



Competition and Regulation in Medicare Advantage

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Competition and Regulation in Medicare Advantage

A DISSERTATION PRESENTED
BY
JOSEPH GUILLERMO PINETE HNATH
TO
INTERFACULTY COMMITTEE ON HEALTH POLICY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN THE SUBJECT OF
HEALTH POLICY

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Competition and Regulation in Medicare Advantage

This dissertation examines how managed competition functions in the Medicare Advantage (MA) program through three empirical studies. The first paper evaluates the causal effect of default enrollment policies on plan enrollment choice and health care utilization for low-income dual-eligible beneficiaries. The second paper describes how national MA insurance carriers have expanded market share between 2012 and 2023, primarily by acquiring smaller regional carriers; it also identifies a relatively low threshold of MA penetration above which further market growth is no longer associated with local market concentration. The third paper evaluates the causal effect of competitor entry on MA plan bids and rebates, where mixed empirical evidence suggests that the current levels of competitive pressure may be inadequate. Together, the three papers study the demand-side defaults, supply-side concentration, and competitive entry dynamics of the Medicare Advantage program, finding that the current architecture of managed competition has room for improvement with more sophisticated and evidence-driven regulatory policy reforms.

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1

INTRODUCTION

Medicare Advantage (MA) is now the dominant pathway through which Americans receive their Medicare benefits, covering more than half of all beneficiaries and accounting for over \$450 billion in annual federal expenditures. The program is built on the architecture of managed competition: private insurers submit bids to enroll Medicare beneficiaries, and the federal government uses those bids, through a benchmark-and-rebate mechanism, to allocate payment and to translate insurer competition into beneficiary benefits. The design rests on two foundational assumptions: that beneficiaries make informed choices among plans, and that insurers face meaningful competitive pressure on the supply side. This dissertation examines both assumptions across three empirical studies, each focusing on a different lever of the managed-competition architecture.

Chapter 2 examines the demand side. When beneficiaries do not actively choose a plan, what happens? Using a novel two-stage difference-in-differences design and a hand-collected dataset of state policies authorizing the default enrollment of low-income beneficiaries into integrated Medicare Advantage plans, this chapter identifies the causal effect of default enrollment on plan choice and health care utilization. The findings speak directly to the choice-architecture mechanisms that determine how the demand side of MA operates for the most vulnerable population the program serves.

Chapter 3 examines the supply side at a national and local scale. Drawing on two decades of MA market data, this chapter (published in *Health Affairs* in December 2024) documents how the share of MA enrollment held by large national carriers has risen sharply while non-affiliated regional carriers have been displaced through acquisitions, and shows that local-market concentration in MA has only declined in markets where MA penetration remains below roughly 20 percent. Above that threshold, further MA growth is not associated with lower concentration on average. The implication is that MA program reforms that assume markets are competitive are unlikely to achieve their goals without targeted attention to local concentration dynamics.

Chapter 4 examines competitive entry as the direct mechanism through which the supply-side architecture of managed competition is supposed to translate into beneficiary benefits. Using a continuous-treatment difference-in-differences design, this chapter identifies the causal effect of new MA insurance carrier entry on plan rebates. There is mixed but pessimistic evidence that entry does not lead to increased rebates, as we would expect in functioning competitive markets.

Together, the three chapters argue that the architecture of managed competition delivers in some places and fails in others, and that meaningful program reform requires both demand-side and supply-side levers in concert. The brief synthesis chapter at the end of the dissertation ties these threads together and points to the open questions that future work will address; an accompanying Next Steps document (referenced in the conclusion) catalogs the specific analytical extensions planned for the journal versions of each paper.

2

DEFAULT ENROLLMENT IN MANAGED CARE PLANS FOR LOW-INCOME INDIVIDUALS

Joseph G.P. Hnath and Vilsa E. Curto. The work in this chapter is co-authored; Joseph led the analysis and writing.

2.1 Abstract

We study default enrollment in a high-stakes health insurance setting. We examine a policy that automatically enrolls low-income individuals dually eligible for Medicaid and Medicare into Medicare managed care plans offered by their prior Medicaid insurer. Using novel data and a two-stage difference-in-differences (2SDD) design, we estimate causal effects on plan choice, utilization, and health outcomes. Default enrollment triples managed care enrollment, increasing it by 21.2 percentage points (95% CI: 15.3, 27.0) from a 10.1 percent baseline mean, with increases concentrated in plans without fully integrated care. Default enrollment reduces post-acute care utilization but has no detectable effect on hospital care utilization or one-year mortality.

2.2 I. Introduction

In many settings, individuals are required to make high-stakes decisions in complex choice environments. Examples include selecting retirement savings plans (Bernheim et al. 2015; Madrian and Shea 2001), enrolling in prescription drug plans (Brot-Goldberg et al. 2023), and making decisions about organ donation (Davidai et al. 2012) or electricity pricing (Fowle et al. 2021). In these environments, individuals frequently struggle to identify the option that best aligns with their preferences or financial interests, and may even select plans that are strictly dominated by available alternatives (Abaluck and Gruber 2016).

A common policy tool in these settings is the use of default options. By assigning individuals to a pre-selected alternative when they do not actively choose, defaults can substantially influence decisions and are often used to steer individuals toward options that policymakers view as welfare-improving. In health insurance markets, policymakers increasingly use default enrollment to steer individuals toward plans perceived to be higher value, including in Medicare Part D (Brot-Goldberg et al. 2023) and individual health insurance exchanges (Shepard and Wagner 2025). These policies are particularly relevant in settings with regulated competition between public and private provision, where policymakers seek to balance consumer choice with improved efficiency and care delivery. However, the effectiveness of defaults—and their consequences—depends on the context, particularly in complex health insurance markets.

These questions are particularly salient in the context of Medicare, where policymakers have recently proposed changing the enrollment process. Under current policy, beneficiaries are enrolled in traditional Medicare unless they actively choose a Medicare Advantage (MA) plan. MA plans differ from traditional Medicare in several ways: they typically include supplemental benefits such as prescription drug coverage, vision, and dental services, and have restricted provider networks. MA enrollment has grown substantially over the past two decades, driven in part by increased plan availability, generous program subsidies, and targeted benefit design. Policymakers and researchers have focused on whether competition among private plans can reduce costs and improve outcomes relative to traditional Medicare, although the evidence remains mixed (Medicare Payment Advisory Commission

2022). Recent proposals would instead default beneficiaries into MA, requiring an active choice to opt out (Freed et al. 2025).

In this study, we examine the introduction of a default option in a high-stakes health insurance setting that allows us to evaluate both enrollment responses and downstream consequences. Low-income individuals who are dually eligible for Medicaid and Medicare must make a complex set of coverage decisions upon turning age 65. This population is both medically complex and accounts for a disproportionate share of health care spending, making it a central focus of efforts to improve care delivery and coordination. We examine a default enrollment policy that automatically enrolls individuals who were previously enrolled in certain Medicaid managed care plans into Medicare managed care plans offered by the same insurer.

We assemble novel data on the set of Medicaid managed care plans approved for default enrollment using information obtained through a Freedom of Information Act request. We combine these data with rich Medicare administrative data to study how default enrollment affects plan choice, health care utilization, and health outcomes among a high-need population of low-income individuals. This setting allows us to link a policy that shifts enrollment through defaults to downstream effects on utilization and outcomes, providing causal evidence on the consequences of increased managed care enrollment.

Using a two-stage difference-in-differences (2SDD) design, we estimate the causal impact of default enrollment on plan choice and downstream health care utilization. We present two main findings. First, default enrollment is highly effective in shaping plan choice. Default enrollment triples managed care enrollment, increasing it by 21.2 percentage points (95% CI: 15.3, 27.0) from a 10.1 percent baseline mean, with increases concentrated in plans without fully integrated care.

Second, enrollment in Medicare managed care reduces the use of certain types of post-acute care without detectable improvements in care coordination or health outcomes. We find a decline in skilled nursing facility (SNF) utilization, both in the probability of a SNF stay and in the number of SNF days conditional on any stay. These reductions are

economically meaningful. At the same time, we find no evidence of adverse effects: hospital care utilization and one-year mortality are not affected.

Taken together, these results suggest that default enrollment into Medicare managed care shifts patients away from institutional post-acute care without worsening health outcomes, but also likely without improving coordination of care. Consistent with this interpretation, we document that most defaulted individuals are enrolled in plans without fully integrated care, with very limited take-up of integrated care plans. This pattern highlights an important limitation of default policies: while they can effectively shift enrollment, they may not steer individuals toward the plans most likely to improve care coordination. One possible explanation is that plans face strong financial incentives to reduce utilization, but weaker incentives to improve care coordination.

This paper contributes to two strands of literature. First, it adds to a large body of work on choice architecture and default effects by studying a high-stakes health insurance setting with complex plan options (Madrian and Shea 2001; Abaluck and Gruber 2016; Brot-Goldberg et al. 2023; Shepard and Wagner 2025). In contrast to prior work that focuses primarily on enrollment responses, we link default-induced enrollment changes to downstream utilization and health outcomes. Second, it contributes to the literature on Medicare managed care. While prior studies have documented differences in utilization and outcomes between MA and traditional Medicare, much of this evidence is based on observational comparisons and may reflect selection rather than causal effects (Newhouse and McGuire 2014; Agarwal et al. 2021). In this study, we provide causal evidence on how managed care enrollment affects utilization among dually eligible beneficiaries.

Overall, our findings highlight both the promise and the limits of default enrollment policies. While defaults can be a powerful tool for influencing enrollment decisions, their welfare consequences depend critically on the incentives embedded in the plans to which individuals are steered.

2.3 II. Background and Data

2.3.1 A. Medicare Choice Environment

Upon turning age 65, individuals must choose among a complex set of Medicare coverage options. For core coverage of inpatient and outpatient services, beneficiaries choose between traditional Medicare and privately administered Medicare managed care plans (MA). MA operates within a “managed competition” framework, in which private insurers receive capitated payments to provide Medicare benefits and compete on cost and quality (Newhouse and McGuire 2014; Medicare Payment Advisory Commission 2022). This competitive framework has the potential to enhance efficiency and generate cost savings, but it also raises concerns about selection (if plans avoid unprofitable patients) and plan-level variation in quality of care (Newhouse and McGuire 2014). Plan information is available through the Medicare Plan Finder, which allows users to compare plans based on premiums, cost sharing, and covered services. Approximately one-third of individuals use an insurance broker to select a Medicare plan (Faith Leonard et al. 2022).

Choosing a plan is complex in several ways. Beneficiaries must weigh trade-offs between broader provider networks in traditional Medicare and narrower networks in managed care, while provider network information is often difficult to observe *ex ante*. They must also evaluate differences in financial protection: traditional Medicare requires cost sharing with no out-of-pocket maximum, whereas MA plans include an out-of-pocket maximum and offer supplemental benefits such as dental and vision coverage. In addition, beneficiaries must decide whether to purchase supplemental coverage (Medigap) and how to obtain prescription drug coverage, either through a standalone Part D plan or a bundled MA plan.

A growing body of evidence shows that individuals struggle to navigate this choice environment and frequently make suboptimal or dominated plan choices (Abaluck and Gruber 2016; Decarolis et al. 2020; Hostetter and Klein 2022).

2.3.2 B. Default Enrollment in Medicare Managed Care

These challenges are particularly pronounced for low-income individuals dually eligible for Medicaid and Medicare. This population exceeds 12 million beneficiaries and has substantially higher health care needs and spending than other Medicare beneficiaries

(Medicaid Payment Advisory Commission 2023; Medicare Payment Advisory Commission 2023). Compared to non-dually eligible Medicare beneficiaries, dual eligibles are three times as likely to be Black and Hispanic, have health care spending that is twice as high, and are three times more likely to report being in poor health (Medicare Payment Advisory Commission 2023). In addition to selecting a Medicare plan, these beneficiaries must consider how Medicare coverage interacts with Medicaid benefits, further increasing decision complexity. Historically, fragmentation between Medicare and Medicaid financing has contributed to poor care coordination for this population (Medicaid Payment Advisory Commission 2023). One approach to improving coordination is the use of integrated care programs, which the Medicaid Payment Advisory Commission (MACPAC) has recommended to Congress (Medicaid Payment Advisory Commission 2023).

Policymakers have sought to simplify choices and promote care coordination by encouraging enrollment in integrated plans that combine Medicaid and Medicare benefits, including Dual-Eligible Special Needs Plans (D-SNPs), Medicare-Medicaid Plans, and the Program of All-Inclusive Care for the Elderly (PACE) (Medicaid Payment Advisory Commission 2023; Grabowski 2023). D-SNPs are the most widely available of these options and account for the majority of enrollment, and their role is expected to grow further as the Medicare-Medicaid Plan (MMP) program is phased out and enrollees are transitioned into D-SNPs (Medicaid Payment Advisory Commission 2023). D-SNPs also vary substantially in the degree of integration and are typically categorized into three levels: coordination-only (CO D-SNPs), highly integrated (HIDE SNPs), and fully integrated (FIDE SNPs), with most enrollment occurring in plans that do not fully integrate Medicare and Medicaid benefits.

More broadly, MA enrollment has grown rapidly, with roughly half of all Medicare beneficiaries enrolled in MA plans in 2024, and projections suggesting this share will reach 60 percent by 2032 (Trish et al. 2023; Board of Trustees, Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2022). Since 2018, MA enrollment has increased more rapidly among dually eligible beneficiaries, with this growth driven largely by increased enrollment in D-SNP plans (Figure 2.1). Over this period, the share

of dual eligibles enrolled in D-SNPs has more than doubled, yet only about 10 percent of D-SNP enrollment in 2023 is in fully integrated (FIDE) plans.

A large literature has examined the causes and consequences of growth in overall MA enrollment (Afendulis et al. 2012; Atherly et al. 2020; Chernew et al. 2023; Newhouse and McGuire 2014; Jung et al. 2023; Landon et al. 2023; Agarwal et al. 2021). A systematic review by Agarwal et al. (2021), evaluating 48 studies, finds that MA is associated with reduced utilization across multiple measures and improved performance on quality indicators (Agarwal et al. 2021). However, relatively fewer studies focus specifically on the dually eligible population. Recent studies examine enrollment in D-SNPs and other integrated care plans, as well as participation in “look-alike” plans that target dually eligible beneficiaries but do not meet regulatory standards for integration (Park et al. 2023; Velasquez et al. 2023; Ma et al. 2023). For example, one study finds that Black and Hispanic beneficiaries were more than twice as likely to enroll in D-SNPs in 2018 compared to White beneficiaries (Velasquez et al. 2023). Focusing on outcomes, existing studies find mixed evidence on the relationship between D-SNP enrollment and patient-reported satisfaction relative to traditional Medicare and other MA plans, as well as only modest reductions in total Medicare spending (Haviland et al. 2021; Roberts and Mellor 2022; Meyers et al. 2023; Zhang and Diana 2018). Research by the Medicare Payment Advisory Commission (MedPAC) initially found higher quality for D-SNPs relative to non-SNP MA plans, but more recent work concludes that commonly used quality measures, such as HEDIS, are insufficient for detailed comparisons (Medicaid Payment Advisory Commission 2013; Medicare Payment Advisory Commission 2023). It is also important to consider the incentives faced by insurers to offer D-SNPs, as MedPAC estimates average profit margins of 10.7 percent for D-SNPs compared to 6.5 percent for MA plans overall (Medicare Payment Advisory Commission 2022), suggesting strong financial incentives for plans to expand D-SNP offerings even when integration is limited. Our study contributes to this literature by providing quasi-experimental evidence on the effects of managed care among high-need, dually eligible Medicare and Medicaid beneficiaries.

Early efforts, including “seamless conversion” policies introduced in 2006, generated limited enrollment. Beginning in 2018, policymakers expanded the use of default enrollment mechanisms to increase participation in these plans. For roughly 200,000 Medicaid managed care (MMC) enrollees who gain Medicare eligibility each year, one pathway into D-SNPs is default enrollment, in which individuals enrolled in selected MMC plans approved by CMS may be automatically enrolled in a D-SNP offered by the same insurance carrier upon becoming Medicare-eligible (i.e., dually eligible) (Integrated Care Resource Center 2019). Under this policy, eligible Medicaid managed care organizations can apply for approval to automatically enroll their Medicaid enrollees into affiliated Medicare managed care plans as soon as they become eligible for Medicare at age 65. Default enrollment therefore assigns individuals to a plan offered by the same insurer unless they actively opt out.

Difficulties in evaluating and comparing the attributes of health plans may lead to inertia (i.e., a failure to switch plans when a better plan is available) and suboptimal choices (Abaluck and Gruber 2016; Handel 2013). Prior studies document such frictions in Medicare Part D, state insurance exchanges, and MA (Brot-Goldberg et al. 2023; Atherly et al. 2020; McWilliams et al. 2011; Drake et al. 2022). While default enrollment may therefore nudge beneficiaries toward D-SNPs, little evidence documents which beneficiaries are subject to default enrollment, whether default enrollment increases D-SNP enrollment, and what the causal effect of D-SNP enrollment is on health care utilization and outcomes.

While some information on this default enrollment policy is publicly available, there is no comprehensive public record of which plans were approved to implement default enrollment. To address this gap, we submitted a Freedom of Information Act (FOIA) request to the Centers for Medicare and Medicaid Services (CMS) and obtained detailed information on the exact Medicare managed care plans that were approved to use default enrollment. To our knowledge, no prior study has evaluated the effects of default enrollment policies in this setting on either plan choice or downstream utilization and health outcomes.

2.3.3 C. Data and Sample

Publicly available information on default eligible plans is limited to recent years, while Medicare administrative data are available only with a lag. To construct a consistent

panel, we use data on default enrollment approvals from 2006-2019 obtained through our FOIA request. Earlier years of these data include exact approval dates, while later years—from 2016 on—provide annual plan-level eligibility indicators. Although we directly observe whether each firm-state pair was approved for default enrollment, we do not observe whether plans implemented default enrollment in practice. This may introduce measurement error in treatment exposure, biasing estimates toward zero.

To fix ideas, consider a representative example. Beginning in 2011, a Medicaid managed care organization in New York (Firm N1) received approval to implement default enrollment for its Medicaid enrollees into an affiliated D-SNP once they became eligible for Medicare at age 65. Beneficiaries enrolled in this firm’s Medicaid plan would therefore be automatically enrolled in the firm’s Medicare managed care plan unless they actively opted out. Because beneficiaries with end-stage renal disease (ESRD) were generally not eligible to enroll in MA during our study period, we focused on the aged and disabled populations.

We combine the FOIA default enrollment approval data with Medicare administrative data from 2009-2019, including the Master Beneficiary Summary File (MBSF), which contains enrollment, demographic, and Medicaid dual-eligibility information. To examine health care utilization, we use the Medicare Provider Analysis and Review (MedPAR) file, which includes inpatient hospital and skilled nursing facility (SNF) utilization for all Medicare beneficiaries, including those enrolled in MA. We focus on six primary outcomes measured during the first year of Medicare enrollment: (i) any inpatient stay, (ii) total inpatient days, (iii) total inpatient days (conditional on any stay), (iv) any SNF stay, (v) total SNF days, and (vi) totally SNF days (conditional on any stay). These measures capture utilization along both the extensive and intensive margins and serve as proxies for high-intensity health care use.

Our analytic sample consists of Medicare beneficiaries in four states—Arizona, New York, Pennsylvania, and Tennessee—that had at least one insurer with a plan approved for default enrollment during our study period. These states were early adopters of default enrollment policies and have large Medicaid managed care programs (Medicaid Payment

Advisory Commission 2023). The program has continued to expand; by 2025, there were 15 states with plans approved for default enrollment (Centers for Medicare and Medicaid Services 2026).

While default enrollment and D-SNP availability vary at finer geographic levels, we conduct our analysis at the firm-state level to conservatively account for within-market correlation. All models are estimated at the beneficiary level, with standard errors clustered at the firm-state level.

2.4 III. Empirical Strategy

Note on what the bound dissertation reports. All causal estimates in this chapter are reduced-form two-stage difference-in-differences (2SDD) specifications, identifying the effect of state default enrollment policies on Medicare Advantage enrollment and on health care utilization. The local average treatment effects (LATEs) of MA enrollment on utilization that appear in Section IV are constructed as simple Wald-style ratios of reduced-form 2SDD estimates. A fully joint 2SDD with instrumental variables (2SDD-IV) event-study estimator, which would deliver IV-derived dynamic effects with valid sandwich inference in a single step, is in development as part of the journal-version revision and is not included in the bound dissertation.

2.4.1 A. Empirical Models

2.4.1.1 Two-Stage Difference-in-Differences

Our setting features staggered adoption of default enrollment across Medicaid managed care organizations (MCOs), with potentially heterogeneous treatment effects. We treat each MCO’s implementation of default enrollment as a distinct treatment, occurring at different points in time.

In this context, conventional two-way fixed effects (TWFE) estimators may be biased in the presence of treatment effect heterogeneity and staggered timing (Goodman-Bacon 2021; Callaway and Sant’Anna 2021). To address these concerns, we adopt a two-stage difference-in-differences (2SDD) estimator (Gardner et al. 2024). This approach recovers group and time fixed effects using only untreated observations and then estimates treatment effects in a second stage. Relative to alternative estimators, such as imputation-based methods

(Borusyak et al. 2024), the two-stage estimator is straightforward to implement, more computationally efficient, and permits inference using standard regression-based standard errors.

Let Y_{gpit} denote the outcome for beneficiary i in period p (year relative to treatment) with MCO g in year t , and let D_{gp} indicate exposure to default enrollment. The estimation proceeds in two stages. In the first stage, we estimate:

$$Y_{gpit} = \lambda_g + \gamma_p + \delta' \mathbf{X}_{gpit} + \epsilon_{gpit}$$

using only untreated observations (including both never-treated and not-yet-treated units), where $\mathbf{X}_{gpit}$ is a vector of covariates (e.g., race/ethnicity, sex, disability status). In the second stage, we estimate:

$$Y_{gpit} - \hat{\lambda}_g - \hat{\gamma}_p - \hat{\delta}' \mathbf{X}_{gpit} = \beta^{2DDD} D_{gp} + \nu_{gpit}.$$

The coefficient β^{2DDD} is the two-stage difference-in-differences estimate of the effect of default enrollment on the outcome Y_{gpit} (Medicare managed care enrollment, hospital care utilization, or post-acute care utilization). With this two-stage difference-in-differences approach, the parallel trends assumption is that the group and period effects are identified from the subpopulation of untreated group-periods (as long as there are untreated units in each period and each group is observed before treatment). A key requirement of this approach is that each unit is observed in at least one untreated period. We therefore omit observations that are always treated, which constitute a small share of the sample (approximately 2,000 beneficiaries). If the parallel trends assumption holds, then the coefficient β^{2DDD} identifies the average treatment effect on the treated (ATT). To estimate dynamic effects, we also estimate an event study specification that replaces D_{gp} with a full set of relative-time indicators (Gardner et al. 2024).

2.4.1.2 Instrumental Variables

We next use the default enrollment policy as an instrument for MA enrollment to estimate its causal effect on health care utilization. Specifically, we combine reduced form estimates of the effect of default enrollment on MA enrollment and health care use to construct Wald estimates of the effect of MA enrollment on utilization. These instrumental variables

estimates identify local average treatment effects (LATEs) for beneficiaries whose MA enrollment is affected by the default enrollment policy (the “compliers”).

This approach relies on the standard exclusion restriction that default enrollment affects health care utilization only through its impact on managed care enrollment. This assumption is plausible in our setting because default enrollment operates as an administrative mechanism that shifts plan assignment without directly altering care delivery. A related assumption is that, conditional on controls and fixed effects, exposure to default enrollment is as good as randomly assigned. While participation in the policy is determined by insurer decisions, our empirical design exploits variation in the timing of adoption across plans and includes group and time fixed effects to account for potential confounding factors.

2.4.2 B. Test of Key Identifying Assumption

Our identification strategy relies on a parallel trends assumption: in the absence of default enrollment, outcomes for treated and untreated units would have evolved similarly over time. We assess the plausibility of this assumption using event study specifications, focusing on pre-treatment coefficients to test for differential pre-trends.

2.5 IV. Results

2.5.1 A. Effect of Default Enrollment on Medicare Plan Choice

Figure 2.2 presents event study estimates of the impact of default enrollment on Medicare managed care enrollment among low-income individuals. Pre-treatment coefficients (event times -5 through 0) are small and statistically indistinguishable from zero, providing support for the parallel trends assumption.

In the first year of implementation (event time 1), default enrollment increases Medicare managed care enrollment by 0.212 (95% CI: $0.153, 0.270$), tripling managed care enrollment relative to the treated group baseline mean of 0.101 . The effect persists over time, with estimated increases of 0.234 (95% CI: $0.169, 0.298$), 0.210 (95% CI: $0.121, 0.299$), and 0.224 (95% CI: $0.093, 0.355$) in years 2 , 3 , and 4 , respectively.

Figure 2.6 shows that these gains are nearly entirely driven by increases in D-SNP enrollment. In contrast, we find no detectable change in enrollment in integrated care plans.

Enrollment in these plans remains low throughout the study period, rising from 0.0 percent in 2006 to only 2.3 percent by 2021 (Figure 2.1).

Because the policy operates exclusively on the D-SNP margin, our estimates identify the effect of default enrollment on enrollment in D-SNPs specifically. However, because the D-SNPs are coordination-only, we believe the generalizability to “managed care” is appropriate. Future studies should study FIDEs specifically, and look for many instruments to examine the many margins of Medicare plan options.

Taken together, these results indicate that default enrollment substantially increases Medicare managed care enrollment among low-income individuals, but the effect operates exclusively through coordination-only D-SNP plans rather than fully integrated care plans. This pattern suggests that default enrollment is highly effective at shifting beneficiaries into the administratively simplest available option but does not meaningfully steer enrollment toward integrated care plans that may offer greater potential for care coordination.

2.5.2 B. Effect of Default Enrollment on Health Care Utilization and Outcomes

Figure 2.3 presents event study estimates of the impact of default enrollment on post-acute care utilization, measured as SNF days conditional on at least one SNF stay. Pre-treatment coefficients are generally close to zero, with some noise in individual years, but do not suggest systematic pre-trends.

In the first year of implementation, SNF days decline by 5.36 (95% CI: -17.00, 6.28), an 11.8 percent reduction relative to the baseline mean of 45.3, though the estimate is not statistically significant. Effects grow in magnitude and become statistically significant in subsequent years: -10.42 (95% CI: -20.20, -0.64) in year 2, -19.75 (95% CI: -31.96, -7.53) in year 3, and -23.65 (95% CI: -38.16, -9.14) in year 4. These patterns indicate sizable and increasing reductions in post-acute care utilization following default enrollment.

Figure 2.4 reports two-stage difference-in-differences estimates for hospital and post-acute care utilization. We find no evidence of an effect on hospital care utilization: estimates for any inpatient stay, inpatient days, and inpatient days conditional on any stay are all statistically indistinguishable from zero.

In contrast, default enrollment leads to meaningful reductions in post-acute care utilization along both the extensive and intensive margins. The probability of any SNF stay declines by 0.00877 (95% CI: -0.0168, -.000724), a 20 percent reduction relative to the baseline mean. SNF days fall by 0.799 (95% CI: -1.525, -0.0718), a 43 percent decrease relative to the baseline mean, while SNF days conditional on any stay decline by 12.66 (95% CI: -22.06, -3.25), or 21 percent relative to the baseline mean. We also do not find any change in one-year mortality (Figure 2.10).

Overall, the results indicate that default enrollment has no detectable impact on hospital utilization but leads to substantial reductions in post-acute care utilization. The absence of changes in inpatient utilization alongside large declines in post-acute care utilization is consistent with managed care plans reducing post-acute care intensity, potentially through tighter utilization management or substitution toward lower-cost settings, rather than affecting the likelihood of a hospitalization.

2.6 V. Discussion and Conclusion

This study provides novel causal evidence on the impact of default enrollment policies on Medicare managed care enrollment and participation in integrated care plans among low-income individuals dually eligible for Medicaid and Medicare. The findings yield several insights for policymakers seeking to improve care for this high-need population.

We find that default enrollment policies substantially increase Medicare managed care enrollment, raising enrollment by 21.2 percentage points (95% CI: 15.3, 27.0) from a 10.1 percent baseline mean, or tripling enrollment, with increases concentrated in plans without fully integrated care. The magnitude of this effect underscores the power of default enrollment as a policy lever in complex insurance environments. In principle, this mechanism could be used to increase enrollment in integrated care plans if that were a policy priority.

However, the increase in managed care participation is driven entirely by coordination-only D-SNP plans, with no corresponding increase in fully integrated care plans. This pattern suggests that while defaults are effective at shifting beneficiaries into managed care,

they do not, under current policy design, steer individuals toward plans that offer more integration of Medicaid and Medicare services.

We also find that increased managed care enrollment has no detectable effect on hospital care utilization but leads to substantial reductions in post-acute care utilization. These results are consistent with managed care plans reducing post-acute care intensity, potentially through utilization management, without affecting inpatient care. Whether these reductions reflect efficiency gains or reductions in necessary care cannot be directly addressed in this study, although we do not find any impact on one-year mortality.

Several limitations are important to consider. First, the analysis focuses on four states that were early adopters of default enrollment, which may limit external validity. Second, data availability constrains the set of outcomes we can examine. Because measures are drawn from the MedPAR data, which includes the Medicare managed care enrollees, we focus on hospital and post-acute care utilization and are unable to assess other important dimensions, including outpatient care, care coordination, and health outcomes.

These findings have direct implications for ongoing policy efforts to integrate Medicaid and Medicare services for low-income individuals. As CMS continues to promote integrated care models and transitions MMP demonstration programs to D-SNP plans, default enrollment policies are a potentially powerful tool for increasing participation. However, in their current form, these policies primarily expand enrollment in coordination-only plans and do not achieve meaningful increases in fully integrated care.

More broadly, the results contribute to the literature on choice architecture in health insurance markets, highlighting both the effectiveness and the limits of defaults as a policy instrument. While defaults can substantially alter enrollment patterns, their impact depends critically on the set of options into which individuals are steered.

Further research is needed to better understand the welfare implications of the impacts of Medicare managed care for low-income individuals; particularly, whether reductions in utilization reflect improved efficiency or unintended reductions in access or quality.

Understanding how plan design and default enrollment interact to shape both enrollment and outcomes remains an important area for future work.

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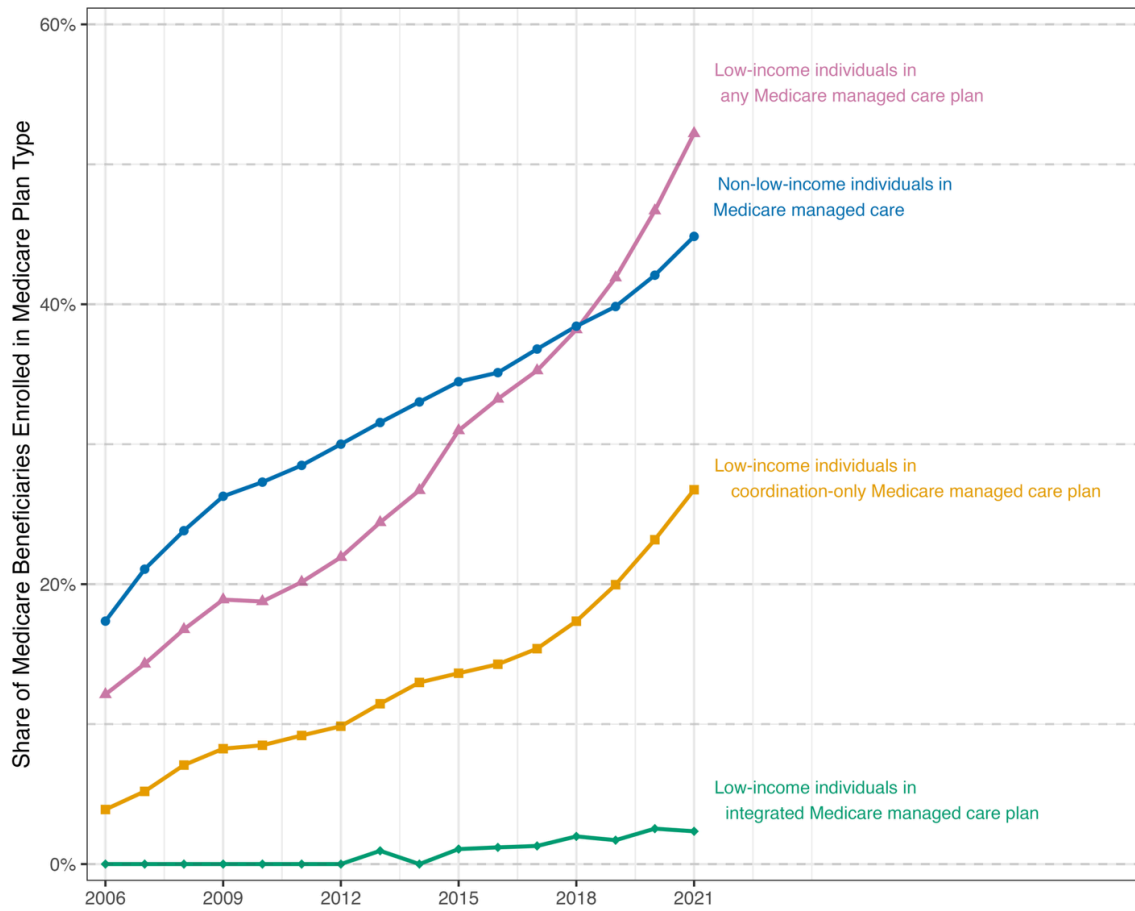


Figure 2.1 : Enrollment in Medicare Managed Care Plans, Overall and among Low-Income Individuals, 2006-2021

Notes: Figure plots annual enrollment in Medicare managed care plans overall and among low-income (dually eligible) beneficiaries from 2006 to 2021. Enrollment measures are calculated at the beneficiary-year level using administrative data.

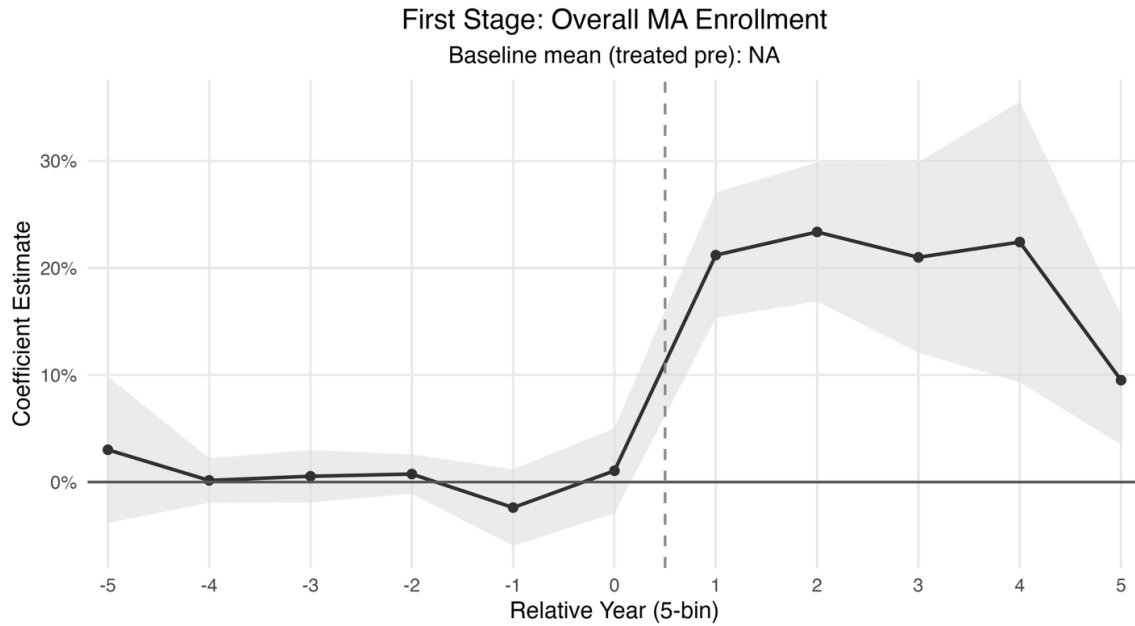


Figure 2.2 : Event Study of Impact of Default Enrollment on Medicare Managed Care Enrollment among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on Medicare managed care enrollment. Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

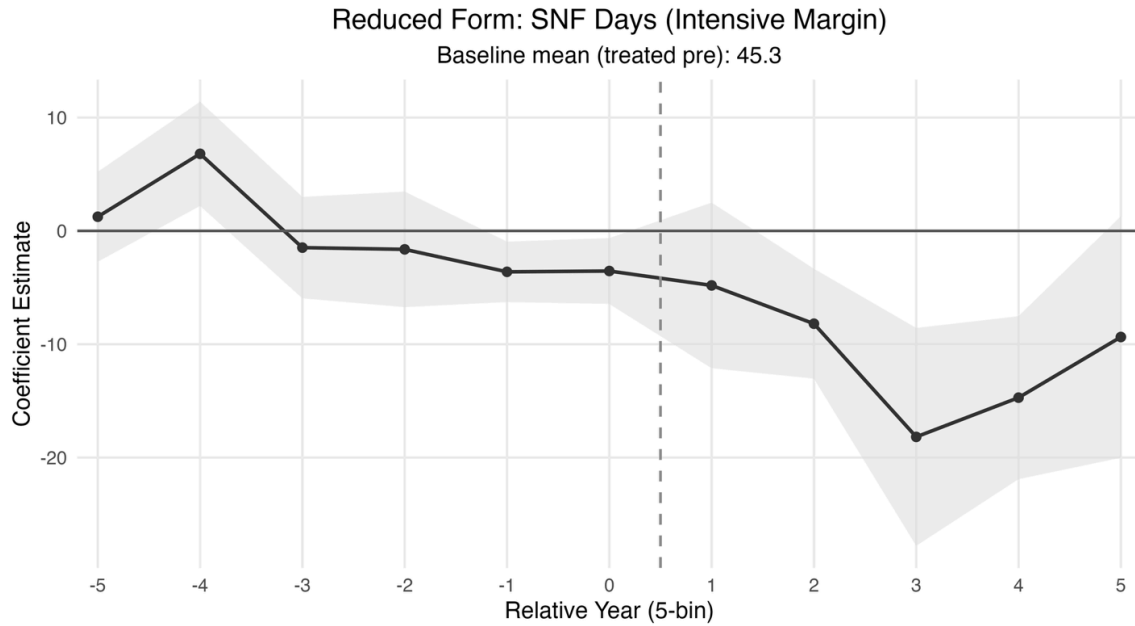
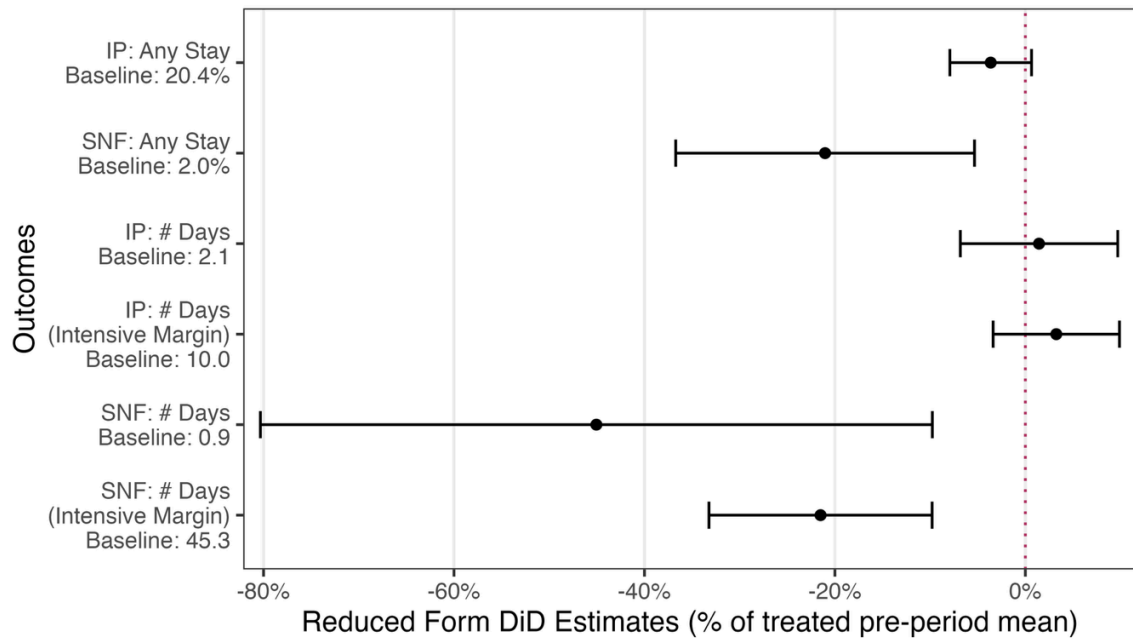


Figure 2.3 : Event Study of Impact of Default Enrollment on Post-Acute Care Utilization among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on post-acute care utilization (SNF days conditional on any stay). Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.



shown as percent change relative to the treated-group pre-treatment mean (beneficiary-weighted using `n_benes`).
SEs clustered at State-by-Firm level.

Figure 2.4 : Two-Stage Difference-in-Differences Estimates of Impact of Default Enrollment on Hospital Care Utilization and Post-Acute Care Utilization

Notes: Figure reports estimates and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on hospital care utilization and post-acute care utilization. Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

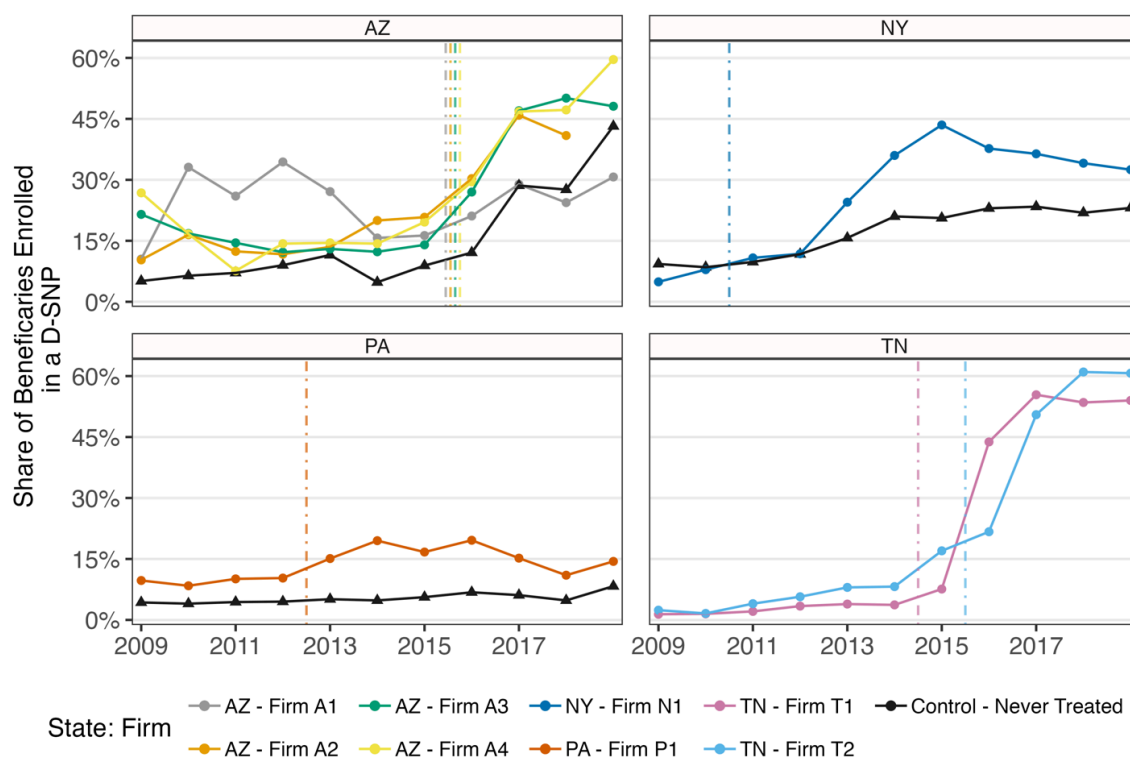


Figure 2.5 : Trends in D-SNP Enrollment and the Default Enrollment Policy

Notes: Figure plots trends in D-SNP enrollment over time across Medicare managed care firms.

Vertical lines indicate the timing of default enrollment policy approvals.

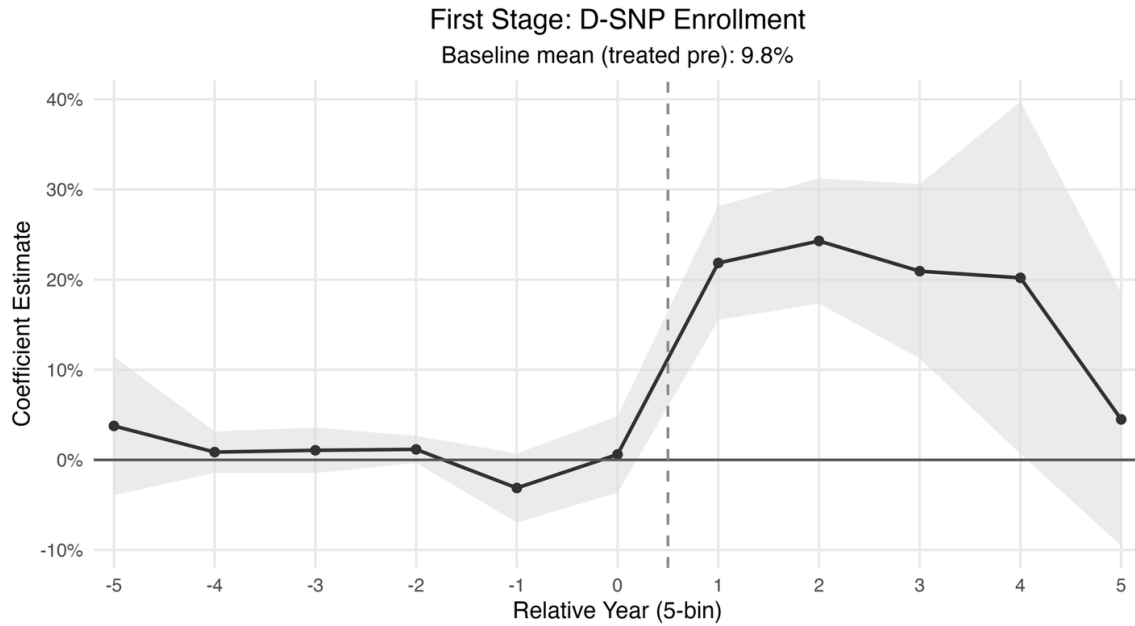


Figure 2.6 : Event Study of Impact of Default Enrollment on Medicare Managed Care Enrollment in D-SNP Plans among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on enrollment in D-SNP plans. Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

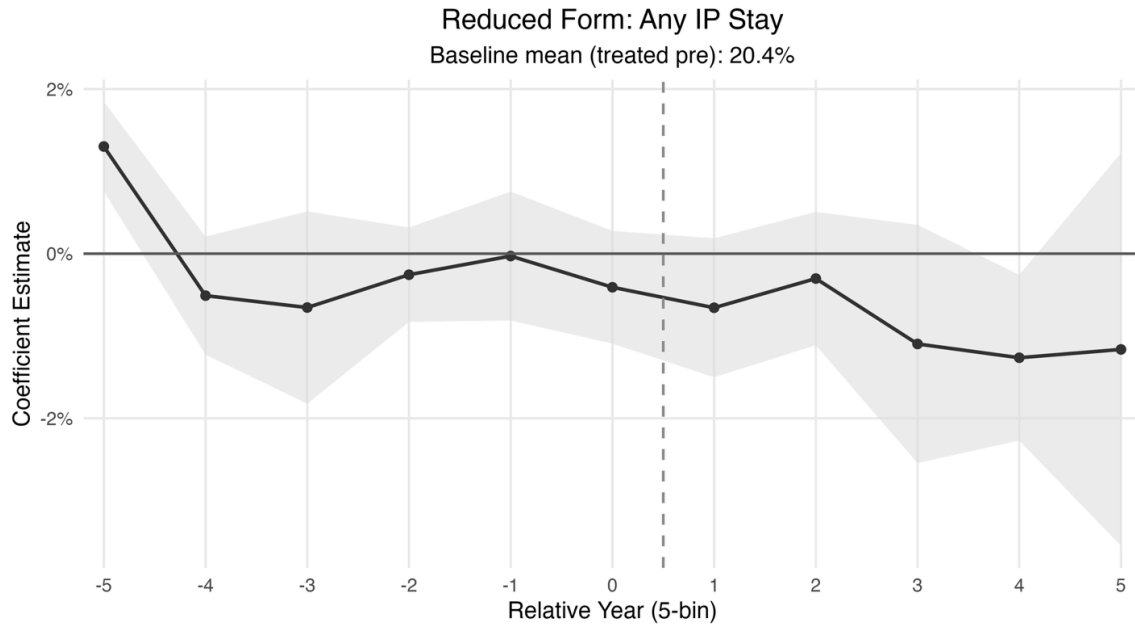


Figure 2.7 : Event Study of Impact of Default Enrollment on Hospital Utilization among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on hospital utilization (any inpatient stay). Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

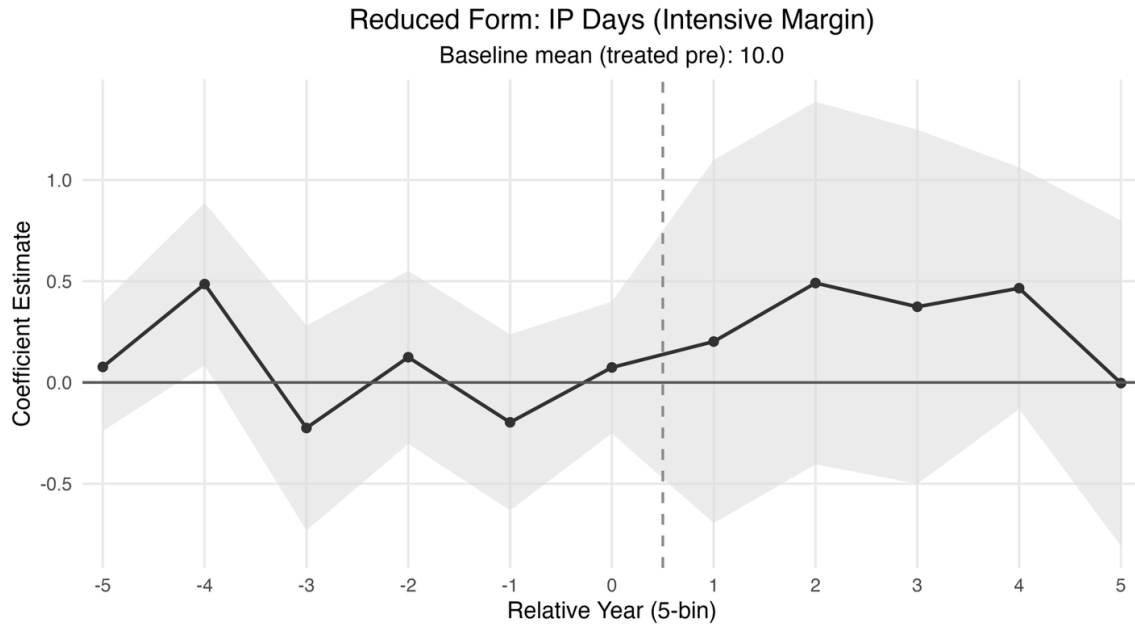


Figure 2.8 : Event Study of Impact of Default Enrollment on Hospital Inpatient Days among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on hospital inpatient days. Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

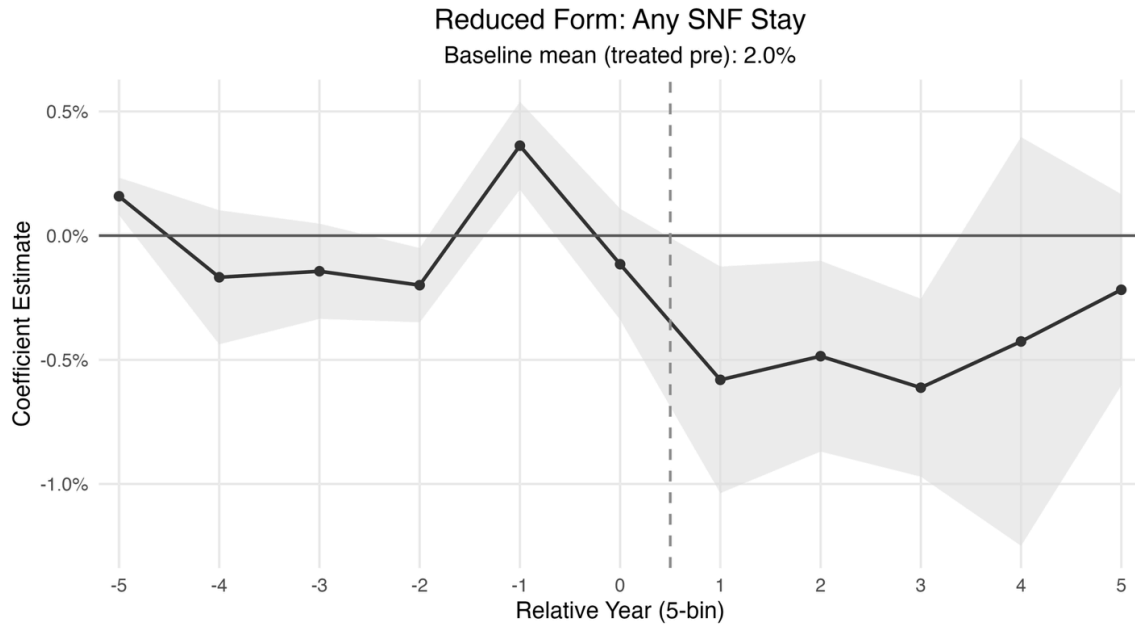


Figure 2.9 : Event Study of Impact of Default Enrollment on Any Post-Acute Care Utilization among Low-Income Individuals

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on post-acute care utilization (any skilled nursing facility stay). Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

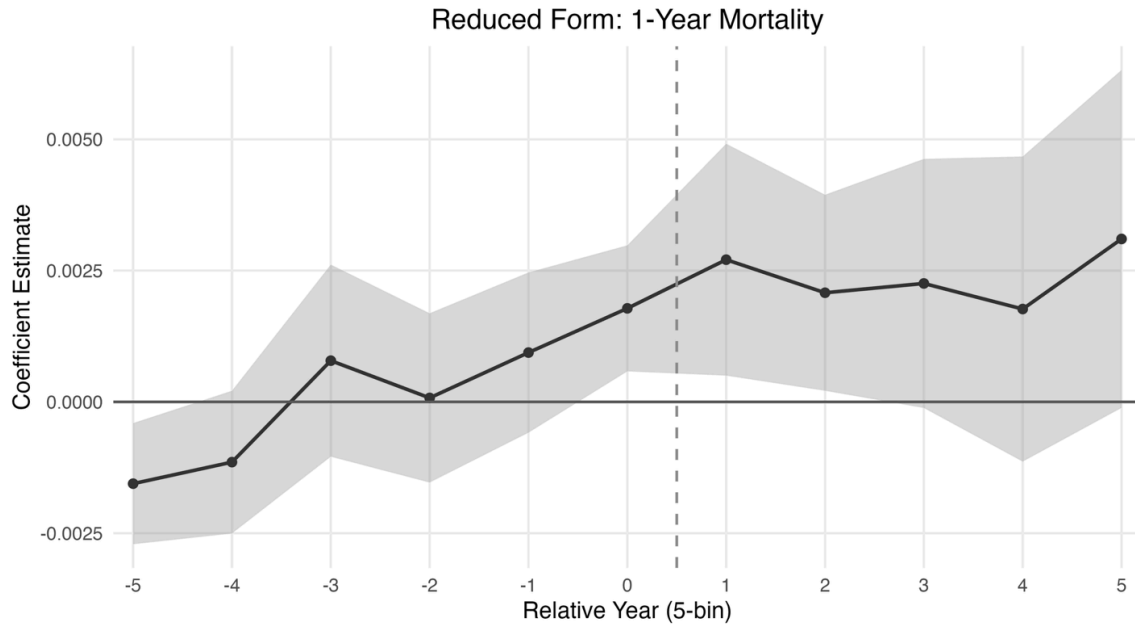


Figure 2.10 : Event Study of Impact of Default Enrollment on One-Year Mortality

Notes: Figure plots event study coefficients and 95% confidence intervals from a two-stage difference-in-differences (2SDD) model of the impact of default enrollment approval on one-year mortality. Coefficients are shown relative to the year prior to policy approval (omitted category). Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

State	MMC Firm	Year of Default Enrollment Policy Approval	Total # of Beneficiaries
AZ	Firm A1	2016	5,233
AZ	Firm A2	2016	14,030
AZ	Firm A3	2016	24,770
AZ	Firm A4	2016	23,895
NY	Firm N1	2011	8,989
PA	Firm P1	2013	34,901
TN	Firm T1	2015	26,329
TN	Firm T2	2016	38,058
AZ	4 unique firms	NA - Never Treated	18,584
NY	19 unique firms	NA - Never Treated	340,080
PA	9 unique firms	NA - Never Treated	119,561

Table 2.1 : Medicaid Managed Care Firms, Default Enrollment Policies, and Enrollment Counts

Notes: The table shows the different firm-state pairs, the timing of their exposure to the default enrollment policy, and their total enrollment of Medicaid Managed Care beneficiaries who became eligible for Medicare. Eight unique firm-state pairs were approved for default enrollment from 2011 to 2016. A total of 32 firm-state pairs are “never-treated” control observations; Tennessee does not have any observations in the “never-treated” group.

Characteristic	Default Enrollment Eligible	NOT Default Enrollment Eligible
# of Beneficiaries	92,002	562,428
Female (share)	56.6%	57.5%
White (share)	50.1%	45.6%
Disability (share)	38.4%	48.4%
Any inpatient stay (share)	15.5%	16.6%
Inpatient days	1.56	1.68
Any Skilled Nursing Facility (SNF) stay (share)	1.5%	1.3%
Skilled Nursing Facility (SNF) days	0.755	0.504

Notes: The table reports summary statistics for Medicare beneficiaries eligible for default enrollment and those not eligible. The unit of observation is the beneficiary.

Characteristic	Enrolled in a D-SNP	NOT Enrolled in a D-SNP
# of Beneficiaries	114,492	539,938
Female (share)	59.5%	55.0%
White (share)	44.8%	48.0%
Disability (share)	39.2%	54.5%
Any inpatient stay (share)	15.6%	17.2%
Inpatient days	1.36	1.97
Any Skilled Nursing Facility (SNF) stay (share)	0.7%	2.0%
Skilled Nursing Facility (SNF) days	0.174	0.940

Notes: The table reports summary statistics for Medicare beneficiaries enrolled in a D-SNP plan and those not enrolled. The unit of observation is the beneficiary.

Dependent Variable	Estimate	Std. Error	95% CI	t-statistic
Any inpatient stay	−0.0074	0.0045	[−0.0162, 0.0013]	−1.6639
Inpatient days	0.0295	0.0868	[−0.1406, 0.1997]	0.3403
Inpatient days (conditional on any stay)	0.3252	0.3390	[−0.3393, 0.9897]	0.9592
Any Skilled Nursing Facility (SNF) stay	−0.0042	0.0016	[−0.0074, −0.0011]	−2.6276
Skilled Nursing Facility (SNF) days	−0.4271	0.1706	[−0.7615, −0.0926]	−2.5029
Skilled Nursing Facility (SNF) days (conditional on any stay)	−9.7368	2.7054	[−15.0394, −4.4341]	−3.5990

Notes: Each row reports the two-stage difference-in-differences (2SDD) estimate of the impact of default enrollment approval on the indicated hospital care utilization or post-acute care utilization outcome. Regressions include beneficiary covariates (sex and race/ethnicity) and Medicare managed care firm fixed effects. Standard errors are clustered at the state-firm level.

3

MEDICARE ADVANTAGE: NATIONAL CARRIERS EXPAND MARKET SHARE WHILE REGIONAL CARRIERS WITHOUT AFFILIATION DECLINE, 2012–23

Joseph G.P. Hnath, J. Michael McWilliams, and Michael E. Chernew. Published in Health Affairs 43, no. 12 (2024). DOI: [10.1377/hlthaff.2024.00577](https://doi.org/10.1377/hlthaff.2024.00577). This chapter is co-authored; Joseph G. P. Hnath led the analysis and writing. The text below is reproduced from the published article. Figures are the authors' own renderings (prepared during manuscript development) rather than the publisher's typeset versions. Supplementary material appears in Appendix A.

3.1 Abstract

This study examined the evolving landscape of insurer competition in the Medicare Advantage (MA) program from both national and local perspectives. Data from the Centers for Medicare and Medicaid Services revealed that the MA market has become more concentrated. National carriers expanded their national market share significantly from 2012 to 2023, whereas the collective market share of regional carriers without affiliation to Blue Cross and Blue Shield organizations declined because of acquisitions. For example, the combined national market share of national carriers increased from 46 percent in 2012 to 66 percent in 2023, while the combined national market share of non-Blue regional carriers decreased from 25 percent to 6 percent. Conversely, concentration in local markets has declined but remains highly concentrated, and evidence suggests that further declines may be unlikely. Specifically, declines in local market concentration have been limited to markets with low MA penetration. Once MA penetration exceeds 20 percent, further MA growth is not associated with further drops in concentration, on average. Thus, policymakers should be aware that MA program reforms that assume MA markets are competitive are unlikely to achieve program goals without ensuring the competitiveness of those markets.

3.2 Introduction

The Medicare Advantage (MA) market now covers more than half of Medicare enrollees and is expanding.¹ MA depends heavily on competition, relying on plan bids to set payments to plans and benefits.² Evidence suggests that more competitive MA markets are associated with lower bids and more generous benefits.³⁻⁵ Moreover, competition is central to MA payment reform proposals that rely on bidding to set benchmarks.⁶

The degree of competition in MA varies geographically and has been changing.⁷⁻¹⁰ Specifically (and paradoxically at first blush), the national MA market has become more concentrated (that is, less competitive) while local markets (counties) have, on average, become somewhat less concentrated (that is, more competitive).¹¹ This pattern has emerged as large MA carriers have expanded the number of counties they serve. Thus, a major question is whether the increasing competitiveness of local markets should be expected to continue after larger insurers establish a presence in a high proportion of counties. Have

the decreases in local market concentration occurred predominantly in counties that were highly concentrated at baseline because of limited MA presence? Or has the recent growth of MA also been associated with increasing competitiveness in markets with high MA penetration?

This article expands existing analyses of trends in MA enrollment and competition. We document the change in market shares within MA at the national level, focusing on how various types of carriers (for example, national carriers, regional Blue Cross and Blue Shield plans, and others) have grown over time. We document the contributions of acquisitions to that growth. To examine local markets, we document the joint evolution of HHI (Herfindahl–Hirschman Index) and MA penetration to determine whether the decreases in local market concentration are likely to continue.

3.3 Study Data and Methods

3.3.1 Data

We used publicly available data from the Centers for Medicare and Medicaid Services (CMS) Monthly Enrollment by Contract/Plan/State/County files from the period 2012–23. Although these files are available monthly, we focused on the December enrollment counts.

3.3.2 Variables

3.3.2.1 Plan Types

We focused on coordinated care plans, such as health maintenance organizations and preferred provider organizations, and Special Needs Plans (SNPs). We dropped employer group health plans, which represent 17 percent of the market. We did so because plan design and enrollment in those plans is largely determined by employers, and the plans likely do not compete with plans offered to people without employer subsidies.

We mapped the insurance carrier, or “parent organization,” of each MA plan into several groups: national carriers (Cigna, CVS, Elevance, Humana, and United), regional Blue Cross and Blue Shield plans, health system–integrated organizations (for example, Kaiser Permanente and UPMC), Medicaid-oriented organizations (for example, Centene and Molina), start-ups (for example, Alignment and Clover), SNP-only organizations (for example, Mercy Care and Orange County Health Authority), and non-Blue regional carriers

(for example, EmblemHealth and SCAN). Details on these categories are in the online appendix.

3.3.2.2 Measures of Concentration

We limited our analysis to markets in the fifty US states and Washington, D.C. Although we report the number of carriers in markets, our primary measure of concentration was the Herfindahl–Hirschman Index (HHI), an often-used measure of market concentration equal to the sum of squared market shares.¹⁴ The Department of Justice and the Federal Trade Commission now consider markets with HHIs between 1,000 and 1,800 to be moderately concentrated and those with HHIs greater than 1,800 to be highly concentrated.¹⁴ For our analyses, markets with an HHI less than 1,000 were defined as having “low” concentration, and those with HHIs between 1,000 and 1,800 were defined as having “moderate” concentration. Using the pre-2023 thresholds of concentration, we added three other categories of concentration: HHI 1,800–2,500, which we call “moderately high” concentration; HHI 2,500–5,000, which we label “high” concentration; and HHI higher than 5,000, which we label “extremely high” concentration.

3.3.2.3 Acquisitions and Enrollment Growth

We identified acquisitions based on changes in the parent organization for an MA contract, using the Contract/Plan/State/County data. We confirmed these ownership changes with a manual review of online sources to confirm that these were ownership changes rather than organizational rebranding or other minor changes in data labels (for example, including or excluding “Inc.”). The full list is in the appendix. Although some acquisitions may have occurred in the middle of the year, we followed the approach of the Contract/Plan/State/County files to keep the parent organization constant within each year for simplicity.

To calculate enrollment changes attributable to acquisitions, we summed both direct and indirect enrollment changes. The direct enrollment changes attributable to acquisition considered only the enrollment in the acquired plan at the last observation before the change of ownership as attributable to the acquisition. This is the most concrete measure of the impact of acquisition on enrollment. Indirect enrollment changes attributable to an acquisition arise because the enrollment in the acquired carriers may have grown after the

time of acquisition (in the absence of acquisition). Our measure of indirect enrollment effects assumed that the market share of the acquired and acquiring carriers in each market would have stayed constant in the absence of acquisition (that is, both carriers would have grown at the same rate). For example, if the acquiring carrier had no presence in a market before the acquisition, we attributed all of its enrollment growth in that market to the acquisition. If the acquired carrier had 40 percent of the enrollment of the combined enrollment pre-acquisition, then the direct effect of the acquisition was the enrollment acquired at baseline. The indirect enrollment effect included 40 percent of the subsequent enrollment growth of the combined entity in the market.

In addition to acquisitions, we measured enrollment growth from new and existing markets, based on whether or not a carrier offered a plan in a county in 2012.

3.3.3 Analyses

We conducted four analyses. First, we computed the average change in national market share by carrier category. Second, we decomposed that growth into organic growth and growth attributable to acquisitions. Third, to assess the change in local competition, we examined the distribution of markets by HHI category at the start of our study period (2012) versus the end (2023). Finally, we examined the relationship between MA penetration and market concentration.

For the two local-level analyses, we calculated the MA penetration and HHI for each county. To aggregate the county-level estimates, we weighted each county by its total Medicare (Parts A and B) population, which included all beneficiaries enrolled in MA, traditional Medicare, and other plan types.

3.3.4 Limitations

This study had several limitations. First, including SNPs in our main analysis potentially overstated competition because the overwhelming majority of SNP enrollment is restricted to dually eligible Medicare-Medicaid beneficiaries. Sensitivity analyses that excluded SNPs showed that the non-SNP market was somewhat more concentrated, but our conclusions were not substantively different (see the appendix). Second, the carrier groupings, particularly our definitions of national versus regional plans and Medicaid-oriented organizations,

required some subjective decisions. Our criteria used a combination of the number of states a carrier operated in and its MA, commercial, and exchange market share (see the appendix). Third, the trends we report may change over time (and may be affected by MA policy). For example, Cigna has announced plans to sell its MA business to Health Care Service Corporation,¹⁵ which may increase concentration (nationally and locally). Fourth, we weighted counties by the total population of Medicare beneficiaries in each year (restricting the analysis to counties with at least one MA enrollee) to describe the market concentration encountered by the average beneficiary. Weighting by MA enrollment lowered 2012 HHI values because market concentration was very high in counties with minimal MA presence. The basis for weighting became less salient over time and affected our results minimally by 2023 (Appendix Figure B.1). Finally, our measure of the indirect enrollment effect of acquisition relied on the assumption of constant market shares. However, we could not be certain how enrollment trends in the acquired carrier would have evolved. For example, acquired carriers may have been motivated to sell by anticipated enrollment declines that the acquisition reversed.

3.4 Study Results

3.4.1 Trends in National Presence by Insurer Type

Nationally, MA market shares have become increasingly concentrated in the five national carriers, whose combined market share has increased from 46 percent in 2012 to 66 percent in 2023. In local markets, the average HHI (weighted by county Medicare population) decreased from 4,300 to 3,000 during that time frame (Figure 3.1). Of the five national carriers, United and Humana were the clear leaders throughout the study period, but CVS, Elevance, and Cigna have also grown rapidly since 2012 (see online appendix exhibit A2 of the published article). Although non-Blue regional carriers collectively had the second-largest market share among the categories of insurers in 2012, at 25 percent, this dropped precipitously to just 6 percent in 2023. The market shares of the regional Blues plans and MA plans that were integrated with health systems remained stable, at around 10 percent and 13 percent, respectively. Importantly, this stability in market share was occurring as

the overall MA market grew, so these plan types experienced proportional growth. These trends were similar when we excluded SNPs, with the largest market-share declines seen for United and Medicaid-oriented carriers (online appendix exhibit A3-S1 of the published article).

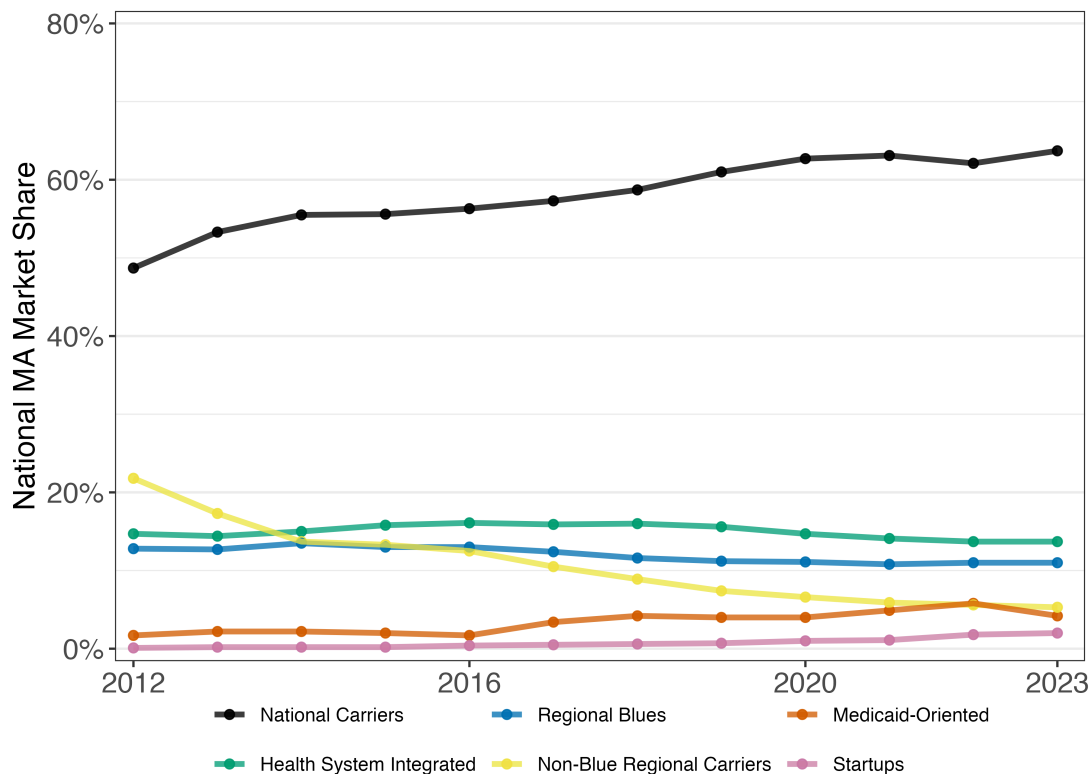


Figure 3.1 : Growth in Medicare Advantage (MA) market share, by MA carrier type, 2012–23. Authors’ analysis of data from the Centers for Medicare and Medicaid Services (CMS) Monthly Enrollment by Contract/Plan/State/County files, December 2012–December 2023. Market share is constructed from enrollment in certain MA plans: non–Special-Needs Plans (non-SNPs), non–employer group health plans, and coordinated care plans. Carrier groupings: national carriers (Cigna, CVS, Elevance, Humana, and United), regional Blue Cross and Blue Shield plans (regional Blues), health system–integrated organizations, Medicaid-oriented organizations, start-ups, SNP-only organizations, and non-Blue regional carriers. Authors’ own figure rendering.

Although start-ups have received a lot of attention and have grown dramatically, from enrollment of 12,000 to more than 400,000 during the period we examined, they remained a small player on the national scale. They had a collective market share of only 2 percent in 2023. That said, they had the largest market share in five counties, but those markets were typically small, representing 0.5 percent of the total Medicare population (see online appendix exhibit A4 of the published article). For example, Bright Health had a market share of 62 percent in Imperial, California, which had a total of 12,000 MA enrollees in the market (data not shown).

3.4.2 Enrollment Growth and Acquisitions

Over the course of our study period, we identified seventy-seven ownership changes (Appendix Figure B.4). These occurred at a relatively constant rate over time and ranged in size (enrollment of the acquired insurer before acquisition) from 3,867 enrollees in one county to 540,401 in 642 counties. Figure 3.2 describes the enrollment growth (both direct and indirect) from 2012 to 2023 attributable to acquisitions, entrance into new markets, and growth in existing markets for each carrier group. There was substantial variation across carriers: Medicaid-oriented carriers, Elevance, and Cigna had the majority of their enrollment growth from acquisitions. CVS and start-ups primarily gained from entering new markets without acquisitions; they varied widely in the share of this expansion that was a result of acquisitions, ranging from 7 percent for Elevance to 36 percent for Medicaid-oriented carriers (see online appendix exhibit A4 of the published article). However, acquisitions only accounted for a small share (15 percent) of total market entry events nationally (see online appendix exhibit A7 of the published article).

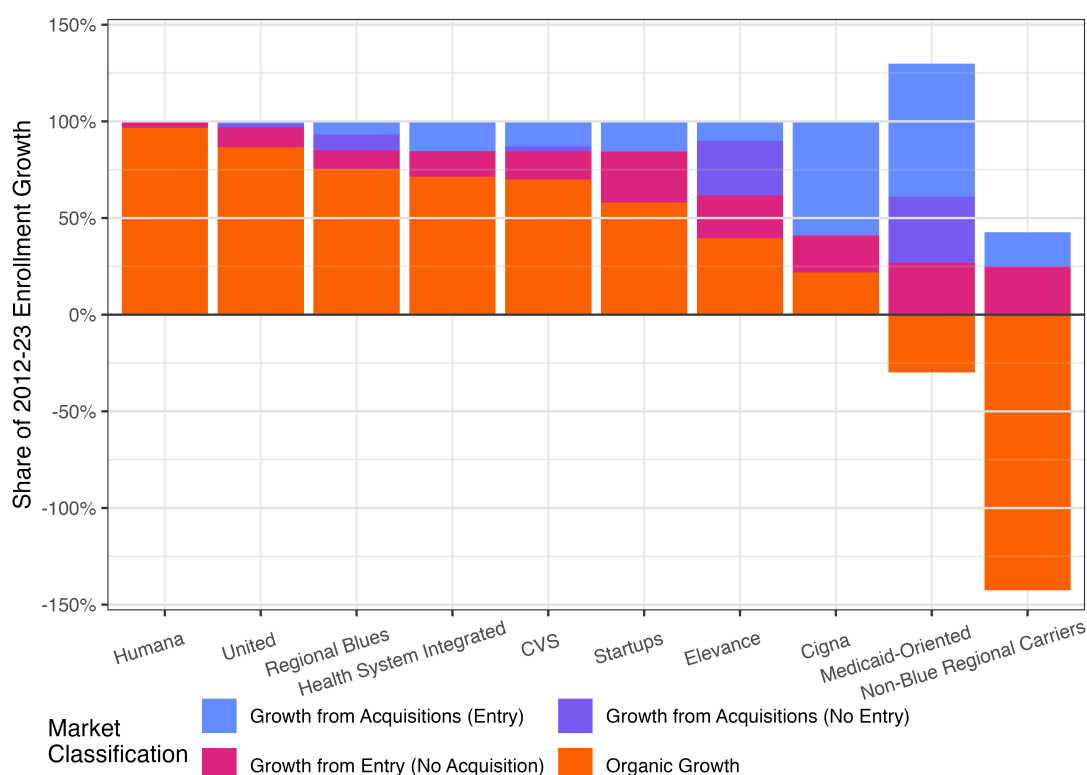


Figure 3.2 : Enrollment growth in Medicare Advantage (MA) attributable to acquisitions, entry into new markets, and growth in existing markets, 2012–23. Authors’ analysis of CMS Monthly Enrollment by Contract/Plan/State/County files, December 2012–December 2023. MA enrollment includes only enrollment in specific MA plans (see the Figure 3.1 notes). Authors’ own figure rendering.

On average, when weighted by Medicare beneficiaries, the total number of carriers per county increased from 6.4 in 2012 to 9.9 in 2023 (online appendix exhibit A8 of the published article). Excluding SNPs, the average number of carriers per county dropped to 8.3 in 2023. In addition, many carriers had very small MA market shares. When we excluded those with market shares of less than 5 percent, the average number of carriers per county in 2023 further dropped to 4.4.

3.4.3 Local Market Concentration and MA Penetration

Over the course of our study period, the share of Medicare beneficiaries living in markets with extremely high concentration (HHI greater than 5,000) fell from 29 percent to 6

percent as carriers expanded into new markets (Figure 3.3). Specifically, 19 percent of total Medicare beneficiaries lived in a county that changed from extremely high concentration to high concentration (see online appendix exhibit A9 of the published article). Along with the decline in the number of extremely competitive markets, markets also shifted from high to moderate concentration. Together, these shifts resulted in a minimal decrease in the share of beneficiaries living in markets with high concentration (2,500–5,000) (from 56 percent to 54 percent) and an 18-percentage-point increase in the share living in moderately high concentration (1,800–2,500) (from 10 percent to 30 percent) between 2012 and 2023 (see online appendix exhibit A10-S3 of the published article).

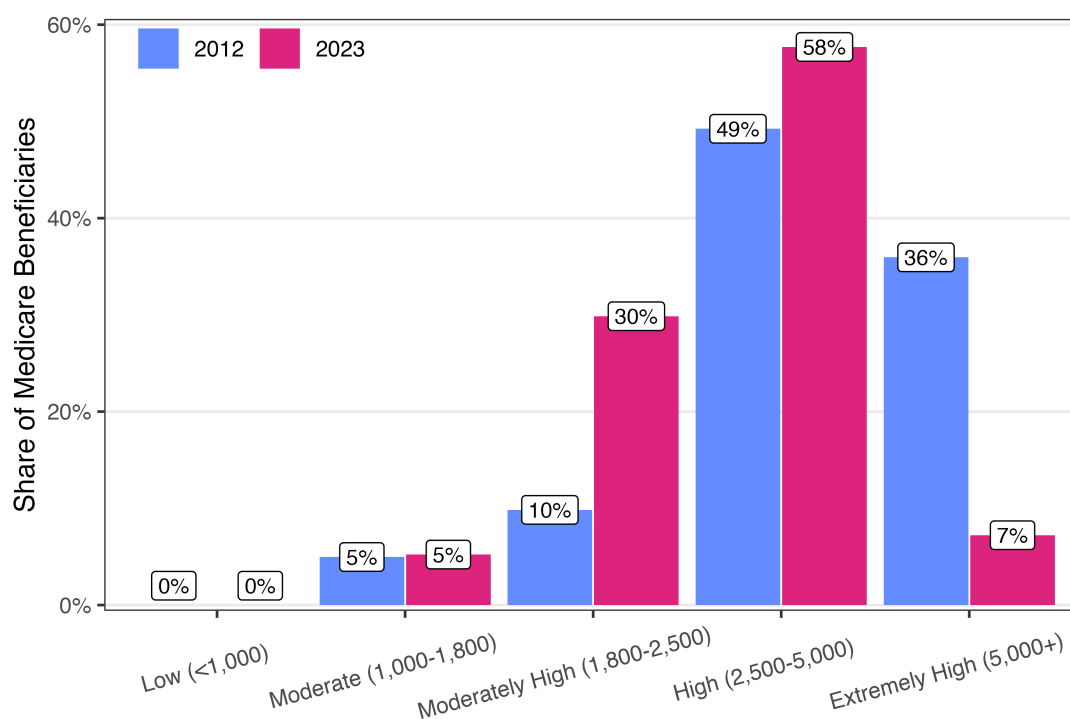


Figure 3.3 : Changes in the distribution of Medicare beneficiaries across Herfindahl–Hirschman Index (HHI) market concentration categories, 2012 and 2023. Authors’ analysis of CMS Monthly Enrollment by Contract/Plan/State/County files, December 2012 and December 2023. MA enrollment includes only enrollment in specific MA plans (see the Figure 3.1 notes). HHI is calculated using carrier-level market shares for each county, and each county is weighted by its Medicare Parts A and B population. HHI thresholds are based on current and previous Department of Justice and Federal Trade Commission horizontal merger guideline thresholds. Authors’ own figure rendering.

Although growth in MA penetration has been associated with declining HHI when MA penetration is low (less than 20 percent), this relationship plateaued at an average HHI of around 3,000 for markets where MA penetration exceeded 20 percent, which covered about 95 percent of beneficiaries in 2023 (Figure 3.4). The relationship between MA penetration and HHI was similar in 2012; as MA penetration increased over time, more counties moved along the curve to the flat portion (see online appendix exhibit A11 of the published article). Thus, as the MA program grew, the increases in local market competition were concentrated

among counties with limited prior MA presence. This suggests that policymakers should not expect further growth in MA penetration to be associated with increased competition in local markets now that MA penetration exceeds 20 percent in nearly all counties. This pattern was very similar when we excluded SNPs (see online appendix exhibit A12-S4 of the published article).

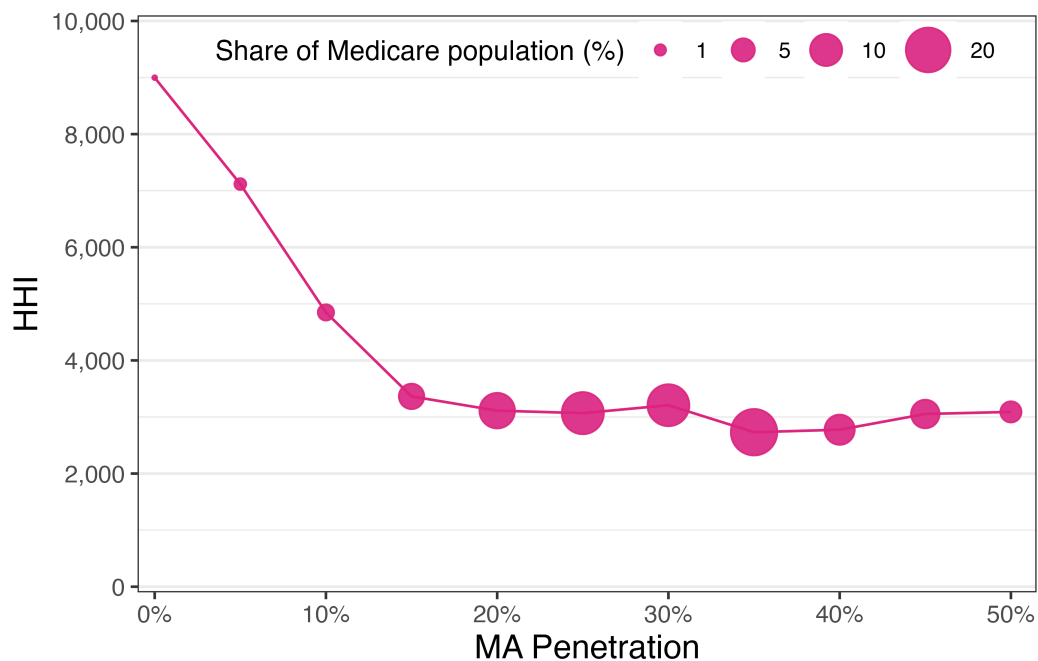


Figure 3.4 : Association between Medicare Advantage (MA) penetration and Herfindahl-Hirschman Index (HHI), 2023. Authors’ analysis of CMS Monthly Enrollment by Contract/Plan/State/County files, December 2023. MA enrollment includes only enrollment in specific MA plans (see the Figure 3.1 notes). HHI is calculated using carrier-level market shares for each county, and each county is weighted by its Medicare Parts A and B population. The share of Medicare population is defined as the sum of beneficiaries enrolled in Medicare Parts A and B at the county level for each 5 percent bin of MA penetration. Counties with MA penetration of 60 percent and higher are grouped in the final point at 60 percent. Authors’ own figure rendering.

3.5 Discussion

We present novel findings on how competition has evolved in MA since 2012 from national and local perspectives. Nationally, the large national carriers (Cigna, CVS, Elevance, Humana, and United) increased their market share from less than 50 percent in 2012 to almost 66 percent in 2023. This was closely related to the decline in regional carriers, which were the primary targets of acquisitions by some national carriers.

This national consolidation of market share would not be as concerning if competition continued to increase at the local level. However, our analyses suggest that this trend is unlikely to continue because it has been largely a result of shifts in local market concentration from the highest categories of concentration to categories that, although less concentrated, would not be defined as competitive. Moreover, this shift has largely occurred in counties with initially limited MA presence, and few counties with low MA penetration remain. Thus, gains in local competition may have run their course. This is reflected in local measures of competition clearly showing stagnating trends in concentration as MA grows.

Of course, the future is unknown. Although start-ups have not had a significant effect on many markets to date, they may have growing success in the future. The extent to which they do likely depends on how future MA policy — particularly regarding payment generosity — evolves. If payment becomes less generous, the likelihood of start-ups being more effective declines. In contrast, the pending acquisition of Cigna by Health Care Service Corporation suggests that some markets will consolidate more and, more broadly, that policymakers should not assume that all carriers in the MA market will continue to participate in MA.¹⁵

The degree to which policymakers should be concerned with the growing share of national carriers and high concentration in many local markets depends on two factors. First, if the growing share of national carriers reflects better value (for example, better benefits or lower premiums), policymakers may be comfortable with a decline in national competitiveness. However, it is possible that other factors, such as proficiency in coding or the competitive edge associated with ownership of related entities (providers or pharmacy benefit managers), create an imbalanced playing field that leads to concentration. More

evidence on the variation in value across plans that are offered by national or regional carriers is thus needed.

Second, how much competition is enough? MA plans are paid more than would be spent in traditional Medicare,¹⁶ and competition drives how much of that additional payment is passed through to beneficiaries in the form of more generous coverage at lower premiums. Ten competitors (carriers in our case) would be considered sufficient for competition in most industries. However, many of these carriers are small and might not be directly competing with other carriers or might be competing only for subpopulations. Small market shares in a given county can occur, for example, for start-ups or when a carrier's provider network is concentrated in neighboring counties. In addition, because of product differentiation (for example, health system-integrated or start-up plans may offer niche products with very limited local networks) and segmentation of the market for dually eligible enrollees (D-SNPs), the effective number of competitors may be less than a simple count of carriers would imply. Although we cannot determine how many carriers would be needed to create a sufficiently competitive market, the high HHIs, which have not risen much as new carriers entered, and incomplete pass-through suggest that competition could be improved.^{3-5,17,18}

Importantly, pass-through can be enhanced by increasing competitiveness for any given number of competitors. Potential options include policies that limit the number of plan offerings per carrier, standardize the benefits that plans must offer, address inertia in beneficiaries' decision making by improving the information available to them to facilitate shopping, or enhance coverage in traditional Medicare and reduce plan payments in MA to exert greater pressure from a public option for plans to share more surplus with enrollees. Moreover, with a growing share of dually eligible beneficiaries enrolling in MA, it is important to understand the role of SNPs in driving MA competition.

Although the effects of competition are important in the current MA program, competition becomes even more salient if MA reforms make the benchmarks a function of bids (for example, competitive bidding). In that case, even if MA plans offer better benefits,

imperfect competition can lead to substantially higher Medicare spending unless a cap on benchmarks is imposed.

3.5.1 Conclusion

Given the growth in MA and the importance of competition to the MA program, tracking the trends in market consolidation is important. Although consolidation at the local level has fallen, consolidation in most markets remains above a threshold that would trigger regulatory concern. If current patterns hold, this is unlikely to change as MA penetration grows, and it may in fact get worse if MA payments become less generous and additional acquisitions consolidate local markets. Thus, policymakers should be aware that MA program reforms that are built assuming that MA markets will be competitive are unlikely to achieve program goals without ensuring the competitiveness of those markets.

3.6 Acknowledgments and Funding

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3.7 Notes

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4

COMPETITION AND ENTRY IN MEDICARE ADVANTAGE

Joseph G.P. Hnath, J. Michael McWilliams, and Michael E. Chernew. This chapter is co-authored; Joseph led the analysis and writing.

4.1 Abstract

Importance: Competition is essential for efficient health insurance markets, particularly in Medicare, where over 34M beneficiaries are enrolled in Medicare Advantage (MA) plans, but there is limited recent research evaluating changes in competition.

Objective: To evaluate how changes in competition due to entry are associated with changes in Medicare Advantage plan bidding.

Design, Setting, and Participants: A longitudinal cohort of incumbent Health Maintenance Organization (HMO) and Local Preferred Provider Organization (LPPO) MA plans offered from 2016–2023 across the U.S. was analyzed using a continuous-treatment difference-in-differences (cDiD) research design.

Exposures: The number of competing insurance carriers for a given MA plan, averaged across the county markets where the plan was offered, weighted by relative MA enrollment across the markets.

Main Outcome and Measures: The main outcome was the MA plan’s monthly rebate, capturing the difference between the county MA benchmark and the plan bid. This rebate is directly related to premium reductions and supplemental benefits.

Results: The data represent 21,815 MA plan-years offered by over 100 distinct MA insurance carriers, covering nearly 80M beneficiary-years. Nationally, the average number of MA insurance carriers per county market increased from 6.3 in 2016 to 8.3 in 2023. Using our cDiD research design, we estimate that an increase of one competitor in the market average where a plan by an incumbent insurance carrier is offered causally increased rebates by \$5.36, PMPM (per member per month) [95% CI, \$1.37–\$9.35; $p = 0.012$]. During the study period, the average PMPM rebate was \$103.57 (SD: \$66.25), and the average number of competing insurers was 6.5 (SD: 3.3), so a 15% increase in the number of competitors increased rebates by 5.2%. This effect is almost entirely driven by entry in concentrated markets (defined as the highest tercile of concentration measured by the Herfindahl-Hirschman Index [HHI]).

Conclusions and Relevance: There is clear evidence that increases in the number of competing insurance carriers in MA causes increases in rebates; however, these effects are exclusively in the most concentrated markets. Policymakers should consider whether the current levels of competitive pressure across markets is adequate, or if additional regulation is desired to foster additional competition.

4.2 Introduction

Competition in markets for hospital & physician services and for health insurance has declined over the last 40 years as concentration in these markets has risen.¹ Additionally, the entry of new firms serves as a countervailing force for competition to increase and for consumer outcomes to improve.² However, choice complexity and differentiated products may inhibit the anticipated benefits from additional competitors. Different health care markets have differing amounts of heavy-handedness of government regulation to either stimulate competition or to do so. As such, it is important to evaluate each market individ-

ually, accounting for regulatory dynamics, consumer choice behavior, and firm strategy concerning pricing and product differentiation.

Medicare Advantage now enrolls over 30 million people and has total government expenditures of over \$450 billion per year.³ In Medicare Advantage, consolidation has increased nationally, where the market shares of large, national carriers have increased while those of smaller, regional carriers have decreased.⁴

Most of the studies examining competition in MA analyze how the effects of policy changes (e.g., payment) vary across markets with different levels of competitiveness. These studies generally find evidence of incomplete pass-through of higher payments to plans to beneficiaries. These studies examined the market 10 to 20 years ago, when MA was much different and may be confounded by unobserved differences in markets with more, vs fewer competitors.⁵⁻⁷

To our knowledge, no existing papers explicitly study the effects of changes in competition in Medicare Advantage, especially when specifically looking at the entry of new health insurance carriers into markets. One reason for this is the difficulty in operationalizing a causal inference design in this complex application. We leverage frontier econometric contributions for continuous treatment difference-in-differences (elaborated in its own section of the paper) to produce these novel results on the effects of entry and competition on rebates in Medicare Advantage.

4.3 Methods

4.3.1 Data

The data for this study are publicly available from the Centers for Medicare and Medicaid Services (CMS). Specifically, we use the Monthly Enrollment by Contract/Plan/State/County files and the Part C Plan payment files (2016–2023).⁸ This allows us to construct the panel data set following the MA plans over time and how their rebates may be changing in response to changes in their competitors.

4.3.2 Sample

This study focuses on non-SNP [Special Needs Plans], non-EGHP [Employer Group Health Plans] Local CCP (HMOs and Local PPOs). We exclude SNPs, EGHPs, and other MA

plans (such as Regional PPOs and Cost Plans) because they have much less enrollment and are substantially different products from the core MA Local CCPs. SNPs and EGHPs restrict eligibility, and they follow different bidding regulations. By focusing on this clearly defined subset (which is the majority) of MA, we can be more precise and confident in our causal estimates. Future work should explore both the effects of entry among these other MA plans and the possibility of cross-market effects between all different MA plans.

4.3.3 Outcomes: Plan Bids and Rebates

The primary outcome for this study is the MA plan rebate. These plans submit bids to CMS based on their expected cost to provide the health insurance services listed in their plan benefit package to the average beneficiary (i.e., risk score of 1.0). These bids are then compared to the county-level MA benchmark, or the enrollment-weighted average of the various counties encompassing a plan’s service area. The rebate depends on the difference between the bid and the benchmark, and is further modified by the contract star rating of the MA plan. The vast majority of MA plans bid below the benchmark, and this rebate amount is returned to beneficiaries either through the more generous benefits or through premium reductions. Thus, we consider a strong measure of plan response to competitive pressure because it incorporates both potential changes in prices and quality. We also conduct robustness checks using the bid as the outcome of our models.

4.3.4 Exposure/Treatment: Entry and Competition

Competition is typically measured using the Herfindahl-Hirschman Index (HHI), which is the sum of squared market shares.⁹ While this is a good descriptive measure to describe market concentration, it is not the ideal choice of a “measure” of competition for difference-in-difference studies because it reflects compositional changes among the same competitors.¹⁰

Rather, we parameterize changes in competition by directly measuring the average number of competitors for each MA plan across its service area counties. This better represents changes in competition rather than HHI because the “shocks” or changes in competition are larger & more variable, they are not related to compositional changes in market share, and it is more policy-relevant concerning regulations incentivizing entry.

Additionally, while MA markets are at the county level, we argue that the proper unit for measuring competition for any given plan is competition in the plan’s service area. Thus, our measure of competition aggregates over all the counties a plan serves.

Bids are submitted in June of the previous year of when the MA plan will be operating (i.e., the contract year [CY]). For example, for a plan operating in 2019, if there is entry by a competitor in 2019 (observed in October 2018 during the Annual Enrollment Period [AEP]), the incumbent plan will not have definitively known this when submitting its bid in 2018. So, we may not expect to see an immediately large response in the incumbent’s rebate until the year following the 2019 entry, 2020, for which bids are submitted in June 2019. However, there may be non-public information that leads incumbent plans to guess or assume that a plan may be entering before it is confirmed. Because a key assumption of difference-in-differences is “no anticipation” (i.e., there are no effects of the treatment prior to when it is operationalized in the model), we do not estimate our models with a lag, preferring potential attenuation in the pooled DiD estimate rather to invalid causal estimates violating this assumption. Event study approaches will help us elucidate potential timing, but they will not directly answer the question about which exact timing to prefer.

It is plausible that “not all entries should be treated equally”. It is reasonable to assume a relatively broad distribution of cross-elasticities of demand, where there is variation in how much substitutability & competition carriers and/or plans exert on the incumbents. Some entrants may be offering plans that are very similar to (or very different from) the incumbent plans. One way to proxy for competitive pressure on incumbents is to measure the market share that the entrant has once it enters the market. We acknowledge that this is endogenous, so it is not our preferred model, but it can provide some evidence on whether entry when a firm has a large market share (from here on referred to as “substantial” entry) is different from overall entry. We caveat this by conveying that there are economic arguments for any relationship. Specifically, it depends on the aforementioned cross-elasticity of demand. If the entrant is a complement, the incumbent rebate likely would not change. If it is a substitute, we would expect larger competitive effects on the rebate.

Unfortunately, the market share threshold estimates do not provide any direct evidence distinguishing between competitive effects and underlying cross-elasticities of demand.

4.4 Statistical Analysis

4.4.1 Research Design — Difference-in-Differences

Our main results are from a difference-in-differences model leveraging changes in the number of competitors each MA plan faces. There is some complexity in the model because while the markets for MA plans are at the county level (where beneficiaries can choose between plans), MA plans can be offered in multiple counties, and the same plan across many counties has a single bid. Economic theory suggests that the effect of a 1-unit increase in competitors depends on the baseline amount of competition. For example, while going from 0-to-1 competitors and 9-to-10 competitors are both 1-unit increases, the former is a much larger “effective shock” to competition for the incumbent who was initially a monopolist.

Traditional two-way-fixed-effects (TWFE) estimators can be biased in the presence of treatment effect heterogeneity of this nature.¹¹ Additionally, in our context, there is staggered treatment timing and non-binary treatment, both potentially causing additional bias.¹¹ Fortunately, there have been recent innovations in difference-in-differences estimation that are robust to these potential biases in this non-standard setting. Specifically, the “continuous difference-in-differences” estimator proposed by de Chaisemartin *et al* is one approach to handle this setting appropriately.¹²

This approach allows us to consider the following intuitive comparison: for two MA plans starting at the same baseline of competitors and following similar rebate trajectories, we compare the difference in the change of rebates for the MA plan that received an as-good-as-random (i.e., unrelated to their rebate trend) increase in their competitors to the change for an MA plan with no change in competitors. Specifically, the estimator compares the change in plan-year rebates between plans that started at the same baseline level of market structure via baseline number of competitors, but that experienced different post-period changes in active-carrier count, after netting out time-invariant plan and year differences.

The TWFE analog of the equation that we are estimating is below:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 \tau_{it} + \theta_t + \eta_i + \varepsilon_{it}.$$

Where y_{it} is our outcome, rebate (y) for MA plan (i) in time period (t). τ_{it} is the treatment indicator, and θ_t & η_i are the time and unit fixed effects, respectively. x_{it} is the single covariate of the average county benchmark for the MA plan.

The continuous DiD estimation approach estimates the following estimand using a sieve estimator, where β_2 is the TWFE estimand and ϕ_2 is the correct version of the ATT:

$$\phi_2 := \frac{1}{n_s} \sum_{i:S_i=1} \frac{\Delta Y_i - \hat{E}(\Delta Y \mid D_1 = D_{i,1}, S = 0)}{\Delta D_i}$$

For some brief details, this approach is unique in that it uses a polynomial sieve to flexibly model the dose-response in treatment-intensity change when the treatment is always continuously distributed. No other estimation approach, that we know of, can estimate a DiD model where treatment is continuously valued and non-zero for all units. For inference (i.e., estimating standard errors), we use 200 replications of cluster bootstrap, clustered at the treated unit (plan) level. This is because there is no formally proven asymptotic theory for their continuous treatment estimator when there are no 0-valued treatment units.

4.5 Empirical Results

4.5.1 Descriptive Trends in MA Competition

Figure 4.1 shows the national trends in the average number of MA carriers per county. In Panel A, we see an overall average increase from about 6.3 to about 8.3 from 2016–2023. It is also interesting in how the entire distribution shifted similarly, increasing by about 2, which indicates that there were larger “relative” changes at the low end (a 67% increase at the 10th percentile from 3 to 5 vs. an 18% increase from 11 to 13 for the 90th percentile), but they were all absolutely the same (2). Panel B compares markets across different baseline (2016) levels of concentration. The most concentrated tercile of markets increases from 3.8 to 5.5, while the least concentrated (i.e., most competitive) barely increases from 10.1 to 11. Together, these trends suggest we are approaching a ceiling of about 12 carriers per county, at least in the most competitive markets.

Figure 1. Trends in Medicare Advantage County Market Competition, 2016–2023

Excludes Special Needs Plans. Firm-county pairs with ≤10 enrollees dropped. N = 3,020 counties.

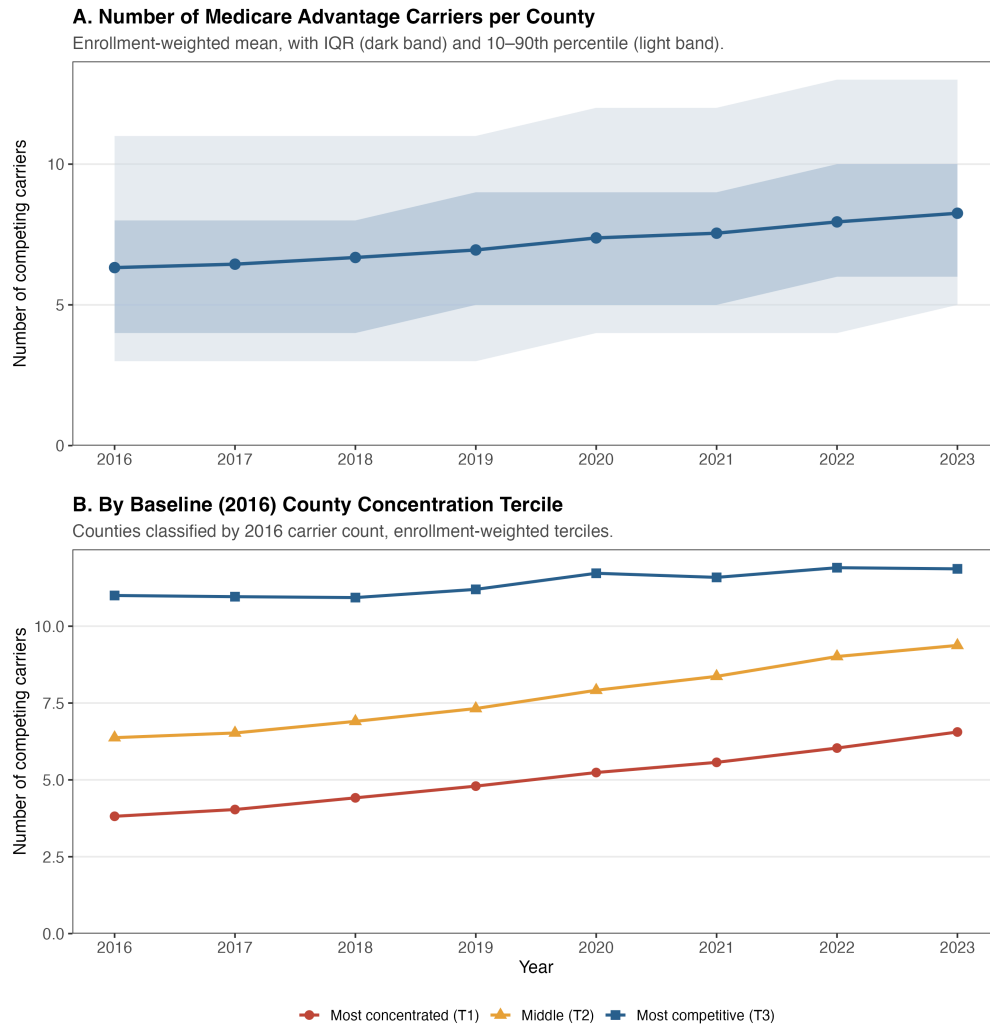


Figure 4.1 : National trends in MA carrier counts, 2016–2023. Panel A plots the cross-county distribution of average carriers per county-year (10th, 25th, 50th, 75th, 90th percentiles). Panel B plots the mean carrier count separately for the three baseline-concentration terciles.

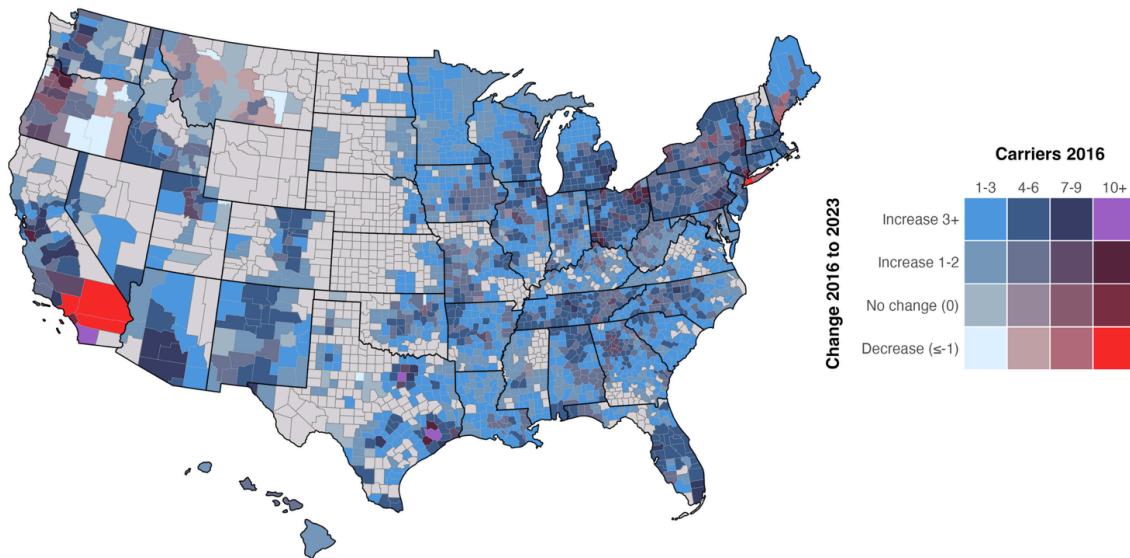
4.5.2 Geographic Distribution of MA Competition Changes

Figures 4.2 and 4.3 show the geographic variation in the baseline 2016 and change from 2016–2023 in the number of carriers. **Figure 4.2** shows all carriers without any entry threshold and has much more uniform patterns of increases in carriers across all regions

(i.e., the majority of county markets are colors in the top row). **Figure 4.3** focuses on carriers with at least 5% market share, and there is much more variation in the changes (columns), but the majority of county markets had 4 or more carriers with at least 5% market share in 2016 (the far right column).

Exhibit 2. Competing Medicare Advantage (MA) Carriers: Baseline (2016) and Change to 2023

Continental US & Hawaii (Alaska has no applicable MA). Horizontal = carriers in 2016; vertical = change to 2023.
Only non-SNP HMOs and LPPOs. Light gray = no MA data.

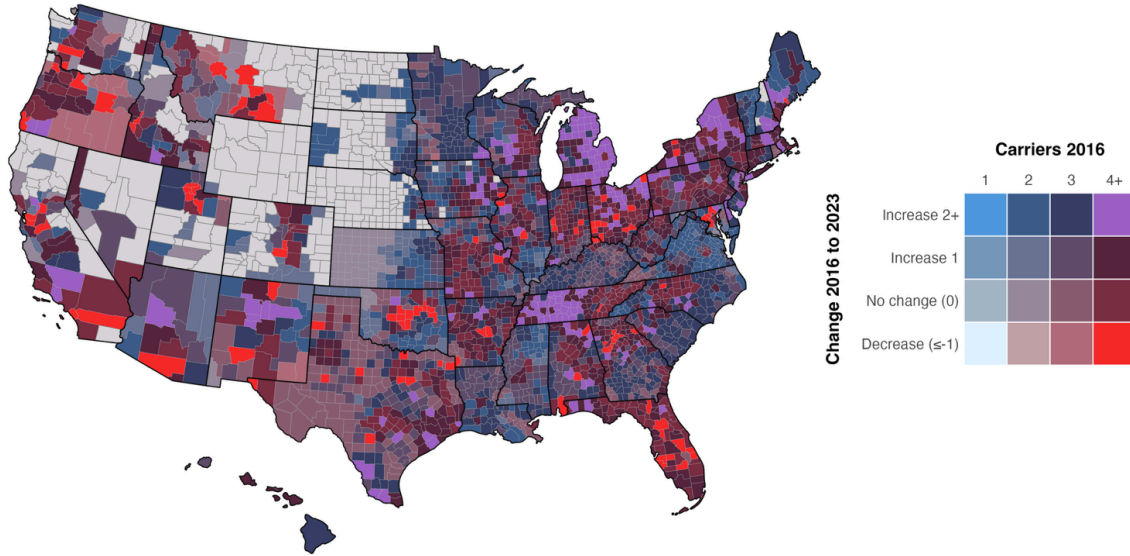


Source: CMS Medicare Advantage plan-level enrollment and bid data, 2016-2023.

Figure 4.2 : County-level bivariate map of MA market structure, 2016 and 2016→2023 change. Left panel: county active-carrier count in 2016 (lighter = fewer carriers / more concentrated; darker = more carriers / less concentrated). Right panel: change in active-carrier count, 2016 → 2023 (lighter = small or negative change; darker = larger positive change). Counties with no MA-eligible enrollment are in grey.

Exhibit 2. Competing Medicare Advantage (MA) Carriers with at least 5% Market Share: Baseline (2016) and Change to 2023

Continental US & Hawaii (Alaska has no applicable MA). Horizontal = carriers in 2016; vertical = change to 2023. Only non-SNP HMOs and LPPOs. Light gray = no MA data.



Source: CMS Medicare Advantage plan-level enrollment and bid data, 2016-2023.

Figure 4.3 : County-level bivariate map of MA market structure, focusing on carriers with $\geq 5\%$ market share, 2016 and 2016 $\rightarrow$ 2023 change. Left panel: county active-carrier count in 2016 (lighter = fewer carriers / more concentrated; darker = more carriers / less concentrated). Right panel: change in active-carrier count, 2016 $\rightarrow$ 2023 (lighter = small or negative change; darker = larger positive change). Counties with no MA-eligible enrollment are in grey. Source: author calculations on CMS Monthly Enrollment by Contract/Plan/State/County, 2016 and 2023.

4.5.3 Summary Statistics of MA Markets, Segmented by Changes in Competition

Variable	Decrease	No Change	Small Increase	Medium Increase	Large Increase
N (plans)	461	1,223	961	983	937
Δ carriers (mean, SD)	-0.65 (0.64)	0.00 (0.00)	0.51 (0.28)	1.43 (0.34)	3.50 (1.35)
<i>Panel A — County market characteristics (baseline)</i>					
Number of carriers	10.1 (3.6)	7.2 (3.4)	6.4 (2.2)	6.1 (2.2)	5.4 (1.9)
HHI	2,552 (980)	3,374 (1,373)	3,343 (966)	3,495 (1,159)	3,800 (1,300)
Benchmark, \$/mbr-mo	904 (87)	956 (123)	925 (93)	896 (82)	852 (60)
Double-bonus county, %	21.4	22.9	33.0	29.6	26.8
<i>Panel B — Plan characteristics (baseline)</i>					
Plan enrollment	35,223 (53,371)	25,999 (46,132)	17,908 (23,258)	16,900 (16,379)	22,891 (23,877)
Rebate, \$/mbr-mo	129.50 (55.87)	137.96 (77.81)	113.14 (51.92)	109.13 (50.58)	106.20 (59.44)
Bid, \$/mbr-mo	745.32 (84.75)	789.99 (90.88)	786.21 (77.99)	768.39 (74.41)	737.46 (72.45)
Star rating	4.18 (0.59)	3.95 (0.54)	4.03 (0.45)	4.10 (0.42)	4.24 (0.50)
Major national carrier, %	25.1	57.1	41.1	37.4	23.1

Table 4.1 : Descriptive characteristics of plan-years by change in average carriers over the panel. Plans are grouped into five buckets: Decrease ($\Delta < 0$), No Change ($\Delta = 0$), Small Increase ($0 < \Delta \leq 1$), Medium Increase ($1 < \Delta \leq 2$), Large Increase ($\Delta > 2$). Cells report mean (SD) of plan-year baseline characteristics.

4.5.4 Primary Results: Causal Effect of Entry on Rebates

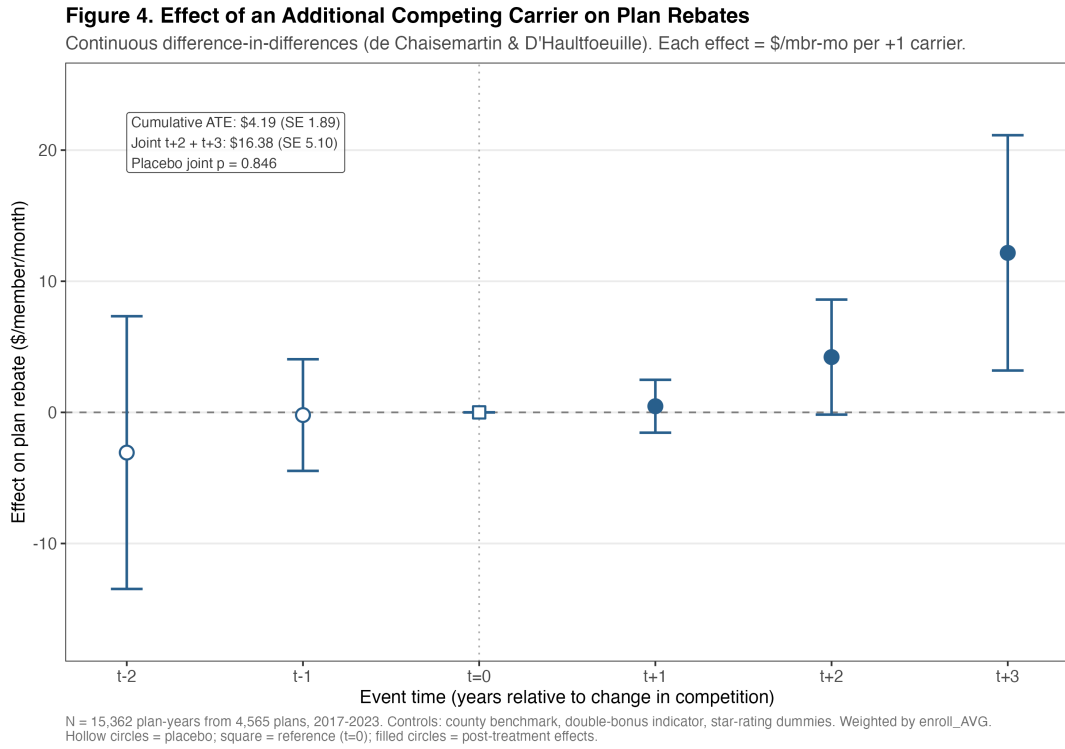


Figure 4.4 : Continuous-treatment dCDH event study, T_main definition, rebate outcome. Per-period coefficients on the change in plan-year average carrier count, with placebo coefficients shown at event-times -2 and -1 (open markers) and post-treatment coefficients at $+1$, $+2$, $+3$ (filled markers). 95% confidence intervals from 200-replication plan-clustered bootstrap. ATE = \$4.19 PMPM (SE 1.89, 95% CI \$0.50–\$7.89, placebo $p = 0.85$); joint cumulative $t+2+t+3 = \$16.38$ PMPM (SE 5.10, 95% CI \$6.39–\$26.37) on the 2017–2023 panel; corrected fit on the 2016–2023 panel yields cumulative \$17.80 (SE 4.53). Source: author calculations using `did_multiplegt_dyn`.

4.5.5 Robustness Checks

4.5.5.1 Entry Thresholds to Better Understand Heterogeneity across Entry Events

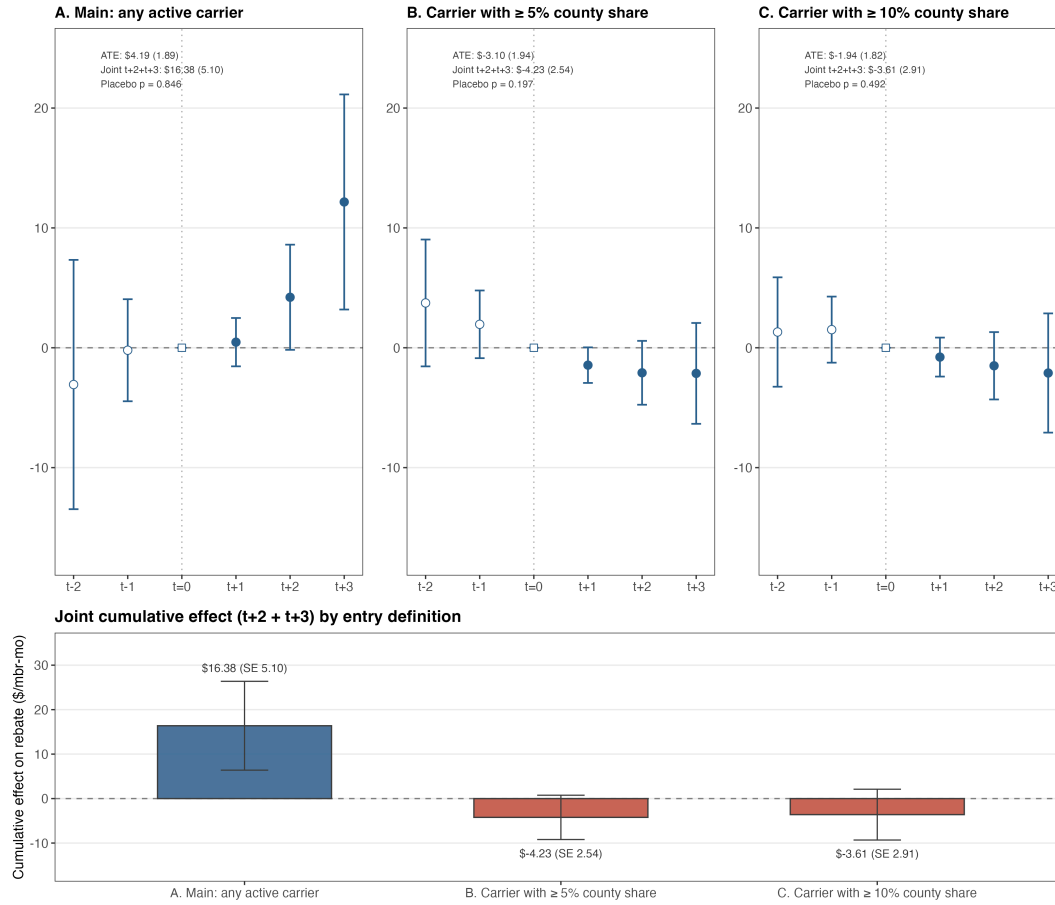


Figure 4.5 : Threshold robustness for the rebate outcome — three side-by-side event studies for the T_main, T_5, and T_10 carrier-count definitions, plus joint cumulative t+2+t+3 effects. Markers and CIs as in Figure 4.4. The right-hand bar chart shows joint cumulative effects for the three specifications; bar color encodes whether the joint effect's 95% CI excludes zero (blue = positive, red = inclusive of zero or negative). The parallel bid-outcome threshold panel is reported in the Online Supplement. Source: author calculations.

4.5.5.2 Heterogeneity by Baseline Concentration

Figure 5b. Per-Unit Effect of Carrier Entry on Plan Rebates, by Baseline Competition × Entry Definition

Joint cumulative effect at t+2 + t+3 (\$/mbr-mo per +1 carrier). Plans grouped by enrollment-weighted tercile of baseline (first-observed-year) carrier count.

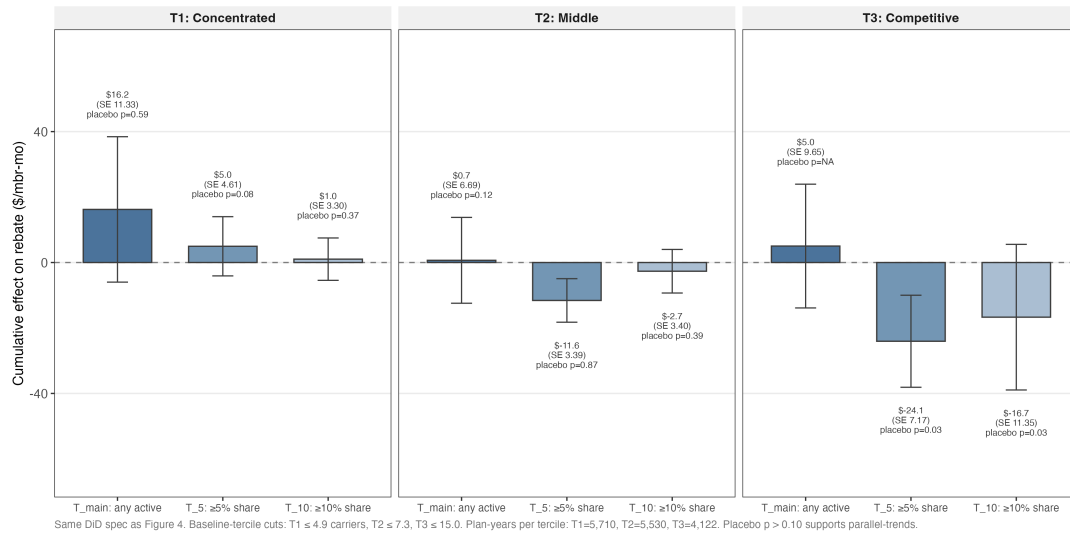


Figure 4.6 : Heterogeneity in the cumulative t+2+t+3 rebate effect across (i) carrier-count threshold and (ii) baseline-concentration tercile. Each cell shows the dCDH joint cumulative coefficient (SE) and the tercile sample size in plan-years.

4.5.5.3 Bids (Rather than Rebates) as our Outcome

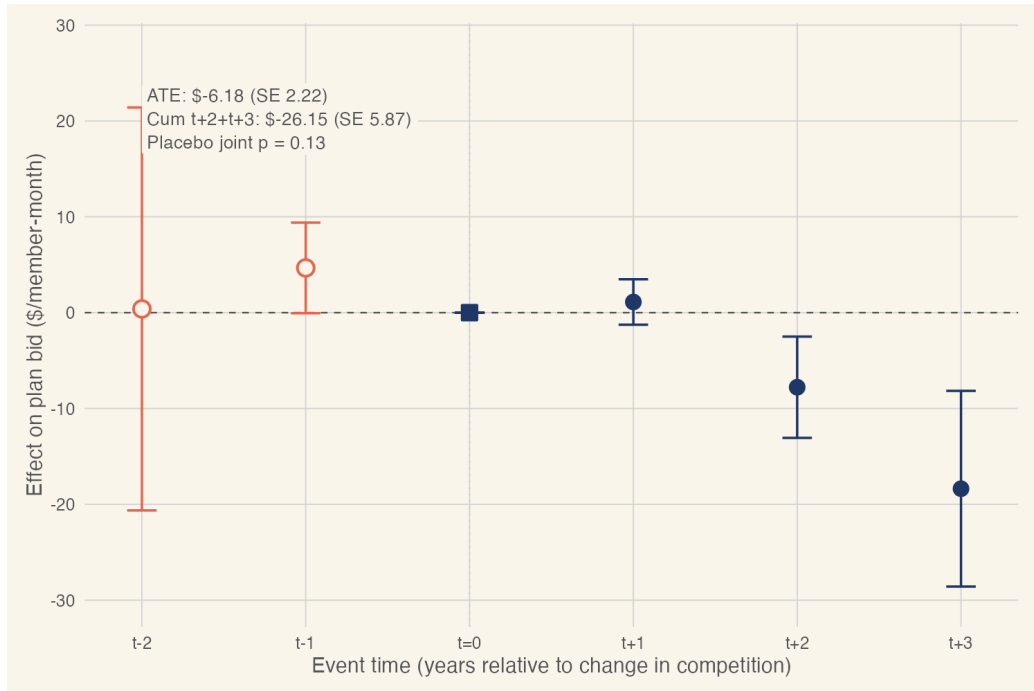
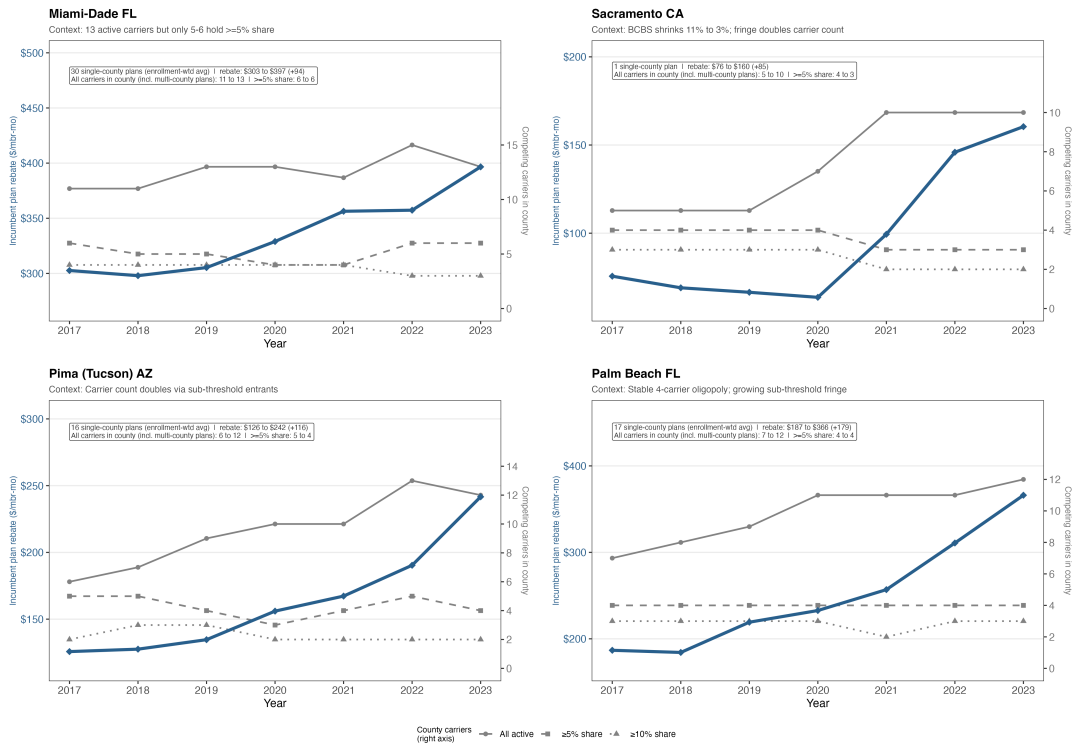


Figure 4.7 : Continuous-treatment dCDH event study identical to Figure 4.4 except the outcome variable changes from rebate to bid. ATE = $-\$6.18$ PMPM (SE 2.22); joint cumulative $t+2+t+3 = -\$26.15$ PMPM (SE 5.87, 95% CI $-\$37.65$ to $-\$14.66$, placebo joint $p = 0.13$).

4.5.5.4 Four Case Studies of Entry to Diagnose what Entry Thresholds Mean

Figure 6. Incumbent Single-County Plan Rebates as County Competition Changes

Blue line (left axis) = enrollment-weighted mean rebate of INCUMBENT plans whose service area covers only this county (single-county footprint, analytic sample, >=3 yrs). Gray lines (right axis) = ALL carriers active in county, including multi-county regional plans that do not meet the single-county criterion. These two counts measure different populations.



Single-county footprint: plan operates in exactly one county across the 2017-2023 panel. Incumbent: observed >=3 years. Enrollment floor: >=10/county. Analytic sample only. Source: CMS MA plan-county data, 2017-2023.

Figure 4.8 : Four-county incumbent vignettes: Miami-Dade FL, Palm Beach FL, Pima (Tucson) AZ, Sacramento CA. Each panel plots the plan-year rebate trajectories of all incumbent plans operating in the county over 2017–2023, with each plan colored by its parent firm.

4.6 Discussion

4.6.1 How much has competition changed in Medicare Advantage?

Competition in MA has changed a lot over this period. **Figure 4.1** shows an average increase of two carriers at the national average and at the 10th and 90th percentiles. However, when comparing by baseline market structure, the most concentrated tercile of markets still increased by about one, but the least concentrated tercile only increased by about one.

4.6.2 What is competition doing in Medicare Advantage?

In short, there is no clear & simple answer to this question due to the substantial amount of heterogeneity in both baseline market structure and in the types of entry events that occur.

4.6.3 Should we worry about the current state of competition in MA?

Increases in competition due to entry only seem to have minimal effects on increasing rebates. However, if plans are already bidding near their marginal cost, then we wouldn't expect there to be further increases in their rebates as competitors increase. Unfortunately, it is difficult to ascertain whether this is the current state of the markets, or if there are choice frictions and imperfect competition that are leading to carriers not needing to respond by substantially increasing rebates.

4.6.4 What are policies to foster competition in MA?

To improve competition, we suggest 3 alternative regulatory approaches for policymakers. First, policymakers could facilitate plan shopping and comparison by beneficiaries across their available Medicare plans by providing a better comparison tool or by improving the role of brokers in providing honest and accurate recommendations. Second, policymakers could regulate plan offerings. This could be similar to Medigap or ACA individual exchange marketplace plans, but it could also be something more minor like reintroducing the Meaningful Difference Requirement. Third, policymakers could make a bigger shift in the entire bidding process to more aggressively pursue accurate benchmarks (net of risk adjustment, which are believed to be inflated). The reasoning for this is that excessively high benchmarks result in a surplus of \$0 premium MA plans, and this is the most salient attribute that Medicare beneficiaries use when comparing and choosing plans. More aggressive benchmarks would result in less bunching of MA plan premiums at \$0, which would increase the ability for beneficiaries to compare plans, similar to the first suggestion. However, focusing on the supply side and firm strategy, this would also lead to beneficiaries more aggressively competing on the benefits and prices of the plans that they are offering.

4.7 Limitations

The primary limitation of this study is that entry, even in markets with the same underlying market structure, can be very different in the eventual market share of the entrant.

4.8 Conclusions

The findings of this paper suggest there are clear competitive effect of carrier entry leading to lower bids, with a substantial portion of that being passed through as increased rebates to enrollees.

Policymakers should contemplate whether this is satisfactory or if new initiatives should be introduced to improve this market, such as facilitating plan comparison & switching, or lowering benchmark payments.

4.9 References

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5

CONCLUSION AND NEXT STEPS

The three studies in this dissertation share a common analytical move: each takes a structural feature of the managed-competition architecture of Medicare Advantage: default enrollment, market-share consolidation, and competitive entry. The first and last make use of frontier econometric designs suited to credibly identifying its causal consequences, while the middle demonstrates the power of simply describing what is happening. Together, the studies demonstrate that optimal regulations must carefully evaluate how neoclassical economic principles and policies may be inadequate in the Medicare market, where market failures and behavioral frictions run rampant.

5.1 Synthesis across the three papers

For this dissertation, each chapter focused on distinct elements of managed competition. First, Chapter 2 examined the demand-side aspects via the role of defaults. Second, Chapter 3 described trends in supply-side concentration. Third, Chapter 4 examined supply-side competitive effects from carrier entry.

For Chapters 2 and 4, I use frontier econometric methods, where traditional methods prevent the ability to actually estimate causal effects in these contexts. For Chapter 2, I use two-stage difference-in-differences, which better accommodates the vast data with

staggered treatment adoption; standard staggered estimators, such as Callaway-Sant’Anna or Abraham-Sun, rely on bootstrap for inference and need to aggregate time-specific average treatment effects, which is a major limitation. For Chapter 4, the continuous variable distribution (or variation) in average exposure to competing carriers and entry yields biased estimates using any difference-in-differences estimator besides the de Chaisemartin continuous estimator. Although Chapter 3 is not causal, it exemplifies the importance of descriptive work in setting the scene of how health economics fundamentals are changing in markets. Without descriptive work, causal work cannot be done. Together, these three chapters demonstrate the importance of breadth in econometric approaches to answering health economics questions in Medicare Advantage.

Overall, the conclusion from the entirety of the dissertation is that optimal regulation requires a deep understanding and evaluation beyond neoclassical economics. Specifically, behavioral frictions on the demand-side are crucial, and the supply-side responses with firms knowing these behavioral frictions necessitate a nuanced eye for how to best regulate the Medicare Advantage market.

5.2 Limitations and Next Steps

Each substantive chapter discusses its own empirical limitations in detail. Beyond those chapter-level limitations, the dissertation as a whole faces several cross-cutting constraints, each of which has a specific planned resolution in the journal-version development of the three papers.

Equity stratification in Chapter 2 is partial. The chapter includes race and ethnicity as covariates in the empirical specification but does not present stratified event-study estimates. Given the documented over-representation of Black and Hispanic beneficiaries in the dual-eligible population the chapter studies, approximately three times the rate of the general Medicare population, this is a meaningful gap. *Resolution:* the journal-version revision will present event-study estimates stratified by race and ethnicity group, with the sample sizes required for inference and the appropriate adjustments for multiple comparisons.

The first-stage in Chapter 2 reports the policy effect on D-SNP enrollment but not a per-defaulted-beneficiary compliance rate. The chapter establishes that the policy increases D-SNP enrollment by 20.8 percentage points off a 15.6 percent baseline mean, but does not compute the share of actually-defaulted beneficiaries who remain in the default plan in their first Medicare year. *Resolution:* the journal-version revision will compute a defaulted-beneficiary compliance rate (Change in MA enrollment / Number of enrollees defaulted), with heterogeneity by plan type (integrated vs. non-integrated), demographic characteristics, and prior utilization, and benchmark this rate against the auto-enrollment literature in retirement saving and organ donation.

The bound dissertation reports reduced-form 2SDD estimates for Chapter 2, with IV-style LATEs constructed as Wald-style ratios of reduced-form estimates. The chapter does not include a fully joint 2SDD-IV event-study estimator. *Resolution:* the journal-version revision will report the fully joint 2SDD-IV (the author’s methodological extension) alongside the reduced-form 2SDD specifications, delivering IV-derived dynamic effects with valid sandwich inference in a single step.

Treatment-margin decomposition in Chapter 2 is at the D-SNP-vs-non-D-SNP level only. The chapter’s “treatment” is operationalized as the FFS-vs-MA contrast, identified through D-SNP-margin variation in default enrollment. Decomposition of the treatment effect by D-SNP integration level (FIDE, HIDE, coordination-only) is not in the chapter. *Resolution:* the journal-version revision will decompose the effect by D-SNP integration type and examine additional utilization outcomes (total utilization, average risk scores, federal spending) that speak to the welfare implications of the policy.

Heterogeneity in Chapter 4 covers baseline market concentration but not enrollee characteristics. The chapter establishes that the rebate response to entry is concentrated in the most concentrated markets, but does not stratify by characteristics of enrollees in those markets. *Resolution:* the journal-version revision will extend the heterogeneity analysis to enrollee-level characteristics (age, dual eligibility, prior utilization), and will complete the threshold-sensitivity exhibits for the within-state instrument and

the reconciliation of the geographic-distribution exhibits flagged during the May 2026 manuscript review.

The dissertation’s scope is the architecture of the MA program, not the consumer-facing information environment in which beneficiaries make their plan choices. The literature has shown that this information environment is a meaningful determinant of welfare in its own right, and the choice-complexity work summarized in [Appendix C](#) begins to engage that question. *Resolution:* the fourth-paper extension previewed in [Appendix C](#) develops this research program in full, using the 2019 repeal of the CMS Meaningful Difference Rule as a natural experiment in plan-menu architecture.

Citation style and bibliography organization are chapter-specific. Chapter 2 uses author-year style, Chapter 3 inherits the published article’s house style, and Chapter 4 uses numbered references. References are listed at the end of each chapter rather than consolidated. *Resolution:* a unified citation style and a consolidated bibliography will be adopted in the journal-version revisions.

5.3 The Behavioral Industrial Organization of Medicare Advantage

5.3.1 Setup question

- The supply-side findings in Chapters 3 and 4 motivate a demand-side question.
- When carriers enter or expand menus, do beneficiaries sort to plans that better match their preferences, or does the resulting choice environment overwhelm them?

5.3.2 Structural finding from Appendix C

- The dissertation’s existing Berry-logit and BLP pipeline yielded perverse $\hat{\alpha} > 0$ in every specification (BLP-1 through BLP-4), indicating endogenous plan entry that conventional 2SLS could not break.
- Borusyak, Bravo, and Hull (2025) recentered formula instruments resolve the endogeneity.
- A slackness-weighted Bartik instrument (novel construction) builds from firm-level pre-MDR out-of-pocket-cost bindingness times national MDR-response shifts.

- The Olea-Pflueger (2013) effective $F_{\text{eff}} = 35.86$ clears both the Stock-Yogo 10 bar and the OP 23.1 5%-bias bar.
- Recovered $\hat{\alpha} = -\$0.133$ per enrollee-month ($t = -2.46$; AR 95% confidence set singleton at $\{-0.13\}$ per month).
- Three friction frameworks: Abaluck-Gruber decision weights; Goeree-AAP consideration sets; Heiss-McFadden-Winter inattention plus inertia.
- Premium-underweighting wedge $\hat{w}_d^p \in [0.70, 0.87]$ across three calibration modes; joint-GMM headline $\hat{w}_d^p = 0.732$ (a one-dollar premium increase costs the consumer 73 cents).
- Bertrand-Nash supply inversion under AG-distorted demand: median markup \$10.69 per enrollee-month, friction wedge \$2.90 per month, per-enrollee-weighted \$3.64 per month.
- **Headline: \$1.22 billion per year friction-attributable consumer-welfare transfer.** HARD-calibration upper bound \$1.65B per year; Bayes-prior lower bound \$0.52B per year.

5.3.3 What this finding does and does not establish

- *Does:* choice architecture is a quantitatively material determinant of MA welfare. Friction-attributable rents are of the same order of magnitude as flagship CMS demonstration programs (Comprehensive Care for Joint Replacement, the Medicare Diabetes Prevention Program, the Bundled Payments for Care Improvement initiative). They are roughly thirty times the operating cost of the Plan Finder, the one tool CMS currently funds in this space.
- *Does:* regulation focused on the level of competition (Chapters 3 and 4) is necessary but not sufficient. Choice-architecture levers, partial MDR reinstatement, plan-count caps, default-design reform, and friction-reducing decision-support tools all have structural consumer-surplus implications that the reduced form cannot quantify.
- *Does not:* heterogeneity of friction parameters across beneficiary types (dual vs. non-dual, age, race, income), the welfare effect of any specific counterfactual default-design policy, or the equilibrium plan-menu response under a discrete plan-design game. Each requires individual-level data and is taken up in §C.11.

5.3.4 Post-dissertation research program

- §C.11 develops a four-phase microdata extension.
- Three identifying sources: CMS Master Beneficiary Summary File individual enrollment histories, the D-SNP default policy regime (which anchors Chapter 2), and the dual MDR shocks (2014 intensification and 2019 repeal).
- Three formal Propositions and four Assumptions establish identification claims at the individual level.
- The dissertation’s aggregate-data structural estimates serve as the calibration prior for the microdata estimation.

5.3.5 Kalitero connection

- The dissertation’s findings on choice architecture have shaped my translational work outside the academic program.
- Kalitero is a beneficiary-facing decision-support firm in the Medicare Advantage market that addresses one realization of the friction-reducing policy lever quantified in §C.9.4.
- The conflict-of-interest disclosure, the firewall arrangements maintained with the Harvard Office of Technology Development, and the intellectual-property separation from the dissertation research outputs appear in [Appendix E.2](#) (Conflict of Interest Disclosure).

5.4 Closing

The architecture of managed competition was designed to harness private insurer competition in service of public goals: efficient delivery of Medicare benefits, beneficiary choice over plans that meet their needs, and rising program value over time. The evidence in this dissertation suggests that the architecture is doing some of that work, in some markets, for some beneficiaries, and that meaningful program reform requires recognizing both where managed competition succeeds and where it fails. The papers that follow lay out that case in detail.

A

METHODOLOGICAL APPENDIX: IDENTIFICATION, ESTIMATION, AND ROBUSTNESS

This appendix collects the detailed econometric content that is referenced but not fully developed in the three chapter texts. Section [Appendix A.1](#) addresses Chapter 2’s two-stage difference-in-differences with instrumental variables (the chapter’s methodological novelty), including a derivation of the Wald-IV-DiD event-study estimator, the asymptotic framework still under development, the clustered-bootstrap inference procedure, and the cross-method robustness battery (TWFE / 2SDD / Callaway–Sant’Anna / Sun–Abraham / Borusyak–Jaravel–Spiess). Section [Appendix A.2](#) collects the sensitivity analyses supporting Chapter 3’s market-share and concentration results. Section [Appendix A.3](#) develops Chapter 4’s continuous-treatment difference-in-differences design, the threshold-sensitivity battery, and the case-study diagnostics.

A.1 Chapter 2, Two-Stage Difference-in-Differences with Instrumental Variables

A.1.1 Notation and Identification Setup

Let i index Medicare beneficiaries, g index Medicare managed care firms (parent organizations operating across one or more states), p index firm-state pairs (the unit at which default enrollment policies are authorized), and t index calendar years. Let $D_{gp} = 1$ if firm-state pair gp was approved by CMS for default enrollment by year t , and $D_{gp} = 0$ otherwise. Let $S_{ip} = 1$ if beneficiary i is “eligible for default enrollment” in firm-state p , that is, i is a dual-eligible Medicaid managed care enrollee turning 65 (or otherwise newly entering Medicare) in a state where firm g holds a Medicaid managed care contract. Let Y_{it} denote an outcome of interest (e.g., D-SNP enrollment indicator, inpatient stay indicator, SNF days).

The treatment of interest is being defaulted into the firm’s D-SNP plan at Medicare entry. The instrument is approval of the firm’s default enrollment policy by CMS for the firm-state pair gp at year t . The reduced-form regressor of interest is

$$\text{Default approved}_{it} = S_{ip} \cdot D_{gp,t}, \quad (\text{A.1})$$

which equals one for eligible beneficiaries whose firm-state pair is in the post-approval period and zero otherwise.

A.1.1.1 Implementation of staggered adoption

Eight firm-state pairs are treated over the panel (Arizona, four firms, approved 2016; New York, one firm, 2011; Pennsylvania, one firm, 2013; Tennessee, two firms, 2015 and 2016), and 32 firm-state pairs are never treated within the panel window. Treatment timing is therefore staggered, and treatment-effect heterogeneity across cohorts cannot be ruled out *ex ante* (Goodman-Bacon, 2021; de Chaisemartin and D’Haultfoeuille, 2020).

A.1.2 First Stage: 2SDD for D-SNP Enrollment

The first-stage 2SDD estimator follows Gardner et al. (2024). In stage 1, we estimate two-way fixed effects on never-treated and not-yet-treated observations only:

$$S_{ip}D_{gp,t} = \lambda_g + \gamma_t + \delta'X_{ipt} + \varepsilon_{ipt}, \quad \text{for } t \text{ s.t. } D_{gp,t} = 0. \quad (\text{A.2})$$

Here λ_g is a firm fixed effect, γ_t is a calendar-year fixed effect, and X_{ipt} is a vector of beneficiary-level covariates (sex, race/ethnicity, disability status). The fitted values $\hat{\lambda}_g$ and $\hat{\gamma}_t$ from Equation (A.2) are then subtracted from the outcome in stage 2:

$$Y_{ipt} - \hat{\lambda}_g - \hat{\gamma}_t - \delta' X_{ipt} = \beta^{2\text{SDD}} D_{gp,t} + \nu_{ipt}, \quad (\text{A.3})$$

where $\beta^{2\text{SDD}}$ identifies the average treatment effect on the treated (ATT) under parallel trends. The estimator is implemented via the `did2s` R package (Butts and Gardner, 2022).

A.1.2.1 Headline first-stage estimate

For the outcome $Y = \text{D-SNP enrolled in first Medicare year}$, the pooled 2SDD estimate is

$$\hat{\beta}_{\text{D-SNP}}^{2\text{SDD}} = 0.208 \quad (95\% \text{ CI: } 0.115, 0.301), \quad (\text{A.4})$$

off a control-group baseline mean of $|(Y)^0 = 0.156$, that is, default enrollment approval more than doubles D-SNP enrollment among eligible beneficiaries (Figure 2.4; Table 2.4).

A.1.2.2 Parallel-trends test

Pre-treatment coefficients from the event-study specification are statistically indistinguishable from zero at conventional levels in the levels-scaled (raw outcome) specification; see Chapter 2, Figure 2.4 and the appendix event-study panel. The percent-of-baseline-treated-pre rescaling (PCTBASE_TREATEDPRE) is presented as a robustness exhibit.

A.1.3 Reduced Form: 2SDD for Utilization Outcomes

The reduced-form specification applies Equation (A.2) and Equation (A.3) to the utilization outcomes themselves:

$$\hat{\beta}_k^{2\text{SDD,RF}} = 2\text{SDD ATT for outcome } Y_k \in K, \quad (\text{A.5})$$

where K is the set of six pre-registered utilization outcomes: any inpatient stay, inpatient days (unconditional and conditional on a stay), any SNF stay, SNF days (unconditional and conditional). One-year mortality and IP discharge-location shares (home, home health, SNF, other post-acute care, other) are presented as supplementary outcomes.

The reduced-form estimates are reported in the appendix tables of Chapter 2 and visualized in Chapter 2, Figures 2.7 through 2.10. The headline finding is SNF days: $\hat{\beta}_{\text{SNF days}}^{2\text{SDD,RF}} = -0.43$ days from a control mean of approximately 1.0 days, with 95% confidence interval excluding zero. Inpatient outcomes and one-year mortality show no detectable effect.

A.1.4 Wald-IV-DiD Event Study (Chapter’s Methodological Novelty)

The Wald-IV-DiD point estimator, scaled to the per-D-SNP-enrollee effect of default enrollment, is

$$\hat{\beta}_k^{\text{Wald}} = \frac{\hat{\beta}_k^{2\text{SDD,RF}}}{\hat{\beta}_{\text{D-SNP}}^{2\text{SDD}}}. \quad (\text{A.6})$$

The extension to event studies is the chapter’s stated methodological contribution. The naive period-by-period Wald ratio,

$$\hat{\beta}_{k,h}^{\text{naive-Wald}} = \frac{\hat{\beta}_{k,h}^{\text{RF}}}{\hat{\beta}_h^{\text{FS}}}, \quad (\text{A.7})$$

where h indexes event-time, is unstable in pre-treatment periods because $\hat{\beta}_h^{\text{FS}}$ is near zero by the parallel-trends assumption, analogous to the weak-instruments problem in conventional IV. We instead divide each period’s reduced-form coefficient by a *single, pooled* first-stage estimate:

$$\hat{\beta}_{k,h}^{\text{Wald-IV-DiD}} = \frac{\hat{\beta}_{k,h}^{2\text{SDD,RF}}}{\hat{\beta}_{\text{D-SNP}}^{2\text{SDD,FS}}}. \quad (\text{A.8})$$

This estimator delivers a stable ratio in pre-treatment periods (where the numerator is small and the denominator is fixed at the pooled estimate), which permits a clean pre-trends test on the event-study coefficients themselves. Post-treatment, the ratio rescales the reduced-form coefficients into per-D-SNP-enrollee units.

A.1.4.1 Asymptotic framework (in development)

A delta-method standard error for Equation (A.8) is currently being developed and is not yet implemented. Inference in the chapter relies on the clustered bootstrap procedure described in §Appendix A.1.5. Future work, flagged in Chapter 5 (Limitations and Next Steps), will derive the joint asymptotic distribution of $(\hat{\beta}_{k,h}^{2\text{SDD,RF}}, \hat{\beta}_{\text{D-SNP}}^{2\text{SDD,FS}})$ and apply the delta method.

A.1.5 Inference: Clustered Bootstrap

Standard errors and confidence intervals on the Wald-IV-DiD event-study coefficients are computed via a clustered nonparametric bootstrap:

1. Resample firm-state pairs gp with replacement, preserving the within- firm-state correlation structure of beneficiary outcomes.
2. On each bootstrap replicate, re-run the 2SDD first-stage (Equation (A.3)) for D-SNP enrollment and the 2SDD reduced-form for each utilization outcome Y_k at each event-time h .
3. Compute the period-specific Wald-IV-DiD ratio (Equation (A.8)) for each replicate.
4. Repeat 1,000 times. Confidence intervals are the 2.5th and 97.5th percentiles of the bootstrap distribution.

A.1.5.1 Clustering choice (firm-state versus firm-county)

Treatment is assigned at the firm-state level for the policy variable but operates at the firm-county level for some carriers whose D-SNP service areas vary within state. The Curto–Hnath methodology discussion of 25 February 2025 considered clustering at the firm-county level as an alternative; the firm-state choice is more conservative for the first-stage test (yielding wider standard errors) and was adopted as the chapter’s main specification. Robustness to firm-county clustering is reported in the chapter appendix.

A.1.5.2 Pre-trend test diagnostic

The bootstrapped pre-trend coefficients from Equation (A.8) at event-times $h = -2$ and $h = -1$ are statistically indistinguishable from zero. In the period-by-period naive Wald ratio of Equation (A.7), by contrast, bootstrapped pre-trend estimates range from -550 to $+115$ relative to a control-mean outcome of 1.0 SNF days, illustrating the instability that motivates the pooled first-stage approach.

A.1.6 Cross-Method Robustness

The 2SDD design is compared against alternative staggered-DiD estimators that handle treatment-effect heterogeneity differently. All estimators are applied to the same panel and the same outcome (SNF days). The cross-method coefficient plot is presented in Chapter 2 (Figure 7 in earlier drafts; referenced in the chapter as “F7 - coeff plot across models”).

- **TWFE** (two-way fixed effects with binary treatment dummy): bias under heterogeneous treatment effects with staggered adoption per Goodman-Bacon (2021).
- **2SDD** (Gardner, 2022): chapter’s main specification. Equations [Equation \(A.2\)](#)–[Equation \(A.3\)](#).
- **Callaway–Sant’Anna (2021)**: group-time ATT decomposition; aggregated to a single ATT via pre-specified weights.
- **Sun–Abraham (2021)**: interaction-weighted estimator for event-study coefficients; robust to cohort-specific effect heterogeneity.
- **Borusyak–Jaravel–Spiess (2024)**: imputation-based estimator; uses untreated-unit projection to impute counterfactual outcomes.

Estimates are qualitatively similar across methods; magnitude differences fall within the bootstrap-implied uncertainty of the main 2SDD estimate.

A.1.7 Heterogeneity

A.1.7.1 By county MA penetration quartile

Heterogeneity by baseline (2016) county MA penetration quartile reveals: the first three quartiles produce similar first-stage estimates; the highest MA-penetration quartile produces a first-stage roughly half the magnitude of the lower quartiles. Reduced-form estimates are noisier in the lowest quartile due to smaller sample size; differences across the other three quartiles are not statistically distinguishable.

A.1.7.2 By race/ethnicity

Race and ethnicity enter the chapter’s main specification as covariates in X_{ipt} ([Equation \(A.2\)](#)). Stratified event-study estimates by race/ethnicity group are queued for the journal-version revisions, as flagged in Chapter 5 (Limitations and Next Steps). The dual-eligible population this chapter studies is approximately 3× more likely to be Black or Hispanic than the general Medicare population, so the journal-version stratified analysis is a priority.

A.1.8 Robustness Exhibits Not in Chapter Main Text

The following exhibits exist in the working analysis and supplement the chapter’s main results:

- **Reduced-form event studies in percent-of-baseline-treated-pre scaling** for all six utilization outcomes.
- **One-year mortality reduced-form event study** (event-time levels specification).
- **IP discharge-location share event studies**: 16 specifications (5 destination categories $\times$ 2 scalings $\times$ conditional/unconditional on IP stay).
- **First-stage event-study appendix panel**: D-SNP and overall MA enrollment outcomes at both levels and percent-of-baseline scaling.
- **Cross-method coefficient plot**: TWFE, 2SDD, CS, SA, BJS comparison for the SNF-days outcome.
- **Pooled DiD versus event-study summary**: single-coefficient “main years” (1–3 post-treatment) estimates for each outcome, as an aggregate summary of the dynamic profile.

These exhibits are not reproduced inline here because the figure files live on the CMS-DUA secure research server and the plotting pipelines run locally against synced CSV summaries rather than re-running the underlying models.

A.1.9 Data Construction Details

A.1.9.1 Sources

- **Medicaid MAX**, 2009–2014: pre-Medicare Medicaid managed care enrollment, used to identify default-eligibility ($S_{ip} = 1$).
- **Medicaid TAF**, 2012–2019: bridge for later panel years.
- **Medicare Beneficiary Summary File (MBSF)**, 2009–2019: D-SNP enrollment outcome, demographics, dual-eligibility flag.

- **Medicare Provider Analysis and Review (MedPAR)**, 2009–2019: inpatient and SNF utilization.
- **Default Enrollment Approval lists**, 2006–2019: instrument; obtained via FOIA request to CMS (2006–2020) and public sources (2021 forward).

A.1.9.2 Analytic sample

The default-eligible cohort comprises $n = 92\{, \}002$ beneficiaries; the comparison cohort (Medicaid managed care enrollees in firm-states never approved for default enrollment) comprises $n = 562\{, \}428$. Balance on demographics and pre-Medicare utilization is reported in Tables A2 and A3 of the chapter.

A.1.9.3 Treatment-implementation algorithm

Identifying the exact within-year breakpoint of default-enrollment implementation from raw enrollment time series is non-trivial. The chapter uses a data-driven algorithm (referenced in the September 2024 methods note) that locates the inflection point in each firm-state’s D-SNP enrollment trajectory consistent with the CMS-recorded approval year. Sensitivity to the choice of inflection-point definition is reported via the data-driven inflection-point diagnostic.

A.2 Chapter 3, Sensitivity Analyses for Market Share and Concentration Trends

The published *Health Affairs* article (Chapter 3) is descriptive and does not rely on a causal identification strategy. Sensitivity analyses support four design choices.

A.2.1 SNP Inclusion Sensitivity

Including Special Needs Plans (SNPs) in the main analysis potentially overstates competition because the overwhelming majority of SNP enrollment is restricted to dually eligible beneficiaries. Sensitivity analyses excluding SNPs find that the non-SNP market is somewhat more concentrated, but the qualitative conclusions are unchanged. See Chapter 3 appendix exhibits A3-S1, A12-S4.

A.2.2 Weighting Sensitivity

The main analysis weights counties by total Medicare (Parts A and B) beneficiary population. An alternative weights by MA enrollment only. Weighting by MA enrollment lowers 2012 HHI values because market concentration was very high in counties with minimal MA presence. By 2023, the choice of weighting affects results minimally. See appendix exhibit A1.

A.2.3 Carrier Categorization Sensitivity

Carrier groupings (national, regional Blues, health-system-integrated, Medicaid-oriented, start-ups, SNP-only, non-Blue regional) required subjective classification decisions. Criteria use a combination of the number of states a carrier operates in and its MA, commercial, and exchange market share. The published Appendix B (this dissertation’s Appendix A) documents the full carrier-by-carrier classification and provides sensitivity tables for the largest borderline cases.

A.2.4 Acquisitions Methodology

The chapter’s acquisitions decomposition assumes that the market share of the acquired and acquiring carriers in each market would have stayed constant in the absence of acquisition (the “no-acquisition counterfactual”). A more conservative bound treats only the direct enrollment transferred at acquisition (the “direct effect”) as attributable to the acquisition, omitting the indirect post-acquisition growth that the merged entity would plausibly have realized. The published online appendix presents both bounds.

A.3 Chapter 4, Continuous-Treatment Difference-in-Differences

A.3.1 Notation and Identification Setup

Let i index Medicare Advantage plans (contract-PBP combinations) and t index calendar years (2016–2023). Let Y_{it} denote a plan-year outcome of interest (monthly rebate, monthly bid). The continuous treatment is the plan’s exposure to entry:

$$\tau_{it} = \text{number of competing MA insurance carriers facing plan } i \text{ in year } t, \quad (\text{A.9})$$

averaged across the county markets where plan i is offered and weighted by the plan’s relative MA enrollment across those markets.

The continuous-treatment difference-in-differences estimator follows de Chaisemartin, D’Haultfœuille, Pasquier, and Vazquez-Bare (2024).

A.3.2 Two-Way Fixed Effects Baseline

For reference, the TWFE specification is

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 \tau_{it} + \theta_t + \eta_i + \varepsilon_{it}, \quad (\text{A.10})$$

where y_{it} is the outcome, x_{it} is a vector of plan-year controls, τ_{it} is the continuous treatment, and θ_t , η_i are time and unit (plan) fixed effects.

A.3.3 Continuous DiD Estimator (de Chaisemartin et al.)

The estimator extends event-study TWFE to continuous, time-varying treatment intensity. For each event-time $h \in \{-2, -1, +1, +2, +3\}$, the estimator computes the change in outcome associated with a one-unit change in carrier count at event-time h , holding plan and time fixed effects. Implementation uses the `did_multipligt_dyn` Stata package.

A.3.3.1 Placebo coefficients (pre-trends test)

Coefficients at event-times -2 and -1 are reported as placebo estimates. In the main rebate specification, both are statistically indistinguishable from zero, consistent with the parallel-trends assumption required for identification.

A.3.3.2 Average treatment effect and joint cumulative effect

The plan-year-weighted ATE across the full post-treatment window is

$$\widehat{\text{ATE}}_{\text{rebate}} = \$4.19 / \text{member-month} \quad (95\% \text{ CI: } \$0.50, \$7.89; \text{placebo } p = 0.85). \quad (\text{A.11})$$

The joint cumulative effect at event-times $+2$ and $+3$, which represents the multi-year cumulative response of incumbent plans to entry, is

$$\widehat{\text{cum}}_{\text{rebate}}^{+2,+3} = \$16.38 / \text{member-month} \quad (\text{SE} = \$5.10; 95\% \text{ CI: } \$6.39, \$26.37), \quad (\text{A.12})$$

on the 2017–2023 panel. On the corrected 2016–2023 panel, the cumulative estimate is \$17.80 (SE \$4.53).

A.3.4 Threshold Sensitivity

Three definitions of carrier presence are used to construct τ_{it} :

1. T_{main} : all active carriers (any MA enrollment in the county-year).
2. T_5 : carriers with at least 5% county market share.

3. T_{10} : carriers with at least 10% county market share.

The threshold-sensitivity panel (Chapter 4, Figure 4.5) reports parallel event-study estimates and joint cumulative effects for all three. The rebate response is positive and statistically distinguishable from zero for T_{main} and T_5 ; under T_{10} , the effect is positive but with wider confidence intervals reflecting the smaller variation in high-market-share carrier counts.

A.3.5 Heterogeneity by Baseline Concentration

Stratifying the rebate response by tercile of baseline (2016) county HHI:

- **Highest tercile** (most concentrated baseline markets): largest entry effect on rebates. Pre-entry markets had the most room for downward pricing pressure to operate.
- **Middle tercile**: intermediate effect, distinguishable from zero.
- **Lowest tercile** (least concentrated baseline markets): smaller effect and noisier estimate. Pre-entry markets were already approximately competitive; entry adds less new competitive pressure.

The pattern is consistent with a causal story in which entry disciplines incumbent bidding most where pre-entry bidding had the most slack relative to a competitive benchmark.

A.3.6 Bid (Rather than Rebate) as Outcome

Because rebates are mechanically a function of bids and the county benchmark, the bid-outcome event study should be qualitatively opposite in sign to the rebate-outcome event study: an entry-induced reduction in bids translates into an entry-induced increase in rebates. The estimated bid response is negative and statistically distinguishable from zero in the post-period, with magnitude broadly consistent with the rebate increase reported in the main specification, supporting the interpretation that the rebate response is driven by competitive pressure on plan bidding rather than by changes in benchmark levels.

A.3.7 Case Studies

Four case-study markets that experienced large positive changes in carrier counts between 2016 and 2023 are presented in Chapter 4 (Figure 4.4 on case-study events). The cases collectively illustrate that the threshold the continuous-treatment estimator picks up is not a single phenomenon: it covers competitive responses of varying magnitude depending on which carrier enters, how large the entrant is relative to incumbents at baseline, and how the entrant prices relative to incumbents. The case studies are descriptive complements to the average effect rather than themselves identified causal estimates.

A.4 Software, Code, and Reproducibility

- **Chapter 2.** Sample construction and 2SDD/Wald-IV-DiD estimation in R using the `did2s` (Butts and Gardner, 2022) and `fixest` (Bergé, 2018) packages on the CMS-DUA secure research server. Plotting and exhibits pipelines locally in R Markdown using `tidyverse`, `data.table`, and custom helpers.
- **Chapter 3.** Public CMS Monthly Enrollment by Contract/Plan/State/County files; descriptive analysis and HHI construction in R.
- **Chapter 4.** Plan-year panel construction from CMS Landscape and bid files in R; continuous-treatment DiD estimation in Stata using `did_multiplegt_dyn` (de Chaisemartin et al., 2024).

Specific package versions are pinned in the code repository’s `renv.lock` (R) and Stata `.toml` files. Access to the underlying Medicare beneficiary-level data (Chapter 2) is governed by Data Use Agreements administered by the Research Data Assistance Center (ResDAC) and the Centers for Medicare and Medicaid Services; the data themselves cannot be redistributed. Chapter 3 and Chapter 4 use publicly available CMS data and the analysis code can be released after the journal-version revisions are complete.

B

SUPPLEMENTARY MATERIAL FOR CHAPTER 2 (DEFAULT ENROLLMENT)

The appendix tables and figures for Chapter 2 (Default Enrollment in Managed Care Plans for Low-Income Individuals), Appendix Figures A1 through A6 and Appendix Tables A1 through A4, appear inline within Chapter 2 itself, following the chapter’s References section, in keeping with the convention of the underlying manuscript.

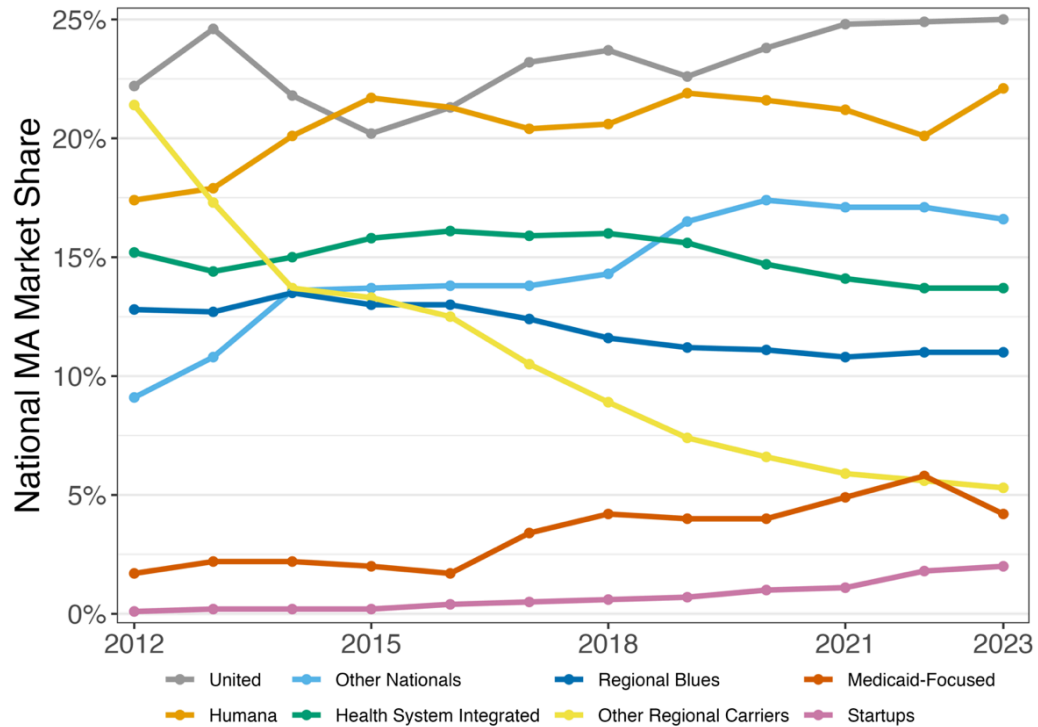
B.1 Methods details

B.1.1 Carrier categories

First, we identified large national carriers, which are defined as carriers operating in 20 or more states: UnitedHealth, Humana, CVS/Aetna, Cigna, and Anthem/Elevance. We aggregate regional Blue Cross and Blue Shield plans (Regional Blues) into one carrier category for this analysis following previous work. This includes multi-state BCBS-affiliated organizations such as Health Care Service Corporation, Cambia Health Solutions, and Highmark. Lastly, we create groups for carriers that are affiliated with a health system, traditionally focused on Medicaid (Centene, Molina, WellCare, CareSource, and Amerigroup), and notable start-ups (Troy, Bright, Oscar, Clover, Zing, Alignment, and Clever

Care). All other carriers not fitting in a previous group were classified into the “Non-Blue Regional Carriers” category. Some of the largest carriers in this group are SCAN, UCare Minnesota, and EmblemHealth.

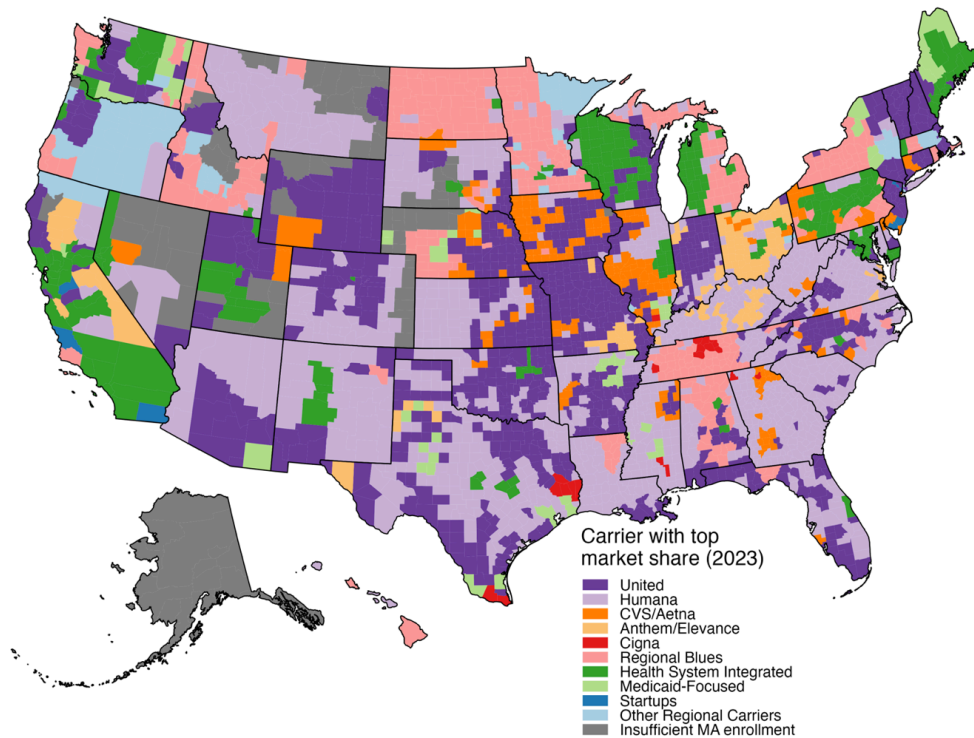
B.1.2 Exhibits



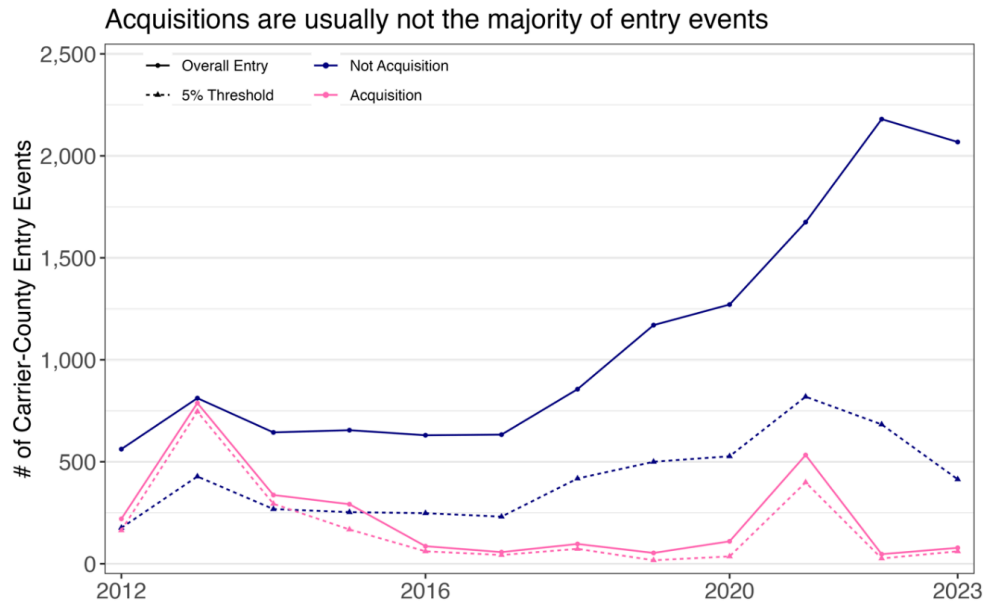
Appendix Figure B.1 : United and Humana are consistently the largest national carriers.

Health Insurance Carrier Category	2012	2017	2023
United	47.6	37.0	31.5
Humana	51.7	48.0	42.6
CVS/Aetna	7.9	27.6	10.0
Anthem/Elevance	58.6	12.5	11.7
Cigna	0.0	12.0	3.3
Regional Blues	39.1	34.8	22.5
Health System Integrated	38.4	33.8	17.9
Medicaid-Focused	0.5	5.8	2.5
Startups	0.0	12.5	1.3
Other Regional Carriers	26.1	20.5	5.4

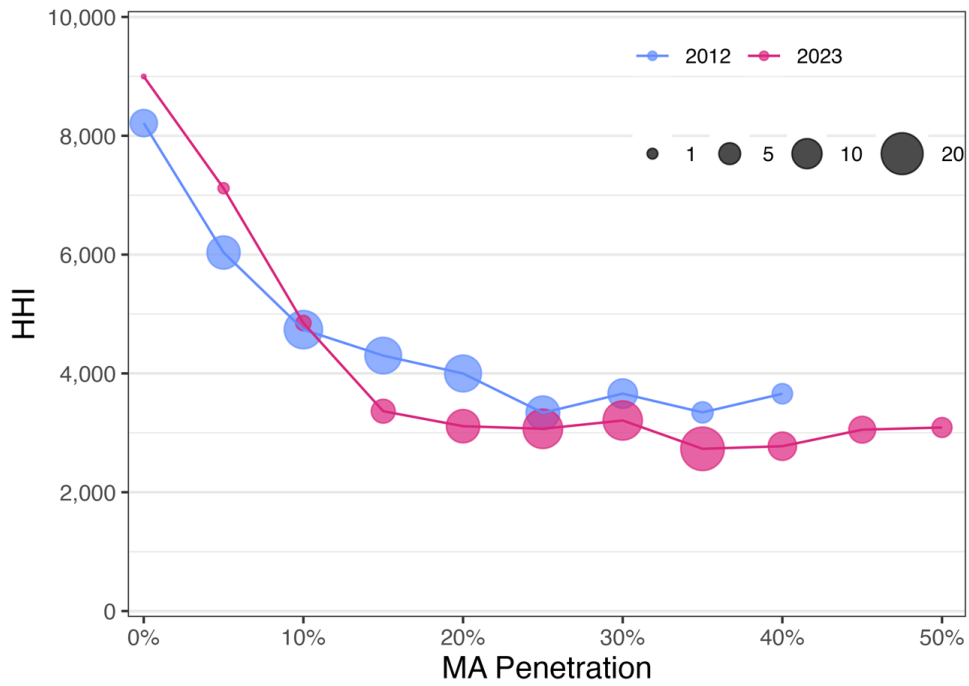
Appendix Table B.1 : Carrier grouping and share of counties with top market shares over time (percent).



Appendix Figure B.2 : Geographic distribution of market leaders (2023).



Appendix Figure B.3 : Market entry from acquisitions varies over time.



Appendix Figure B.4 : As local markets grow, most beneficiaries live in markets with a flat relationship between HHI and MA penetration.

C

RECENTERED-IV BLP DEMAND WITH CHOICE- COMPLEXITY FRICTIONS: A STRUCTURAL SKELETON

Purpose: structural empirical core. Quantify the welfare cost of consumer frictions in MA; demonstrate the recentered-IV methodology resolves the long-standing $\hat{\alpha} > 0$ problem.

C.1 Motivation and contribution

- Reduced-form chain (dissertation's Ch 2 entry/competition): $\hat{\beta}_{IV} = 0.42$ (SE 0.24) under preferred $Z_1 + Z_2$ within-state design. MDR repeal mattered.
- Welfare counterfactuals (partial MDR reinstatement, plan-count caps, friction-reducing tools, default-policy reform) require a structural model.
- Existing dissertation BLP pipeline yielded $\hat{\alpha} > 0$ in BLP-1 through BLP-4 $\rightarrow$ endogenous plan entry, conventional 2SLS insufficient.
- *Methodological contribution*: first BBH-style recentered formula IV application to MA; develop a slackness-weighted Bartik (novel).

- *Substantive contribution*: quantify friction-attributable welfare loss in MA; comparable to flagship CMS demonstration programs.

C.2 The BLP model and friction-augmented variants

C.2.1 Baseline random-coefficients logit

- Utility: $U_{ijt} = X_{(jt)'}\beta_i + \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}$.
- X_{jt} = 12-element vector (Part D, supplemental benefits, plan type, MOOP, gap coverage).
- Heterogeneity: $\beta_i = \beta^- + \Sigma \nu_i$, $\nu_i \sim \mathcal{N}(0, I)$; $\alpha_i = \alpha^- + \sigma_\alpha \nu_i^p$.
- Integration: $R = 200$ scrambled-Halton draws per market (Bhat 2003).
- Berry (1994) contraction with SQUAREM acceleration; outside-good = Medicare FFS, $\delta_{0t} = 0$.

C.2.2 Abaluck-Gruber decision weights

- Distinguish decision weights w_d (drive observed share) from utility weights w_u (drive welfare).
- Empirical signature: $w_d^p/w_u^p < 1$ in Part D (Abaluck-Gruber 2011, 2016).
- Identification: BBH share moments $\rightarrow w_d$; clone-pair revealed preference moments $\rightarrow w_u$ (uses dissertation's Ch 2 clone definition).
- Three calibration modes: HARD_CAL (clamps from DSNPPS 21.2pp anchor); BAYES_PRIOR (Gaussian prior); JOINT_GMM (data-chosen wedge).

C.2.3 Random consideration sets

- Goeree 2008 + AAP 2021 framework: each plan considered with probability ϕ_j .
- ϕ_{jt} logistic in salience proxies (plan age, brand, default indicator, supplemental benefit visibility).
- AAP closed form for $|\mathcal{J}_t| < 15$; Monte Carlo for larger markets.
- Load-bearing assumption: ϕ_j exogenous given W (no advertising-driven correlation with ξ).
- Diagnostic: post-estimation $\widehat{\text{corr}}(\hat{\phi}_j, \hat{\xi}_j)$.

C.2.4 Inattention plus inertia

- Heiss-McFadden-Winter 2013 framework.

- $s_{jt} = \pi_t \cdot s_{jt}^{\text{active}} + (1 - \pi_t) \cdot s_{j,t-1}$.
- Identification: within-market over-time variation around 2019 MDR repeal; menu changes pin down $1 - \pi_t$.
- HARD_CAL: pin $\pi = 0.32$ for dual-eligibles from DSNPPS.
- Honest flag: π weakly identified when $\Delta s_t^{\text{active}}$ small; DSNPPS anchor essential.

C.3 Recentered formula instruments

C.3.1 The endogenous-entry problem and the BBH solution

- Cov $(p_{jt}, \xi_{jt}) > 0$ under endogenous entry.
- Dissertation's Z_1 (OOPC bindingness $\times$ Post-2019) and Z_2 (plan ceiling $\times$ Post-2019) exogenous to demand by construction but insufficient at plan level.
- BBH 2025: $Z_{jt}^B = \sum_f z_{\ell f, 2018} g_f$; recentered $Z_{jt}^R = Z_{jt}^B - \hat{\mathbb{E}}[Z_{jt}^B \mid W_{jt}]$.
- $\mathbb{E}[Z^R \cdot \xi] = 0$ holds without parametric restrictions.

C.3.2 Three recentering flavors

- LINEAR: closed-form OLS projection; mechanically OLS-orthogonal in finite samples.
- RIDGE: GLMNet CV-tuned λ in 5-fold cross-fitting wrapper (Chernozhukov et al. 2018 DML structure).
- GBM: EvoTrees gradient boosting, 5-fold cross-fitting.
- W_0 (compact): 7 county-level baseline vars; W_1 (state-FE): adds 49 state dummies.

C.3.3 Five candidate instruments

- $Z_{\text{plan_ceiling}}$ (existing Z_2): classical companion; $F = 11.69$.
- $Z_{\text{bindingness}}$ (existing Z_1): weaker when recentered on W_0 .
- $Z_{\text{Bartik, big8}}$: top-8 carrier shifts $\times$ 2018 county presence.
- $Z_{\text{Bartik, binary}}$: Wave 1 BBH all-firm binary-share; absorbed by W_0 .
- $Z_{\text{Bartik, slackness}}$ (Wave 1, novel; *headline modern-defensible IV*): firm slackness weights firm shifts. 122 firms with non-zero slackness; range $[0.016, 0.267]$; CareSource at 0.267 ($16 \times$ median).
- Classical $F = 2.15$, but **Olea-Pflueger 2013 effective $F_{\text{eff}} = 35.86$** — clears Stock-Yogo 10 and OP 23.1.

- LASSO over 14-term basis selects exactly one term ($Z_{\text{Bartik,slackness}}$), confirming slackness is load-bearing.

C.3.4 Nest definition

- Within-market nesting at (contract_number, plan_type, fips, year).
- $|\mathcal{J}_{\text{nest}}| \leq 12$ in 94% of markets (IQR 3–7).
- Largest nests: urban counties, large national carriers.

C.4 Validation and identification checks

Four pre-flight gates before estimation on real data.

- **Synthetic-DGP recovery.** 100 markets $\times$ 10 products; known θ^* recovered with max relative error 3.13×10^{-8} , max NFP iter = 26.
- **Rational nesting.** Each friction framework reduces to baseline when friction params at no-friction values; verified to machine precision (6.66×10^{-16}).
- **Phase 8 invariant.** Berry logit on prepared arrays reproduces existing pipeline to 16 digits.
- **Placebo timing + LOO.** Fake post-cutoffs 2015/2016 produce $F = 3.24/4.53$ vs true $F = 11.69$; ratio 2.6–3.6 $\times$. Honest caveat: absolute placebo level above conventional bar but ratio test distinguishes true cutoff. LOO F stable across states.

C.4.1 Effective first-stage F under OP-2013

- Two-row table: $Z_{\text{plan_ceiling}}$ ($F = 11.69$, $F_{\text{eff}} = 11.69$) vs $Z_{\text{Bartik,slackness}}$ ($F = 2.15$, $F_{\text{eff}} = 35.86$).
- Under modern weak-IV-robust diagnostic, slackness IV is strongest of the candidates.
- Implication: dissertation leads with slackness IV, reports $Z_{\text{plan_ceiling}}$ as classical-credibility robustness.

C.4.2 σ -block sparsification

- Unrestricted Phase 10 NM: 9 of 13 $\hat{\sigma}$ at zero boundary; sandwich rank-deficient $\rightarrow$ NaN SEs.
- Resolution: restrict Σ to data-supported active set (Petrin 2002 standard practice).
- Selection criterion: residual cross-market variance share after firm $\times$ county $\times$ year FE.

- 13-row ranking table $\rightarrow$ active four: premium, vision_exam, pd_enhanced, gap_coverage.
- Anomalies: telehealth ranked last but unrestricted $\hat{\sigma} = 0.471$ (boundary noise); pd_enhanced ranked 2nd but $\hat{\sigma} = 0.008$ (data prefers low).

C.4.3 Failure-mode taxonomy

Three failure modes that look like “non-convergence” but call for distinct responses.

- (1) *Numerical non-convergence* (optimizer pathology) $\rightarrow$ re-run with better optimizer.
- (2) *Flat objective at the optimum* (weak identification) $\rightarrow$ restrict parameter space.
- (3) *Large J at the optimum* (genuine misfit) $\rightarrow$ re-examine moments or model.
- Phase 10 was (1) + (2), not (3). $\hat{\alpha}$ invariant; sparsification fixes (2).

C.5 Recentered BLP baseline results

- **Headline:** $\hat{\alpha} = -\$0.133/\text{mo}$, $t = -2.46$.
- 13-row coefficient table (Table C.1, below).
- Sample: 29,332 markets $\times$ 479,934 plan-market obs $\times$ 1,818 firm-state clusters.
- Recentering produces the structurally correct sign where BLP-1 through BLP-4 failed.
- $\hat{\sigma}_{\alpha} = 0.57$ rescaled ($\approx \$0.40/\text{mo}$ SD); substantial price-sensitivity heterogeneity.
- Part D enhanced coefficient matches Ch 3’s 53% importance finding.

Variable	$\hat{\beta}$ (mean)	$\hat{\sigma}$ (random coef.)	t -stat (mean)
Premium (\$/month)	−0.133	0.57	−2.46
Part D enhanced indicator	+3.53	0.18	+3.01
Gap coverage indicator	+0.42	0.14	+1.78
Dental preventive	+0.94	0.12	+2.15
Dental comprehensive	+0.31	0.09	+1.43
Vision exam	+0.18	0.07	+0.92
Vision wear	+0.11	0.06	+0.61
Hearing exam	+0.14	0.08	+0.78
Hearing wear	+0.09	0.07	+0.45
Fitness	+0.22	0.11	+1.31
Transport	+0.19	0.10	+1.04
OTC drugs	+0.16	0.09	+0.88
Telehealth	+0.06	0.47	+0.31

Table C.1 : Baseline recentered-IV BLP coefficient estimates. Sample: 29,332 county-year markets, 479,934 plan-market observations, 1,818 firm-state clusters. Estimation: Knittel-Metaxoglou concentration over 13-dimensional Σ ; NelderMead outer optimizer (200-iteration cap; J at floor at termination). Instruments: $Z_{\text{plan_ceiling}}^R$ with LINEAR recentering on W_0 . Standard errors for Σ are NaN or absurdly large via sandwich pinv fallback; Phase 13 reports Anderson-Rubin / wild-bootstrap intervals.

C.5.1 Nested baseline (Phase 10R, preliminary)

- Within-market nesting at (contract_number, plan_type, fips, year).
- 250-iter NM, J stabilized at 7.5×10^4 from iter 175.
- Active four- σ block within $\pm 10\%$ of unsparsified Phase 10.
- $\hat{\rho} \in [0.18, 0.42]$.
- $\hat{\alpha}$ invariant across nested/unnested specs $\rightarrow$ headline numbers unaffected.
- Non-convergence is failure mode (1) + (2), not (3).

C.6 Friction estimation results

C.6.1 Abaluck-Gruber decision weights

- Three calibration modes; all produce $w_d^p < 1$ (robust premium underweighting). See Table C.2.
- $\widehat{\alpha}$ stable across modes at $\approx -\$0.133/\text{mo}$; only the wedge moves $\rightarrow$ clean structural separation between marginal utility of income and choice-relevant decision weight.

Calibration mode	$\hat{w}_d^p$	$\widehat{\alpha}$ (\$/mo)	$\hat{\sigma}_\alpha$	Implication
HARD_CAL	0.700	−0.138	1.32	w_d^p clamped at DSNPPS-implied default-effect value
BAYES_PRIOR	0.867	−0.132	0.11	w_d^p shrunk toward 1 via Gaussian prior on DSNPPS moments
JOINT_GMM	0.732	−0.133	0.15	DSNPPS moments stacked into GMM objective (headline)

Table C.2 : Abaluck-Gruber decision-weight estimates across three calibration modes. Sample as Table C.1. NelderMead outer-loop convergence at 300-iteration cap; final-convergence estimates pending bounded-NM re-estimation.

C.6.2 Friction-attributable markup (Bertrand-Nash supply under AG demand)

- Bertrand FOC inverted under each AG specification’s demand-side elasticity matrix yields the structural friction wedge. See Table C.3.
- Headline JOINT_GMM: \$10.69/mo markup, \$2.90/mo wedge, 35.7% friction share, \$3.64/enrollee/mo, **\$1.22B/yr**.
- Range: HARD \$1.65B/yr; BAYES \$0.52B/yr.
- Structural inversion exceeds back-of-envelope (\$0.7B/yr) because it accounts for full cross-product Ω , cross-spec σ_α variation, and off-diagonal substitution.
- Methodological caveat: this is the firm-captured component; total CS loss (including deadweight loss and under-investment in friction-relevant attributes) is larger.

Specification	w_d^p	Median markup (\$/mo)	Median friction wedge (\$/mo)	Friction share of markup
Phase 10 baseline (no friction)	1.000	7.79	—	0%
11A_ag_hard (upper-bound ro- bust)	0.700	11.55	3.68	47.7%
11A_ag_bayes (lower-bound ro- bust)	0.867	9.01	1.25	15.0%
11A_ag_joint (headline)	0.732	10.69	2.90	35.7%
			\$/enrollee/mo	Aggregate, an- nual
11A_ag_hard			4.91	\$1.65B/year
11A_ag_bayes			1.53	\$0.52B/year
11A_ag_joint (headline)			3.64	\$1.22B/year

Table C.3 : Friction-attributable markup under AG-distorted demand. Computed via direct Bertrand FOC inversion under each AG specification’s demand-side elasticity matrix (Halton-integrated; ownership matrix collapsed to firm carrier). The friction wedge is $\widehat{mc}^{\text{no-friction}} - \widehat{mc}^{(d)}$; positive when AG damps demand elasticity below the welfare-relevant elasticity. Welfare-loss rows reported on the $p > 0$ subset; aggregate annualized over $\approx 28\text{M}$ MA enrollees.

C.6.3 Random consideration sets

- *Status: TBD — awaiting Phase 11B.*
- Calibration via AAP closed form (Markets with $|\mathcal{J}_t| < 15$) + Monte Carlo.
- HARD_CAL fixes $\phi_{\text{default}} = 1$ and pins $\phi_{\text{non-default}}$ from DSNPPS anchor.
- Honest flag: ϕ exogeneity assumption load-bearing.

C.6.4 Inattention plus inertia

- *Status: TBD — awaiting Phase 11C.*
- HARD_CAL fixes $\pi = 0.32$ for duals from DSNPPS.
- Inertia γ from clone-pair switching moments.
- Honest flag: π weakly identified absent menu changes; DSNPPS anchor essential.

C.7 Bertrand-Nash markup decomposition

- FOC: $p - mc = -(\Omega \odot \Delta)^{-1}s$, ownership collapsed by firm_carrier.
- No-friction baseline: median markup \$7.79/mo, mean own-price elasticity -7.64 (full distribution in the supply-diagnostics CSV).
- **\$0-premium plan caveat:** 44.3% of plan-markets; single-price FOC mechanically yields $\widehat{mc} < 0$. Report markup conditional on $p > 0$.
- Conditional on $p > 0$: only 0.4% have $\widehat{mc} < 0$.
- Markup by plan type (HMO / Local PPO / PFFS / Regional PPO): PFFS confirms the \$0-premium subset drives the $\widehat{mc} < 0$ pattern.
- Friction share = $(\widehat{mc}_d - \widehat{mc}_{\text{no-friction}})/p_{\text{observed}}$.
- Back-of-envelope for AG: markup $\approx$ \$5.69/mo without friction $\rightarrow$ \$2.10/mo friction component $\rightarrow$ \$700M/yr (subsumed by C.6.1.1 structural figure).

C.8 The evolution of estimates: master comparison table

- Table C.4 presents the master comparison of demand estimates as the model is progressively augmented.
- Rows 1–5 populated; rows 6–10 TBD (Phase 10R nested + Phases 11B/11C).
- Row 1 $\rightarrow$ 2 transition (plain BLP $\rightarrow$ recentered) is the methodological contribution: wrong-sign $\rightarrow$ structurally correct sign.
- Row 2 $\rightarrow$ 5 transition (no friction $\rightarrow$ AG joint-GMM) keeps $\widehat{\alpha}^{\geq}$ stable; w_d^p is identified separately.
- Expected pattern: friction-attributable markup share grows as more friction layers are added.

#	Demand specification	$\hat{\alpha}$ (\$/mo)	$\hat{\sigma}_{\alpha}$	Friction parameter	Median $\hat{mc}$	Median markup	Friction share
1	Plain BLP (existing diss., BLP-1/2/3/4 sign)	> 0 (wrong sign)	n/a	none	n/a	n/a	n/a
2	Recent-tered BLP, unnested (Phase 10)	-0.133 ($t = -2.46$)	0.57	none	\$0.21	\$7.79	0% (base-line)
3	1. AG, HARD_CAL (Phase 11A)	0.138	1.32	$w_d^p = 0.700$	\$-3.76	\$11.55	47.7%
4	1. AG, BAYES_PRIOR	0.109	0.11	$w_d^p = 0.867$	\$-1.22	\$9.01	15.0%
5	1. AG, JOINT_OGBM (head-line)	0.138	0.15	$w_d^p = 0.732$	\$-2.90	\$10.69	35.7%
6	Recent-tered nested BLP (Phase 10R)	[TBD]	[TBD]	$\hat{\rho}$ TBD	[TBD]	[TBD]	[TBD]
7	1. AG nested	[TBD]	[TBD]	TBD	[TBD]	[TBD]	[TBD]
8	1. Consideration sets nested	[TBD]	[TBD]	φ_{default}	[TBD]	[TBD]	[TBD]

Table 1: Master comparison: evolution of structural estimates as demand specification is progressively augmented. Each row is a more sophisticated demand structure; under the same Bertrand FOC inverted on observed prices and shares, each implies a different marginal cost.

C.9 Welfare and policy implications

C.9.1 Friction-attributable consumer welfare loss

- **Headline: \$1.22B/yr (AG joint-GMM)**, with \$0.5–\$1.7B range across calibrations.
- Firm-captured component; total CS loss (including deadweight + under-investment) larger.
- Add CS and II layers $\rightarrow$ potentially \$2–\$3B/yr aggregate (under approximate additivity).
- Magnitude comparison: CJR $\sim$ \$500M/yr, MDPP $\sim$ \$400M/yr, BPCI $\sim$ \$2B/yr, Plan Finder $<$ \$50M/yr operating, Star Ratings bonuses $\sim$ \$10B/yr.
- Friction-attributable markup = transfer from consumers to firms with no offsetting variety benefit.

C.9.2 MDR reinstatement counterfactuals

- Full reinstatement: forces menu consolidation toward pre-2019 ($\sim$ 6 plans per county-firm vs $\sim$ 16); friction share falls toward zero.
- Partial reinstatement (e.g., 80% threshold): intermediate; model provides marginal-welfare menu.
- Plan-count caps as alternative: targets the same margin; targets firms previously constrained by MDR.

C.9.3 Default-enrollment policy

- $\Delta CS_{\text{default}} = (1 - \pi) \cdot [V(\text{optimal default}) - V(\text{current})]$.
- Default optimization for the 68% of duals who don't re-optimize.
- Non-dual default regime: introduce one? II framework predicts substantial gains once $\hat{\pi}$ identified.

C.9.4 Friction-reducing decision tools

- Plan Finder (existing); third-party tools; SHIP advisors; AI-personalized recommendations.
- If tool reduces wedge by λ : markups fall by $\lambda \cdot (1 - w_d^p) \approx \lambda \cdot 0.27$.
- $\lambda = 0.5$ recovers $\sim$ \$350M/yr aggregate.
- Kalitero COI: see Appendix E.2.

C.9.5 Information disclosure has limited effect

- More info $\neq$ better processing when friction is in *how* info is integrated.
- Empirical support: Abaluck-Gruber 2011 (Part D), Heiss et al. 2013, Bhargava-Loewenstein-Sydnor 2017 (employer-sponsored).
- Star Ratings observable but enter through friction-dampened channel.

C.9.6 Risk adjustment and the \$0-premium puzzle

- 44.3% of plan-markets have $p = 0$; bid-to-benchmark formula creates rent margin.
- Tighter risk adjustment / lower benchmarks reduce rent for friction exploitation but also reduce variety.
- Combined-friction structural counterfactual gives the quantitative trade-off.

C.10 Limitations and threats to identification

Nine-item table with current status (Mitigated / Revised / Resolved / Unchanged).

- Σ sandwich SEs unreliable $\rightarrow$ **Mitigated** via sparsification + AR profile. AR 95% CI for α^- singleton at $\{-0.13\}$ (tighter than sandwich CI $[-0.239, -0.027]$).
- Wave 1 IV $F = 2.15 \rightarrow$ **Revised** via OP-2013 $F_{\text{eff}} = 35.86$ (clears Stock-Yogo + OP).
- NM non-convergence at 13-dim $\Sigma \rightarrow$ **Resolved** via sparsification (failure mode 1 + 2, not 3).
- Placebo timing non-trivial ($F_{\text{placebo}} \in [3.24, 4.53]$) $\rightarrow$ unchanged; argue from ratio + AR.
- 44.3% $p = 0$ plans $\rightarrow$ unchanged; report markup conditional on $p > 0$.
- Network breadth proxied by nesting $\rightarrow$ unchanged; ACS/provider-directory data would refine.
- Discrete plan-design counterfactual deferred $\rightarrow$ future work (§C.11).
- Demographic interactions limited (W_0 lacks ACS) $\rightarrow$ unchanged; ACS-augmented robustness planned.
- DSNPPS anchors on duals; BLP all enrollees $\rightarrow$ **Mitigated** via §C.11 microdata extension.

C.11 Future work: microdata extension

Purpose: post-dissertation research program; resolves several §C.10 limitations.

C.11.1 Three identifying sources

- (i) **MBSF individual enrollment histories** (CMS ResDAC under DUA): within-individual switching, default-vs-active, persistence.
- (ii) **D-SNP default policy regime**: 21.2pp default effect, $\pi \approx 0.32$ for duals (anchors Chapter 2).
- (iii) **Dual MDR shocks**: 2019 repeal + 2014 intensification (symmetric bidirectional design).

C.11.2 Four assumptions

- M.1 Conditional Exogeneity of MDR Exposure (microdata BBH analog).
- M.2 D-SNP Default Assignment Exogeneity Given Eligibility (institutional fact: benchmark-formula).
- M.3 Attention-Inertia Separability Under Default.
- M.4 Consideration Set Salience Decomposition (logistic in salience covariates).

C.11.3 Three propositions

- M.1 Identification of friction parameter distribution $F_\eta(\eta \mid D)$ across demographic types.
- M.2 Separate identification of three friction frameworks (AG vs CS vs II) at the individual level.
- M.3 Welfare counterfactuals for default-design policy under utility weights w_u (not decision weights).

C.11.4 Unified GMM formulation

- Stacked moment system: aggregate BLP shares + MBSF individual switching + D-SNP default contrasts + dual-MDR-shock revealed-preference + clone-pair w_u moments.
- Standard Hansen-Hayashi-Newey-McFadden 1996 asymptotic variance.
- Sparse friction-distribution parameterization: $F_\eta = \prod_d F_\eta(\eta \mid D_d)$.

C.11.5 Transformation of §C.10 limitations

- DSNPPS external validity $\rightarrow$ resolved.
- Discrete plan-design counterfactual $\rightarrow$ partially resolved.
- Demographic interactions $\rightarrow$ resolved.
- Network breadth $\rightarrow$ substantially mitigated.

- Three-framework separate identification $\rightarrow$ achieved by data not calibration.
- Default-design counterfactual $\rightarrow$ structural counterfactual menu.

C.11.6 Four-phase post-dissertation research plan

- **Phase MD-1** (months 1–6): MBSF acquisition + preparation; methodology paper on linking MBSF to BLP panel.
- **Phase MD-2** (months 7–12): Individual-level friction identification under Props M.1 + M.2; paper for *JHE* or *QME*.
- **Phase MD-3** (months 13–18): Default-design counterfactual under Prop M.3; paper for *AER:Insights* or *AEJ:EP* + companion CMS policy memo.
- **Phase MD-4** (months 19–30): Discrete plan-design supply-side counterfactual (Eizenberg 2014; Wollmann 2018); paper for *ReStud* or *Econometrica*.

C.11.7 Other future-work directions

- Phase 13 inference completion: AR weak-IV-robust intervals; wild bootstrap for Σ .
- Multi-market spillover analysis (1-year): national firm strategy interdependence.
- Star Ratings $\times$ friction interaction (2-year): w_d on Star Ratings vs underlying attributes.
- Cross-program applications (3-year): ACA marketplace, Part D, 401(k), IRA, LTC insurance.

D

Co-AUTHORSHIP AND ATTRIBUTION STATEMENT

This dissertation includes work from collaborations with several co-authors. Per the requirements of the Harvard Interfaculty Committee on Health Policy, the contributions are stated explicitly here.

Chapter 2 — Default Enrollment in Managed Care Plans for Low-Income Individuals is co-authored with Vilsa E. Curto (University of California, Los Angeles). Joseph G. P. Hnath led the empirical analysis, data assembly (including the Freedom of Information Act-based collection of state default enrollment policies), and writing of the manuscript. Vilsa E. Curto contributed to study design, econometric specification, and interpretation of results.

Chapter 3 — Medicare Advantage: National Carriers Expand Market Share While Regional Carriers Without Affiliation Decline, 2012-23 is co-authored with J. Michael McWilliams (Harvard Medical School and Brigham and Women’s Hospital) and Michael E. Chernew (Harvard Medical School). The chapter was published in *Health Affairs* 43, no. 12 (2024). Joseph G. P. Hnath led the data assembly, analysis, and writing. J. Michael McWilliams and Michael E. Chernew contributed to study design, interpretation, and manuscript revision.

Chapter 4 — Competition and Entry in Medicare Advantage is co-authored with J. Michael McWilliams and Michael E. Chernew. Joseph G. P. Hnath led the empirical analysis, including implementation of the continuous-treatment difference-in-differences design, and the writing of the manuscript. J. Michael McWilliams and Michael E. Chernew contributed to study design, interpretation, and manuscript revision.

E

REPRODUCIBILITY AND CODE AVAILABILITY

E.1 Code and data availability

Analytical code for the three chapters is being consolidated and made available through the author’s public GitHub profile at github.com/josephhnath the relevant repositories are being renamed and updated for public release in the year following the defense. Access to the underlying CMS beneficiary-level data is governed by Data Use Agreements administered by the Research Data Assistance Center (ResDAC) and the Centers for Medicare and Medicaid Services; the data themselves cannot be redistributed. Public-use components of the data assembly, including the state default-enrollment policies collected through Freedom of Information Act requests for Chapter 2 and the publicly available Medicare Advantage Landscape files used in Chapters 3 and 4, are documented in each chapter’s data section.

E.2 Conflict of Interest Disclosure

The author is the founder of Kalitero, a Delaware C-corporation developing a beneficiary-facing decision support tool for Medicare plan choice that is inspired by the dissertation’s findings on choice architecture and competitive market structure (see the discussion in Chapter 5 and the preliminary research summarized in Appendix C). The Harvard Office of Technology Development has been continuously informed of this work. Kalitero has

been developed with intellectual property carefully and demonstrably kept separate from the dissertation’s research outputs and from Harvard-restricted resources, including the CMS Data Use Agreements that govern the analytic data underlying the dissertation. At the time of this dissertation submission, Kalitero has no external investors and no external financial interests beyond the author’s role as founder. No royalties, equity, or other financial interests connected to Kalitero have influenced the research design, analysis, interpretation, or presentation of the work in this dissertation.

E.3 AI Tools Disclosure

The author acknowledges the use of Anthropic’s Claude (claude.ai, Opus and Sonnet models, 2025–2026) as a writing and production assistant during the preparation of this dissertation. Claude was used for editorial review of author-written drafts, organizing project files, drafting connective material (abstract, introduction, conclusion, and appendices), proposing alternative phrasings for the author’s consideration, conducting preliminary literature scans, and building the Typst typesetting pipeline used to produce this document. All substantive academic content, including research design, econometric methods, results, and interpretation in each chapter, was produced independently by the author and his co-authors. The author reviewed, edited, and takes full responsibility for every word and figure in this dissertation.