) |
| Vintage | 0.019*** | 0.020*** | 0.015*** | 0.016*** | 0.244*** | 0.243*** |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.010) | (0.010) |
| Constant | 0.094** | -0.006 | 0.541*** | 0.502*** | -9.115*** | -9.093*** |
| | (0.042) | (0.040) | (0.026) | (0.025) | (0.118) | (0.116) |
| Year FE | Y | Y | Y | Y | Y | Y |
| Region FE | Y | Y | Y | Y | Y | Y |
| Parent group FE | Y | Y | Y | Y | Y | Y |
| Observations | 7,045 | 7,045 | 7,045 | 7,045 | 7,045 | 7,045 |
| R-squared | 0.658 | 0.654 | 0.738 | 0.735 | 0.700 | 0.700 |

*Note:* All models include year, CMS regions, parent group fixed effects, and control variables. Standard errors are clustered at the CMS region level and shown in parenthesis