BROOKINGS

REPORT | SEPTEMBER 2025

WILL MEDICARE ADVANTAGE'S RISE STRENGTHEN OR WEAKEN FAVORABLE SELECTION?

SAMANTHA CROW AND MATTHEW FIEDLER

We thank Richard Frank, Gopi Shah Goda, and seminar participants at Brown University for helpful comments and conversations and thank Chloe Zilkha, Rasa Siniakovas, and Christopher Miller for excellent research, editorial, and web posting assistance, respectively. This work was supported by a grant from Arnold Ventures. All errors are our own.

Executive summary

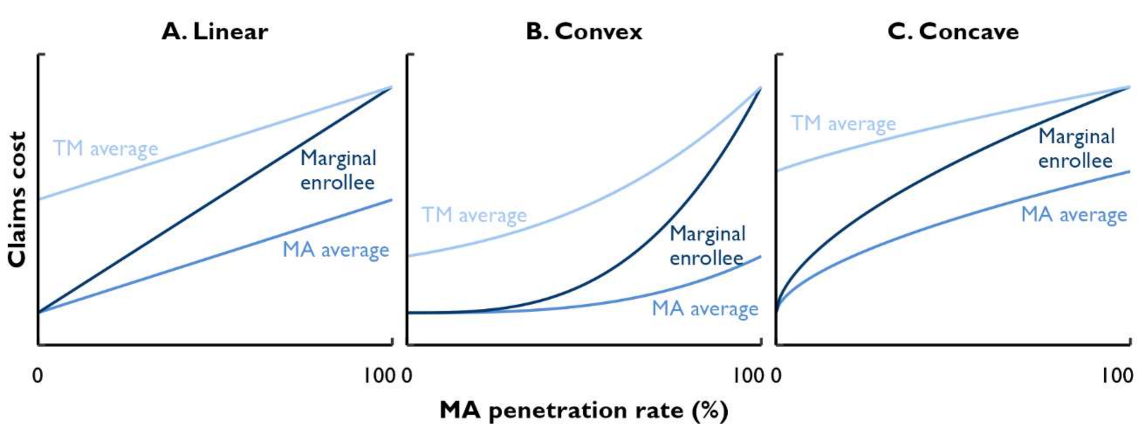
Medicare Advantage (MA) has attracted a steadily rising share of Medicare beneficiaries in recent years, a trend that is projected to continue in the years to come (Ochieng et al. 2025; CBO 2024; Trustees 2025). At present, beneficiaries who choose MA are "favorably selected," meaning that they cost less to cover than those who choose traditional Medicare (TM), even after adjusting for the beneficiary characteristics accounted for in the MA risk adjustment system (e.g., Curto et al. 2019; MedPAC 2025). Because payments to MA plans are based on the average spending of TM enrollees, favorable selection increases the effective generosity of those payments—by an estimated 11% in 2025, according to the Medicare Payment Advisory Commission (MedPAC 2025). Observers have raised concerns that selection may intensify if MA penetration continues to rise, perhaps necessitating fundamental changes to how MA plans are paid (e.g., McWilliams 2022; Jacobson and Blumenthal 2022; MedPAC 2023; Lieberman et al. 2023).

This paper examines the effect of MA penetration on selection, with three main findings:

- **It is unclear *a priori* whether higher MA penetration will strengthen or weaken favorable selection.** Favorable selection arises because beneficiaries with a higher propensity to choose TM over MA tend to cost more to cover. A corollary of this fact is that the "marginal" beneficiaries who shift from TM to MA when MA penetration rises tend to cost *more* than those already in MA but *less* than those who remain in TM. Thus, rising MA penetration tends to raise the average cost of *both* MA and TM enrollees. The net effect on the difference in average cost between these two groups—or, equivalently, on the degree of favorable selection into MA—depends on which average rises faster.

  The model presented in this paper shows that this net effect depends on the *curvature* of the relationship between beneficiary costs and their propensity to enroll in MA, as depicted graphically in Figure ES-1. If this relationship is convex (e.g., because there is a small group of very-high-cost beneficiaries who almost always choose TM), then favorable selection tends to increase as MA penetration rises, as depicted in Panel B of the figure. By contrast, if this relationship is concave (e.g., because there is a small group of very-low-cost beneficiaries who almost always choose MA), then favorable selection tends to decline as MA penetration rises, as depicted in Panel C. If this relationship is linear, then favorable selection does not vary with MA penetration, as depicted in Panel A.

Figure ES-1. Favorable Selection vs. MA Penetration in Three Scenarios



- **Simple comparisons of selection patterns in counties with higher and lower MA penetration rates suggest that MA penetration has little effect on favorable selection, but these comparisons have limitations.** One strategy for measuring the degree of favorable selection into MA is to compare the claims spending and risk scores of TM "stayers" (enrollees who remain in TM from one year to the next) to those of TM-to-MA "switchers" (enrollees who switch from TM in one year to MA in the next year). This method of measuring selection has been used extensively in prior work (e.g., Brown et al. 2014; Newhouse et al. 2015; Jacobson et al. 2019; Lieberman et al. 2023; MedPAC 2025).

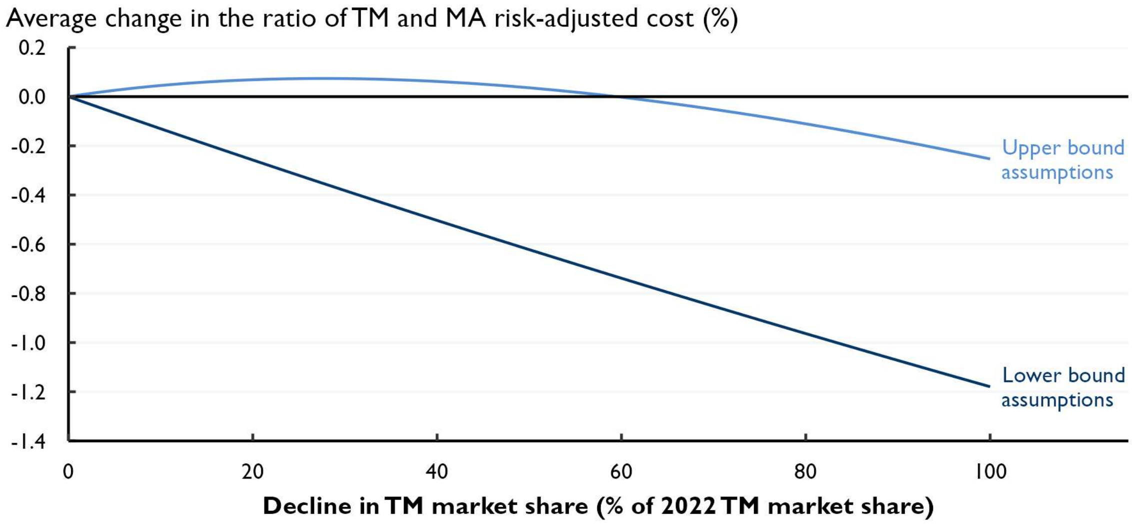
  Some recent work has shown that stayer-switcher differences are similar in counties with higher and lower MA penetration rates (Lieberman et al. 2023; MedPAC 2025), a finding we replicate in our data. For two reasons, however, these cross-sectional comparisons are an imperfect guide to how changes in MA penetration affect favorable selection.

  First, counties with higher MA penetration rates may differ in other ways that mask any effect of MA penetration on stayer-switcher differences. Indeed, we present some evidence that *changes* in MA penetration are associated with declines in stayer-switcher differences, which is consistent with concerns that persistent differences across counties confound the cross-sectional relationship between penetration and stayer-switcher differences. Second, TM-to-MA switchers may not be perfectly representative of MA enrollees overall, so the effect of MA penetration on stayer-switcher differences may not coincide with the effect of ultimate interest: the effect on the difference between the average TM enrollee and the *average* MA enrollee. Notably, it is plausible that TM-to-MA switchers more closely resemble the enrollee on the *margin* between TM and MA than the average MA enrollee; as illustrated in Figure ES-1, the gap between the marginal enrollee and the average TM enrollee may shrink when MA penetration rises even as the gap between the average MA enrollee and the average TM enrollee grows or remains steady.

- **Our analysis addresses the limitations of prior analyses but reaches a similar conclusion: rising MA penetration is unlikely to have much effect on favorable selection into MA.** We estimate a structural model of the relationship between MA penetration and selection using county-year panel data on stayer-switcher differences and MA penetration. The model structure allows us to explicitly account for the possibility that TM-to-MA switchers may not be representative of MA enrollees overall. Using data for multiple years also allows us to control for persistent differences across counties that may confound the cross-sectional relationship between MA penetration and stayer-switcher differences.

  Our results imply that further increases in MA penetration would have little net effect on favorable selection, as illustrated in Figure ES-2. Concretely, we estimate that a decline in TM's market share of 50% from its 2022 level would result in between a negligible increase and a 0.6% decrease in the risk-adjusted cost of the average TM enrollee relative to the average MA enrollee, depending on our assumptions. Our estimates are precise enough to rule out increases larger than 0.9% or declines larger than 1.3% with 95% confidence.

Figure ES-2. Change in Selection versus Change in TM Market Share



Note: Lines depict the average change in the ratio of TM and MA risk-adjusted cost for the specified assumptions and decline in TM market share from its 2022 level, weighting each county by the number of Part A and B enrollees in the county in 2022. See main text for details.

Our findings suggest that further increases in MA penetration would have only small effects on the degree of favorable selection into MA. This has at least two implications. First, it suggests that changes in selection (and their corresponding effects on the generosity of MA payments) are unlikely to meaningfully amplify or dampen underlying trends in MA penetration. In particular, it suggests that TM is currently at little risk of entering a selection-fueled “death spiral” in which increases in MA penetration exacerbate favorable selection, boost payments to MA plans, and thereby allow plans to lure still more beneficiaries away from TM.

Second—and related—it appears unlikely that rising MA penetration will change selection patterns in ways that substantially reduce the accuracy of MA payments. This joins earlier findings that rising MA penetration is unlikely, at least in the medium-run, to reduce TM enrollment to a level where the estimates of local TM costs used to set MA payment benchmarks become statistically unreliable (Crow et al. 2025). A corollary is that while the MA payment system’s *current* accuracy problems (e.g., MedPAC 2025) may offer a compelling rationale for MA payment reform, concerns that rising MA penetration will exacerbate these accuracy problems likely do not.

Introduction

Medicare Advantage (MA) has attracted a steadily rising share of Medicare beneficiaries in recent years, a trend that is projected to continue in the years to come (Ochieng et al. 2025; CBO 2024; Trustees 2025). At present, beneficiaries who choose MA are "favorably selected," meaning that they cost less to cover than those who choose traditional Medicare (TM), even after adjusting for the beneficiary characteristics accounted for in the MA risk adjustment system (e.g., Curto et al. 2019; MedPAC 2025). Because payments to MA plans are based on the average spending of TM enrollees, favorable selection increases the effective generosity of those payments—by an estimated 11% in 2025, according to the Medicare Payment Advisory Commission (MedPAC 2025). Observers have raised concerns that selection may intensify if MA penetration continues to rise, perhaps necessitating fundamental changes to how MA plans are paid (e.g., McWilliams 2022; Jacobson and Blumenthal 2022; MedPAC 2023; Lieberman et al. 2023).[2]

This paper aims to estimate how rising MA penetration will affect patterns of selection into MA. To start, we present a simple model of the relationship between MA penetration and selection. The model shows that whether selection becomes more or less favorable as MA penetration rises depends on the precise shape of the relationship between MA penetration and the cost of the enrollees on the margin between MA and TM, making this a fundamentally empirical question.

To explore this question, we examine how selection and MA penetration vary both across counties and over time. We measure selection at the county-year level by comparing the claims spending and risk scores of TM "stayers" (enrollees who remain in TM from one year to the next) to those of TM-to-MA "switchers" (enrollees who switch from TM in one year to MA in the next year). This method of measuring selection has been used extensively in prior work (e.g., Brown et al. 2014; Newhouse et al. 2015; Jacobson et al. 2019; Lieberman et al. 2023), and it underlies MedPAC's national estimates of favorable selection into MA (MedPAC 2025).

We first use these data to replicate prior findings that stayer-switcher differences are similar in counties with higher and lower MA penetration rates (Lieberman et al. 2023; MedPAC 2025). For two reasons, however, these cross-sectional comparisons are an imperfect guide to how changes in MA penetration affect favorable selection. First, counties with higher MA penetration may differ in other ways that mask any effect of penetration on stayer-switcher differences. Second, TM-to-MA switchers may not be perfectly representative of MA enrollees overall, so the effect of MA penetration on stayer-switcher differences may not coincide with the effect of ultimate interest: the effect on the difference between the average TM enrollee and the *average* MA enrollee.

To address these problems, we estimate a structural model of the relationship between MA penetration and selection using county-year panel data on stayer-switcher differences and MA penetration. Using data for multiple years also allows us to control for persistent differences across counties that may confound the cross-sectional relationship between MA penetration and stayer-switcher differences. The model structure allows us to explicitly account for the possibility

[2] This concern is distinct from the concern that falling TM enrollment will reduce the number of TM enrollees whose experience can be used to construct the estimates of local TM spending used to set MA benchmarks, thereby increasing sampling and non-sampling error in those estimates. Crow et al. (2025) conclude that these sample size concerns will remain modest, at least in the medium-run.

that TM-to-MA switchers may not be representative of MA enrollees overall and thereby estimate how MA penetration affects the difference between the average TM and MA enrollees.

The paper proceeds as follows. We first present our theoretical model of how MA penetration affects favorable selection, after which we describe our data and measures. We then revisit the cross-sectional relationship between MA penetration and stayer-switcher differences before examining the relationship between *changes* in MA penetration and changes in stayer-switcher differences. We then present and estimate our structural model. A final section discusses the implications of our findings for the future of the MA program and MA payment reform efforts.

Model

We begin by laying out a simple model of selection into MA that builds on models of selection used in prior work (Einav et al. 2010; Einav and Finkelstein 2011; Glazer and McGuire 2017). We use the model to illustrate how changes in MA penetration affect the nature of selection into MA and to provide a conceptual framework to guide the empirical analysis that follows.

Model setup

Consider a population of Medicare beneficiaries that is normalized to size one and indexed by $q \in [0,1]$, with beneficiaries arrayed so that higher values of q correspond to a higher propensity to select TM over MA. Concretely, beneficiary q is the beneficiary on the margin between MA and TM when the share of enrollees choosing MA, which we denote Q, equals q.

Beneficiary q incurs claims $c(q)$ when enrolled in TM. Because $c(q)$ reflects costs when (perhaps counterfactually) enrolled in TM, it is a pure measure of claims risk; in particular, it excludes any effects of MA plans' utilization management activities. Given evidence of favorable selection into MA, we assume that c is strictly increasing in q; that is, beneficiaries with a higher propensity to choose TM (or, equivalently, a lower propensity to choose MA) have higher costs.

The average cost of MA and TM enrollees when MA penetration is Q are given, respectively, by

$$c^{\mathrm{MA}}(Q) = \frac{1}{Q}\int_0^Q c(q)dq \quad \text{and} \quad c^{\mathrm{TM}}(Q) = \frac{1}{1-Q}\int_Q^1 c(q)dq\,. \tag{1}$$

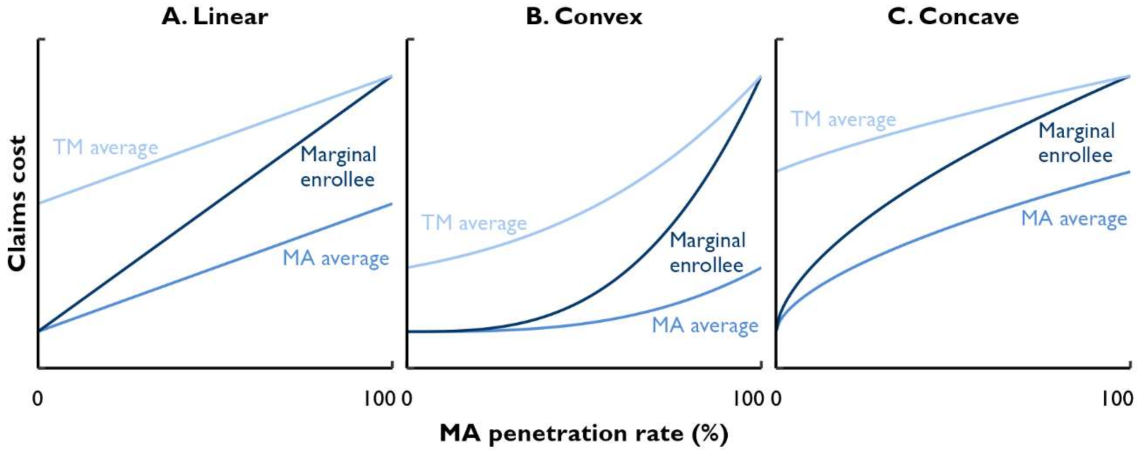
It is easy to see that since c is strictly increasing, $c^{\mathrm{TM}}(Q) > c^{\mathrm{MA}}(Q)$ for all Q; that is, there is favorable selection into MA at all levels of MA penetration. We note that this statement pertains to "gross" selection before considering risk adjustment. We incorporate risk adjustment below.

MA penetration and favorable selection

We now consider how the degree of favorable selection into MA, which can be measured by the difference $c^{\mathrm{TM}}(Q) - c^{\mathrm{MA}}(Q)$, changes when MA penetration changes. It is clear that the average cost of *both* MA and TM enrollees must rise as MA penetration rises; this is because the enrollee on the margin between MA and TM has higher costs than the average MA enrollee but lower costs than the average TM enrollee. Thus, shifting the marginal enrollee from TM to MA raises the average cost of both groups. It follows that the net effect of rising MA penetration on the degree of favorable selection into MA depends on which of these two averages increases more quickly.

This depends, in turn, on the *shape* of the relationship between MA penetration and the cost of the marginal enrollee. Figure 1 lays out three scenarios, and Appendix A provides the full

Figure 1. Favorable Selection vs. MA Penetration in Three Scenarios



mathematical details. If the cost of the marginal enrollee rises linearly with MA penetration, as depicted in Panel A, then the average cost of MA and TM enrollees will rise exactly in parallel as MA penetration rises, and the degree of favorable selection is constant.

If the cost of the marginal enrollee is a convex function of MA penetration, as depicted in Panel B, then the average cost of TM enrollees rises faster than the average cost of MA enrollees as MA penetration rises, and favorable selection increases. One way this type of convexity could arise is if there are a small number of very costly enrollees with a high propensity to enroll in TM and little variation in costs across the rest of the propensity distribution.

By contrast, if the cost of the marginal enrollee is a concave function of MA penetration, as depicted in Panel C, then the average cost of TM enrollees rises more slowly than the average cost of MA enrollees as MA penetration rises, and favorable selection falls. One way this type of concavity could arise is if there are a small number of very-low-cost enrollees with a high propensity to enroll in MA and little variation in costs across the rest of the propensity distribution.

Risk adjustment and payment accuracy

The benchmarks used to determine payments to MA plans are supposed to reflect the cost that MA enrollees would incur if enrolled in TM, that is, $c^{\mathrm{MA}}(Q)$. Because this counterfactual average cost is not observed, the Centers for Medicare and Medicaid Services (CMS) instead computes the actual average claims spending of TM enrollees, $c^{\mathrm{TM}}(Q)$, and “risk adjusts” this amount using estimates of the average claims risk of TM and MA enrollees. Thus, the accuracy of benchmarks and, in turn, payments to MA plans depends not on the gross difference in claims risk between MA and TM enrollees but instead on how much of that difference remains after risk adjustment.

To formalize the role of risk adjustment, we let $r(q)$ denote the risk score of beneficiary q if enrolled in TM. Focusing on the risk scores enrollees would receive if enrolled in TM allows us to abstract from the distinct payment accuracy issues created by MA plans’ highly successful diagnosis coding efforts (e.g., Geruso and Layton 2020; MedPAC 2025) and focus on selection. We let $r^{\mathrm{TM}}(Q)$ and $r^{\mathrm{MA}}(Q)$ denote the average risk scores for beneficiaries enrolled in each market segment when the MA penetration rate is Q, defined analogously to $c^{\mathrm{TM}}(Q)$ and $c^{\mathrm{MA}}(Q)$.

Payments to MA plans are adjusted by multiplying TM average spending by the factor $r^{\text{MA}}(Q)$ / $r^{\text{TM}}(Q)$. The accuracy of this approach depends on how this factor compares to the ideal factor $c^{\text{MA}}(Q)$ / $c^{\text{TM}}(Q)$. One convenient way of expressing the net payment error is thus:

$$\ln\left(\frac{c^{\text{MA}}(Q)\ /\ c^{\text{TM}}(Q)}{r^{\text{MA}}(Q)\ /\ r^{\text{TM}}(Q)}\right) = \underbrace{\left[\ln c^{\text{TM}}(Q)\ - \ln c^{\text{MA}}(Q)\right]}_{\text{gross favorable selection}} - \underbrace{\left[\ln r^{\text{TM}}(Q)\ - \ln r^{\text{MA}}(Q)\right]}_{\text{favorable selection captured in risk scores}}\ . \qquad (2)$$

This approximately equals the percentage payment error attributable to the risk adjustment system's failure to fully offset differences in claims risk due to selection. As the right-hand-side of equation (2) shows, it can be viewed as the difference between two terms. The first term reflects the proportional gross difference in claims risk, while the second term reflects the portion of that difference that is offset by the risk adjustment system. As above, each of these terms may grow or shrink as MA penetration rises, depending on how the claims risk and risk scores of the marginal enrollee vary with MA penetration.[3] It is therefore theoretically ambiguous whether the net payment error gets larger or smaller as MA penetration rises.

Data and measures

The prior section shows that it is theoretically ambiguous whether increases in MA penetration will increase or decrease selection, so we now examine this question empirically. This section describes our data and how we use those data to construct the key measures used in our analysis.

Data

We rely on Medicare claims and enrollment data, as well as long-term care Minimum Data Set files, for 2007-2022, accessed via the Virtual Research Data Center. The claims data allow us to observe the claims spending and diagnoses of TM enrollees. The enrollment data permit us to observe beneficiaries' enrollment status in each month, including whether they have Part A coverage, Part B coverage, or both, and whether they receive that coverage through MA or TM. The enrollment data also report each beneficiary's county of residence at each point in time. Finally, the Minimum Data Set files allow us to identify periods in which an individual is resident in a long-term care facility, which is needed to construct CMS-HCC risk scores.

Measuring selection

Measuring selection into MA is challenging because enrollee outcomes differ between MA and TM for reasons other than differences in enrollee characteristics. Notably, utilization is higher in TM than in MA for comparable enrollees, likely due to differences in plan design and utilization management practices between MA plans and TM (Curto et al. 2019; Teigland et al. 2023). Additionally, risk scores are higher in MA than in TM for comparable enrollees, reflecting MA plans' incentives to capture as many diagnoses as possible to increase their payments (Geruso and Layton 2020; Kronick and Chua 2021; MedPAC 2024). Thus, naïve comparisons of spending and risk scores between MA and TM enrollees are likely to overstate favorable selection into MA.

To overcome this obstacle, we measure selection by comparing the prior-year spending and risk scores of enrollees who newly switched from TM to MA ("TM-to-MA switchers" or "switchers")

[3] In general, the degree of convexity required for favorable selection to increase as MA penetration rises will be slightly larger when measuring selection in proportional terms, as in equation (1).

and those who remained in TM ("TM stayers" or "stayers"). Because this method compares spending and risk scores *while beneficiaries are enrolled in TM*, it avoids biases from differences in utilization or diagnosis coding intensity between MA and TM. As noted above, this type of switcher-stayer comparison underlies MedPAC's national estimates of favorable selection into MA (MedPAC 2025), and it has been widely used in prior research on selection into MA (e.g., Brown et al. 2014; Newhouse et al. 2015; Jacobson et al. 2019; Lieberman et al. 2023).

Our implementation of the "switcher-stayer" methodology largely follows that described in MedPAC (2024). To create selection measures for year t, we begin by identifying beneficiaries who were enrolled in TM with both Part A and Part B coverage for all of years $t-1$ and $t-2$; requiring enrollment in year $t-2$ ensures that we observe the diagnosis information needed to compute enrollee risk scores for year $t-1$. We exclude beneficiaries who have claims during these years for which Medicare was the secondary payer, as well as beneficiaries enrolled in Medicare due to end-stage renal disease at any point during this period.

We next categorize enrollees as switchers if they enroll in MA at any time in year t and as stayers otherwise. We then calculate spending and risk scores in year $t-1$ for each beneficiary and calculate mean spending and risk scores for each county of residence i, year t, and status $j \in \{\text{TM stayer}, \text{TM-to-MA switcher}\}$. We include all Part A and Part B spending except hospice spending since CMS pays for hospice care directly for MA enrollees. We calculate risk scores using the software and diagnosis filtering logic that CMS published for that year.

In what follows, we let c_{it}^{j} and r_{it}^{j} denote the resulting measures of mean claims spending and risk scores, respectively, and we let $n_{it}^{j} = c_{it}^{j} \,/\, r_{it}^{j}$ denote the corresponding measure of risk-adjusted spending. Differences between TM stayers and TM-to-MA switchers are a strong indicator of selection. Concretely, if $c_{it}^{\text{TM stayer}}$ exceeds $c_{it}^{\text{TM-to-MA switcher}}$, that is indicative of favorable gross selection into MA, while if $n_{it}^{\text{TM stayer}}$ exceeds $n_{it}^{\text{TM-to-MA switcher}}$, that is indicative of favorable selection into MA after accounting for risk adjustment. We emphasize that TM-to-MA switchers may not be representative of MA enrollees overall, so while stayer-switcher differences are a good guide to the *direction* of selection, they are an imperfect guide to the *magnitude* of the differences between the average TM enrollee and the average MA enrollee. We discuss the implications of this fact for our current research effort in much greater detail below.

Unlike MedPAC, we are interested in the county-year estimates themselves, not in aggregating them to obtain national estimates of favorable selection. Nevertheless, when we seek to match MedPAC's national estimates, we can nearly do so, as shown in Figure B-1 in Appendix B.[4]

Other analytic details

The other main input into our analyses is county-year estimates of MA penetration, which we denote by Q_{it} for county i and year t. The denominator for this ratio consists of the total number of enrollment months in which the beneficiary had both Part A and B coverage and did not have end-stage renal disease in the relevant county and year, while the numerator is the subset of those months in which the beneficiary was enrolled in MA. Where we weight analyses by Medicare enrollment, we use the denominator of this ratio. All analyses use the sample of 1,730 counties

[4] The small differences between our estimates and MedPAC's likely at least partly reflect rounding.

with at least 3,500 enrollee-months in the switcher-stayer universe in each year, which ensures that each county-level estimate meets disclosure requirements in all years.[5]

How do stayer-switcher differences vary in the cross-section?

We begin by examining how stayer-switcher differences vary across counties with different levels of MA penetration at a given point in time. As we discuss below, interpreting this cross-sectional relationship as reflecting the causal effect of MA penetration on favorable selection into MA requires strong—and likely implausible—assumptions. But we view these analyses as a useful starting point, particularly as a point of comparison to prior work.

Methods

For these analyses, we regress stayer-switcher (log) differences on MA penetration:

$$\ln\left(z_{it}^{\text{TM stayer}}\right) - \ln\left(z_{it}^{\text{TM-to-MA switcher}}\right) = \alpha + \beta Q_{it} + \epsilon_{it}, \quad (3)$$

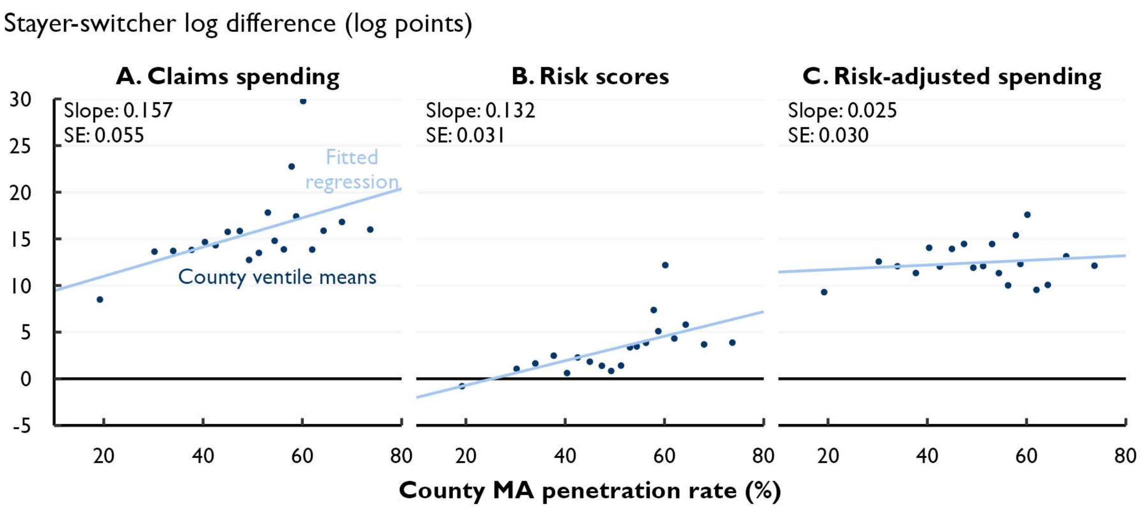
where z_{it}^{j} is the enrollee characteristic of interest (claims, risk scores, or risk-adjusted claims spending). We estimate this equation by ordinary least squares, weight each county observation by total Part A and B enrollment, and calculate heteroskedasticity robust standard errors. We estimate the regression separately for each year 2008-2022.

To provide a less parametric depiction of the relationship between stayer-switcher differences and MA penetration, we also categorize counties into ventiles based on MA penetration, defining each ventile so that it accounts for an equal share of Medicare enrollment. We then calculate the weighted mean of the relevant outcome variable and MA penetration within each ventile.

Results

Figure 2 depicts the results for the 2022 plan year. Panel A shows that the difference between the claims spending of TM stayers and TM-to-MA switchers is larger in counties with higher MA

Figure 2. Stayer-Switcher Differences vs. MA Penetration, 2022

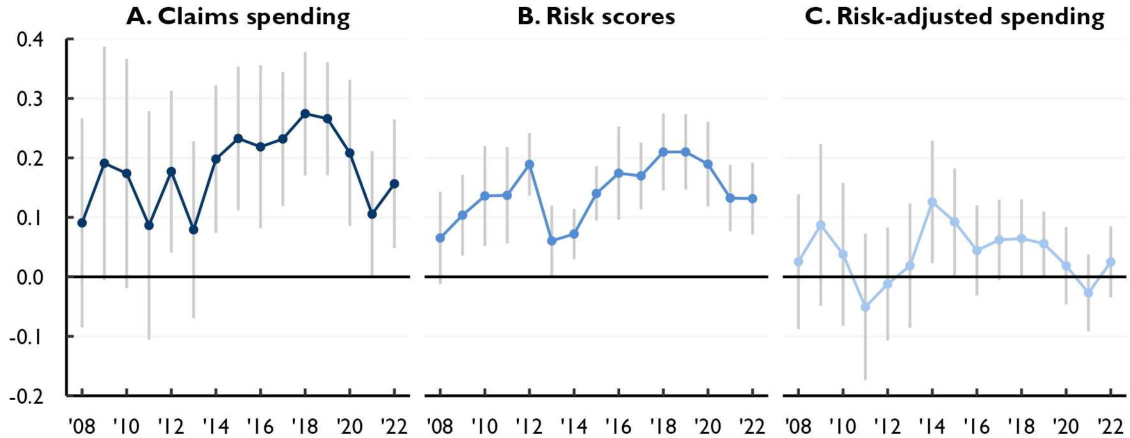


Note: Fitted regression reflects the results from estimating equation (3). Each point represents means for a ventile of counties defined by MA penetration with an equal share of Medicare enrollment. See text for details.

[5] Counties that meet this criterion account for approximately 94% of beneficiaries in all years.

Figure 3. Stayer-Switcher Differences and MA Penetration, 2008-2022

Slope of relationship between stayer-switcher log difference and MA penetration



Note: Points reflect the coefficient on MA penetration from estimating equation (3) for the relevant outcome variables and years. Error bars are 95% confidence intervals. See text for details.

penetration. Specifically, a 10 percentage point increase in county MA penetration correlates with a 1.57 log point increase in the stayer-switcher difference in claims spending. However, Panel B shows that counties with higher MA penetration also have larger stayer-switcher differences in risk scores. Consequently, as depicted in Panel C, stayer-switcher differences in *risk-adjusted* spending vary little with MA penetration. To be precise, a 10 percentage point increase in MA penetration correlates with a (statistically insignificant) 0.25 log point increase in the difference in risk-adjusted spending between TM stayers and TM-to-MA switchers.

To illustrate how this pattern has evolved over time, Figure 3 plots the slope coefficients from estimating equation (3) separately for each year 2008-2022. The results show that the relationship between stayer-switcher differences and MA penetration has been relatively steady over this period. Counties with higher MA penetration have consistently had larger stayer-switcher differences in claims spending, but also commensurately larger differences in risk scores, so stayer-switcher differences in risk-adjusted spending have varied little with MA penetration. This accords with prior research that has found little relationship between MA penetration and stayer-switcher differences in risk-adjusted spending (Lieberman et al. 2023; MedPAC 2025).

Limitations of cross-sectional stayer-switcher comparisons

For at least two reasons, the cross-sectional relationships estimated above may not reveal the causal effect of MA penetration on the degree of favorable selection into MA. First, there is the usual concern about confounding: counties with higher MA penetration may differ from counties with lower penetration in other ways that affect the relative risk of MA and TM enrollees. One especially plausible concern is that insurers may compete harder for enrollees (e.g., by offering better benefits or investing more in marketing) in counties where favorable selection is more intense, thereby raising MA penetration in these counties.[6] This would bias the slope coefficients estimated above upward relative to the underlying causal effect of interest.

Second, stayer-switcher differences do not precisely align with the measure of favorable selection of ultimate interest: the difference in risk between the average TM enrollee and the average MA enrollee. This is because enrollees newly switching to MA may systematically differ from the average MA enrollee.[7] In the language of the model presented earlier in the paper, it is plausible that MA switchers may more closely resemble the *marginal* MA enrollee than the *average* MA enrollee.[8] As depicted in Figure 1, increases in MA penetration raise the cost of the marginal MA enrollee by more than the cost of the average MA enrollee. This suggests that, when MA penetration rises, stayer-switcher cost differences may increase by less (or decrease by more) than cost differences between the average MA and TM enrollees. This would bias the slope coefficients estimated above downward relative to the underlying causal effect of interest.

How do stayer-switcher differences change within counties over time?

To assess the first of the two concerns identified above, we now examine how within-county changes in stayer-switcher differences correlate with changes in MA penetration. These analyses may be viewed as difference-in-differences analyses with a continuous treatment variable. As in other contexts, the virtue of this approach is that focusing on within-county changes can help address confounding from time-invariant differences in county characteristics.

Methods

For these analyses, we run a set of "long-difference" regressions:

$$\Delta_{t_0}^{t_1}\left[\ln\left(z_{it}^{\text{TM stayer}}\right) - \ln\left(z_{it}^{\text{TM-to-MA switcher}}\right)\right] = \alpha + \beta\Delta_{t_0}^{t_1}Q_{it} + \epsilon_i, \tag{4}$$

where $\Delta_{t_0}^{t_1}$ denotes the within-county change in the relevant variable from year t_0 to year t_1 and z_{it}^{j} once again denotes the enrollee characteristic of interest (claims, risk scores, or risk-adjusted claims spending). We estimate this equation by ordinary least squares, weight each county observation by total Part A and B enrollment in year t_1, and calculate heteroskedasticity robust standard errors. In our main analyses, we focus on changes from 2008 through 2022 (that is, we take $t_0 = 2008$ and $t_1 = 2022$), which is the full period for which we have data. We do so because we are most interested in long-run changes and because this maximizes the precision of our estimates; however, we consider alternative time periods in sensitivity analyses.

The coefficient of interest from this regression is β, which we seek to interpret as the average causal effect of a marginal change in MA penetration on stayer-switcher differences. Following

[6] A caveat is that some recent evidence has suggested that, at the margin, increases in the generosity of MA payments do not currently increase MA enrollment (Schwartz et al. 2023; Murray et al. 2024). If this is true, it would suggest that greater favorable selection is unlikely to boost enrollment at the margin.

[7] The point that TM-to-MA switchers may not be representative of MA enrollees overall is well understood. Indeed, MedPAC (2024) invests substantial effort in accounting for this fact when constructing its national estimates of favorable selection. To our knowledge, however, the implications of this fact for the relationship between MA penetration and stayer-switcher differences have not been noted previously.

[8] By contrast, TM stayers are likely fairly representative of TM enrollees overall since new beneficiaries and beneficiaries who were enrolled in MA in the prior year are a small fraction of TM enrollment (Xu et al. 2023).

Callaway, Goodman-Bacon, and Sant'Anna (2024), interpreting β in this way requires making a few key assumptions.[9] The first is that the expected change in the outcome for a given change in MA penetration takes the linear functional form laid out in equation (4). The second is a version of the usual parallel trends assumption: namely, the expected change in the outcome that a county would have experienced if MA penetration had remained the same equals the expected change in the outcome for counties that actually experienced no change in MA penetration. The third is that the average causal effect of MA penetration on the outcome of interest is the same across counties experiencing different-sized changes in MA penetration.

Consistent with discussion in Callaway, Goodman-Bacon, and Sant'Anna, we need only the first two assumptions to give *some* causal interpretation to β. In particular, under these two assumptions, the amount $\beta\Delta_{t_0}^{t_1}Q_{it}$ is the average effect of a change in MA penetration of $\Delta_{t_0}^{t_1}Q_{it}$ for counties experiencing an increase of that size. However, the third assumption is required to interpret β as the causal effect of a marginal change in MA penetration. Without the third assumption, β may reflect *both* the effect of a marginal change in MA penetration *and* differences in the effect of a given change across counties with different changes in MA penetration.

We note that the case for these assumptions is far from ironclad. Notably, changes in MA penetration could be correlated with other changes in county characteristics that affect stayer-switcher differences, which could lead to a violation of the parallel trends assumption. That may be of particular concern since we are relying on changes in MA penetration that arose endogenously rather than due to a policy change. Indeed, to the extent that county characteristics evolve over time, the same mechanisms that have the potential to confound the cross-sectional relationship could confound these longitudinal relationships as well.

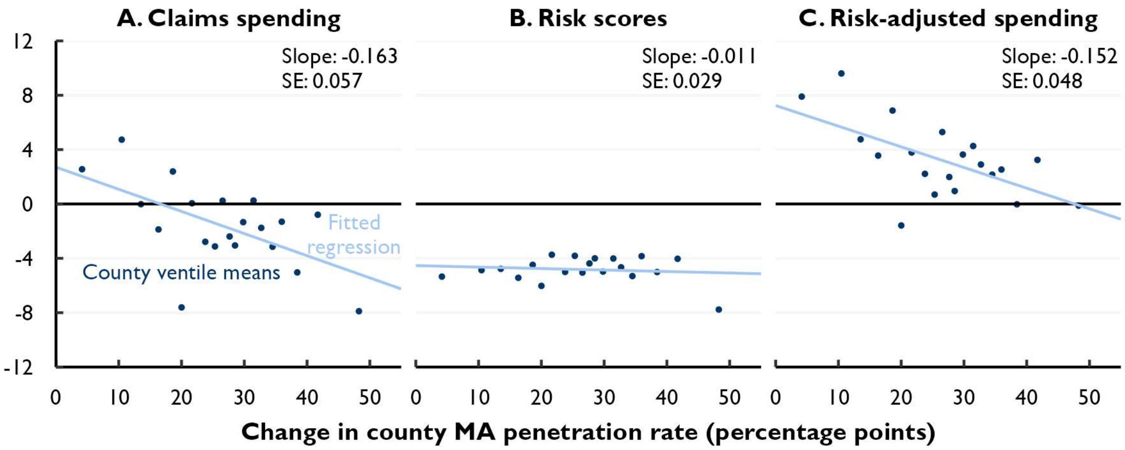
While this approach has limitations, it may nevertheless be the best available. Some past work has used instrumental variables strategies to study the effects of changes in MA penetration on various outcomes of interest (e.g., Baicker et al. 2013; Cabral et al. 2018), with MA payment rates typically serving as the instrument. However, recent work suggests that marginal changes in MA payment rates currently have relatively small effects on MA penetration (Schwartz et al. 2023; Murray et al. 2024), which suggests that this strategy is not currently viable. Absent a viable instrumental variables strategy, we believe a difference-in-differences strategy is worth pursuing.

As with our cross-sectional analyses, we supplement our regression analyses with analyses that provide a less parametric depiction of the relationship between changes in MA penetration and changes in stayer-switcher differences. Specifically, we categorize counties into ventiles based on their change in MA penetration over the period of interest, defining each ventile so that it accounts for an equal share of Medicare enrollment. We then calculate the weighted mean of the change in the relevant outcome variable and the change in MA penetration for each ventile.

[9] Callaway, Goodman-Bacon, and Sant'Anna consider a setting where all units are "untreated" in the base period, which is not the case here. But this framework can be translated into their framework by simply defining each unit's treatment dose relative to its treatment dose in the base period. See also de Chaisemartin et al. (2022) and de Chaisemartin, D'Haultfœuille, and Vazquez-Bare (2024).

Figure 4. Changes in Stayer-Switcher Differences & MA Penetration, '08-22

Change in stayer-switcher log difference (log points)



Note: Fitted regression reflects the results of estimating equation (4). Ventiles are defined by ranking counties by the change in MA penetration and placing an equal share of Medicare enrollment in each group. See text for details.

Results

Figure 4 reports the results. Panel A shows that counties experiencing larger increases in MA penetration experience larger declines in stayer-switcher claims spending differences, while Panel B shows that changes in stayer-switcher risk score differences are essentially unrelated to changes in MA penetration. Consistent with this, changes in MA penetration are associated with declines in stayer-switcher differences in risk-adjusted spending, as shown in Panel C. Concretely, a 10 percentage point increase in the MA penetration rate translates into a 1.52 log point decrease in the stayer-switcher difference in risk-adjusted spending. The difference between this longitudinal estimate and the near-zero cross-sectional estimate obtained above lends some credence to the view that the cross-sectional relationship is confounded to some degree. Notably, the implied bias is positive, which is consistent with the hypothesis laid out above that MA plans compete harder for enrollees in counties with a greater propensity toward favorable selection.

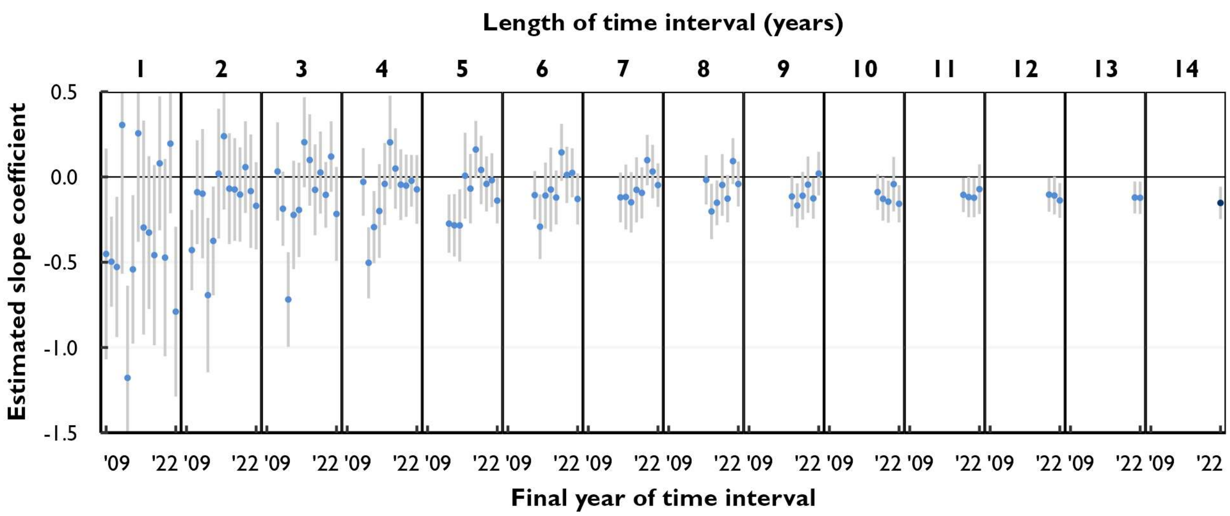
Table 1 presents the full set of regression coefficients for the base version of equation (4) when the outcome is risk-adjusted spending, as well as estimates for two alternative specifications. Specifically, column (2) adds a control for the MA penetration rate in the base period, which amounts to modifying the parallel trends assumption to hold only conditional on this baseline penetration rate; the results are virtually unchanged. Column (3) additionally allows the effect of changes in MA penetration to vary based on the baseline penetration rate. Here, the point estimates suggest that an increase in MA penetration reduces stayer-switcher differences by more in areas that start with higher MA penetration, but this interaction is imprecisely estimated, and the overall average marginal effect of a change in MA penetration is little changed, as shown in Panel B. On balance, we conclude that there is little clear evidence that equation (4) is mis-specified, although we have little power to distinguish equation (4) from plausible alternatives.

Table 1: Alternative Longitudinal Regression Specifications

	(1)	(2)	(3)
A. Regression coefficients			
Change in MA penetration	-0.152	-0.154	-0.049
	(0.048)	(0.058)	(0.101)
Base period MA penetration		-0.003	0.105
		(0.049)	(0.102)
Change in MA penetration x base period MA penetration			-0.519
			(0.408)
Intercept	0.072	0.074	0.049
	(0.015)	(0.024)	(0.032)
B. Average marginal effects			
Change in MA penetration	-0.152	-0.154	-0.172
	(0.048)	(0.058)	(0.059)
N	1730	1730	1730
R^2	0.011	0.011	0.014

Note: Column (1) reports the results from estimating equation (4) according to the methods described in the text where the outcome variable reflects risk-adjusted spending. Column (2) reports the results from estimating a model augmented with a control for base period MA penetration, and column (3) additionally includes an interaction between the change in MA penetration and base period MA penetration. Average marginal effects are weighted by county Part A and B enrollment. Standard errors are in parentheses.

Figure 5. Effect on Risk-Adjusted Stayer-Switcher Log Difference by Time Interval



Note: Points represent the slope coefficient from estimating equation (4) for the specified time interval where the outcome is the log stayer-switcher difference in risk-adjusted spending. Error bars represent the corresponding 95% confidence intervals. Some confidence interval extend beyond the plot area. See text for details.

Figure 5 examines how our results would differ if we estimated equation (4) using data for shorter time intervals rather than using data for the full 2008-2022 period, focusing on the versions where the outcome variable is risk-adjusted spending. The figure displays the estimated slope coefficient (and the associated 95% confidence interval) corresponding to each possible time interval, categorized by the length of the interval and the final year of the interval.

Estimates using short time intervals (e.g., 1-4 years) are quite imprecise and largely uninformative. Estimates using longer time intervals vary from the full-period estimate to some degree, as would be expected, but they provide little evidence that the relationship between changes in MA penetration and changes in stayer-switcher differences has fundamentally changed over time in ways that would cast doubt on the relevance of the full-period estimate.

Structural analysis

The preceding analysis helps address the concern that the cross-sectional relationship between MA penetration and stayer-switcher differences is confounded, but it does not address the concern that TM-to-MA switchers are unrepresentative of MA enrollees overall. As discussed above, this latter concern may make the effect of MA penetration on stayer-switcher differences an imperfect guide to the effect of ultimate interest: the effect of MA penetration on the difference between the average TM enrollee and the *average* MA enrollee.

We proceed by considering a range of assumptions about the nature of TM-to-MA switchers, and, thus, what observed stayer-switcher differences represent. Under each such assumption, we can use our county-year data on MA penetration and stayer-switcher differences to estimate a version of the selection model that was presented at the beginning of this paper. We can then use the estimated models to simulate how favorable selection would change under various counterfactuals for MA penetration, allowing us to assess the range of relationships between MA penetration and favorable selection that are potentially compatible with the data.

The assumptions that we consider fall between two poles. The first is that switchers are representative of enrollees on the margin between TM and MA, in which case stayer-switcher differences correspond to the difference between the average TM enrollee and this marginal enrollee. The second is that switchers are representative of MA enrollees overall, in which case stayer-switcher differences correspond to the difference between the average TM enrollee and the average MA enrollee. We also consider a range of intermediate assumptions.

Empirical model

Our empirical model is a version of the theoretical model presented at the beginning of the paper. Concretely, we assume that when county i and year t has MA penetration rate Q, the enrollee on the margin between TM and MA has expected claims cost when enrolled in TM of

$$c_{it}(Q) = \alpha_{it}^{c}\left(1 + \beta_{it}^{c} Q^{\gamma^{c}}\right),$$

and expected risk score when enrolled in TM

$$r_{it}(Q) = \alpha_{it}^{r}\left(1 + \beta_{it}^{r} Q^{\gamma^{r}}\right).$$

As above, letting $c_{it}(Q)$ reflect a beneficiary's cost when enrolled in TM makes $c_{it}(Q)$ a pure measure of claims risk, while letting $r_{it}(Q)$ reflect risk scores when enrolled in TM allows us to abstract from plans' diagnosis coding efforts and focus narrowly on selection.

For each characteristic $z \in \{c, r\}$, the α_{it}^z parameters control the overall level of claims costs and risk scores, while the β_{it}^z parameters control how much the characteristics of the marginal enrollee vary with MA penetration and, thus, the overall intensity of selection in county i and year t. The γ^z parameters control the *curvature* of the relationship between MA penetration and the characteristics of the marginal enrollee. Per our theoretical analysis, the γ^z parameters thus determine whether selection tends to become more or less intense as MA penetration rises.

Given this structure, the expected mean characteristics of MA and TM enrollees can be obtained via formulas analogous to those in equation (1). For each characteristic $z \in \{c, r\}$, we obtain:

$$z_{it}^{TM}(Q) = \alpha_{it}^z \left[1 + \frac{\beta_{it}^z}{\gamma^z + 1} \frac{1 - Q^{\gamma^z + 1}}{1 - Q}\right] \quad \text{and} \quad z_{it}^{MA}(Q) = \alpha_{it}^z \left[1 + \frac{\beta_{it}^z}{\gamma^z + 1} Q^{\gamma^z}\right].$$

We next specify how the claims spending and risk scores observed for TM stayers and MA switchers correspond to these underlying structural objects. Our empirical model does not capture the underlying beneficiary-level dynamics in coverage choices, so this aspect of our modeling approach is necessarily somewhat more ad hoc.

Because TM stayers account for the overwhelming majority of all TM enrollees in any given year (Xu et al. 2023), TM stayers are likely to be approximately representative of TM enrollees as a whole. Consistent with this, we assume that the amounts observed for TM stayers equal the structural mean value for TM enrollees plus a white noise error term:

$$\ln z_{it}^{\text{TM stayer}} = \ln z_{it}^{TM}(Q_{it}) + \epsilon_{it}^{z,\text{ TM stayer}},$$

where Q_{it} is the observed MA penetration rate in county i and year t, and $\epsilon_{it}^{z,\text{ TM stayer}}$ is the error term. Here, the error term $\epsilon_{it}^{z,\text{ TM stayer}}$ is understood to capture factors outside the model, including the fact that the real-world population of TM stayers is finite, which may cause the observed mean values for TM stayers to deviate from their underlying expected values.

Specifying the corresponding relationship for TM-to-MA switchers is more complex because, as discussed above, it is unclear how the population of switchers corresponds to the population of MA enrollees as a whole. We therefore model the observed means for MA switchers as follows:

$$\ln z_{it}^{\text{MA switcher}} = \theta \ln z_{it}(Q_{it}) + (1 - \theta) \ln z_{it}^{MA}(Q_{it}) + \epsilon_{it}^{z,\text{ MA switcher}}.$$

Choosing $\theta = 1$ corresponds to the case where switchers are assumed to be representative of enrollees on the margin between MA and TM, while choosing $\theta = 0$ corresponds to the case where switchers are representative of MA enrollees overall. Intermediate values of θ correspond to scenarios where switchers fall somewhere in between these two extremes. As above, the error term is interpreted as capturing factors that have not been explicitly modeled.

Combining the above implies that stayer-switcher log differences are then given by

$$\ln z_{it}^{\text{TM stayer}} - \ln z_{it}^{\text{MA switcher}} = \ln z_{it}^{TM}(Q_{it}) - \theta \ln z_{it}(Q_{it}) - (1 - \theta) \ln z_{it}^{MA}(Q_{it}) + \epsilon_{it}^{z,\text{Diff}}, \qquad (5)$$

where $\epsilon_{it}^{z,\text{ Diff}} \equiv \epsilon_{it}^{z,\text{ TM stayer}} - \epsilon_{it}^{z,\text{ TM switcher}}$. We assume that the composite error $\epsilon_{it}^{z,\text{ Diff}}$ is normally distributed with mean zero and with variance $\sigma_{0,z}^2 + E_{it}^{-1} \sigma_{E,z}^2$, where E_{it} is TM enrollment in county

i and year t. Allowing this variance to vary with TM enrollment is consistent with the view that part of what the error term captures is noise created by the fact that the TM population is finite.

Identifying the model requires placing some structure on the β_{it}^{z} parameters. One appealing approach would be to assume a "two-way fixed effects" structure $\beta_{it}^{z} = \lambda_i^z + \mu_t^z$. This structure would allow for unrestricted time-invariant differences across counties and, as such, would address the confounding concerns that arose in our cross-sectional analyses and thereby motivated our difference-in-differences analyses. Indeed, our difference-in-differences analyses rely on very closely related identifying assumptions. However, because this approach gives rise to as many county effects (λ_i^z) as there are counties, it suffers from an incidental parameters problem that has no easy solution in the context of this non-linear model (e.g., Lancaster 2000).

We instead adopt a correlated random effects structure. Specifically, we assume that

$$\beta_{it}^{z} = \mu_t^z + \lambda^z \bar{Q}_i + \nu_i^z, \qquad (6)$$

where $\bar{Q}_i$ is the mean MA penetration rate for county i over time and ν_i^z is a random effect distributed as $N(0, \tau_z^2)$. Importantly, this structure still allows for persistent differences across counties that may be related to a county's level of MA penetration. As such, this structure at least partially addresses the confounding concerns with our cross-sectional analyses. Indeed, in the context of a linear panel data model, this structure would be identical to the two-way fixed effects approach (Mundlak 1978). Wooldridge (2019) provides a recent treatment of the use of correlated random effects to model unit-level heterogeneity in the context of a non-linear model.

Estimation

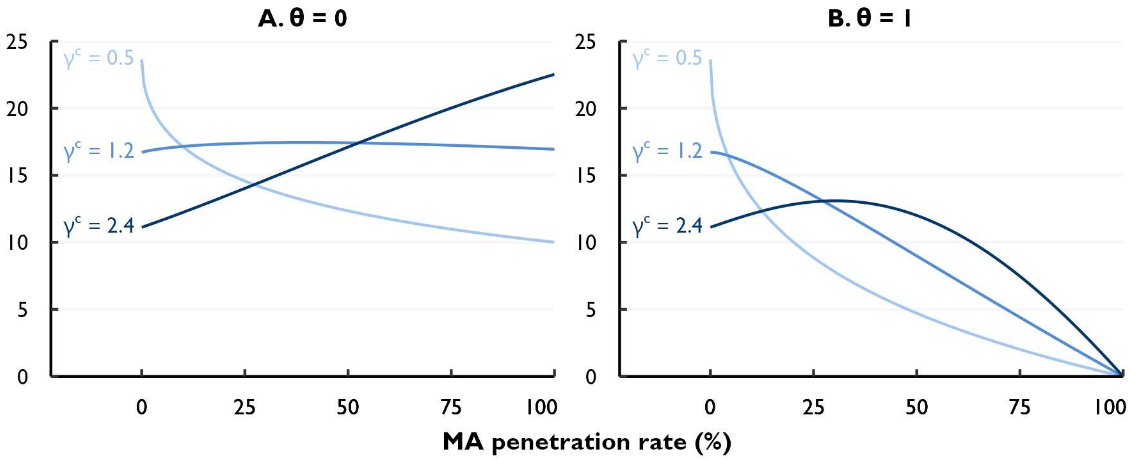
For a specified value of θ, equations (5) and (6) constitute a fully specified parametric model for stayer-switcher log differences. Thus, we estimate this model by maximum likelihood, once for each outcome $z \in \{c, r\}$ and each value $\theta \in \{0, 0.25, 0.5, 0.75, 1.0\}$. We use the nlme R package, which implements the estimation algorithms described in Lindstrom and Bates (1990) and Pinheiro and Bates (1996). To facilitate convergence, we first fit a restricted version of each model with a fixed value of γ^z and then use the resulting estimates as starting values when estimating the full model. Consistent with our focus on "long differences" in the preceding section, we estimate the models using a sample that contains observations for 2008 and 2022.

Before presenting the results, we briefly discuss what features of the data identify the key parameters. The time effects μ_t^z that enter β_{it}^{z} are identified by the overall magnitude of stayer-switcher differences in the two data years, while the coefficient λ^z on the mean level of MA penetration is identified by how stayer-switcher differences differ across counties with different levels of mean penetration; the variance of the random effect v_i^z is then identified by the degree of persistence across counties beyond that explained by the included variables.

The features of the data that identify the γ^z parameters depend on the value of θ. To illustrate this, Figure 6 depicts how the (expected) stayer-switcher log difference in claims spending varies with MA penetration for two values of θ and with β_{it}^{c} fixed at 0.4. Panel A depicts the case with $\theta = 0$, which corresponds to assuming that TM-MA-switchers are representative of MA enrollees overall. In this case, this relationship is upward sloping for high values of γ^c, downward sloping for low values, and roughly flat for intermediate values. Thus, in this scenario, the parameter γ^c is

Figure 6. Stayer-Switcher Differences for Illustrative Values of γ^c

Expected stayer-switcher log difference in claims spending (log points)



Note: Figure plots the expected value of the right side of equation (5) for the values of θ and γ^c shown and $\beta^c_{it} = 0.4$.

identified by the slope of the relationship between greater MA penetration and the stayer-switcher difference (conditional on the other variables in the model).

Panel B, on the other hand, depicts the case with $\theta = 1$, which corresponds to assuming that TM-MA-switchers are representative of MA enrollees on the margin between MA and TM. In this case, the relationship is always downward sloping for high enough values of MA penetration (since the average cost of a TM enrollee and the cost of the marginal enrollee coincide when MA penetration equals one), but the *curvature* of this relationship depends on γ^c: it is convex for low values of γ^c, concave at higher values, and roughly linear at intermediate values. Thus, in this scenario, the parameter γ^c is identified by the curvature of the relationship between greater MA penetration and stayer-switcher differences (again, conditional on the other variables in the model).

Results

Table 2 reports the resulting parameter estimates for the two polar assumptions about the nature of TM-to-MA switchers (that is, for $\theta \in \{0,1\}$). There are two immediate takeaways. The first is that there are large, persistent differences across counties in their propensity to experience selection into MA. These differences are correlated with counties' observed levels of MA penetration (as shown by the fact that the λ^z coefficients are generally sizeable and statistically significant), but much of this variation is idiosyncratic (as shown by the fact that the random effect standard deviations τ_z are also sizeable). The existence of persistent cross-county differences strengthens the rationale for the panel data approaches we use in this paper.

The second is that different assumptions about the nature of TM-to-MA switchers lead to meaningfully different estimates. In particular, when switchers are assumed to be representative of MA enrollees overall, the estimated curvature parameters γ^z are less than 1.0 for both claims costs and risk scores, implying that the relationship between MA penetration and each of these features of the marginal enrollee is (mildly) concave. On the other hand, when switchers are assumed to be representative of the marginal MA enrollees, the estimated curvature parameters

Table 2: Estimates of Structural Model

	(1)	(2)	(3)	(4)
Switcher assumption	$\theta = 0$ (switchers are average MA enrollees)		$\theta = 1$ (switchers are marginal enrollees)	
Outcome variable	Claims cost	Risk scores	Claims costs	Risk scores
Parameters entering $\boldsymbol{\beta_{It}^{z}}$				
Year effect for 2008 (μ_{2008}^{z})	0.306	0.090	0.271	0.079
	(0.035)	(0.012)	(0.050)	(0.017)
Year effect for 2022 (μ_{2022}^{z})	0.265	-0.037	0.334	-0.072
	(0.025)	(0.011)	(0.037)	(0.016)
Effect of mean MA penetration (λ^{z})	0.170	0.197	0.612	0.358
	(0.104)	(0.039)	(0.156)	(0.057)
Random effect std. dev. (τ_{z})	0.168	0.052	0.277	0.095
	(0.013)	(0.007)	(0.016)	(0.007)
Curvature parameter ($\boldsymbol{\gamma^{z}}$)	0.926	0.788	1.409	1.138
	(0.160)	(0.160)	(0.126)	(0.138)
Residual error parameters				
Residual error intercept ($\sigma_{0,z}$)	0.078	0.048	0.084	0.047
	(0.005)	(0.003)	(0.005)	(0.002)
Residual error slope ($\sigma_{E,z}$)	46.013	18.655	43.646	17.755
	(1.091)	(0.596)	(1.129)	(0.602)
N	3,460	3,460	3,460	3,460

Note: The table reports the results from estimating the model specified in equations (5) and (6) by maximum likelihood under two distinct assumptions about the characteristics of TM-to-MA switchers and for two different outcome variables: claims spending and risk scores. Standard errors are in parentheses. See text for additional details.

are greater than 1.0 for both claims costs and risk scores, implying that the relationship between MA penetration and these features of the marginal enrollee is moderately convex.

We now use the fitted models to estimate how a marginal increase in MA penetration would affect selection. The selection measures of interest are the log differences $\Delta_{it}^{z}(Q) \equiv \ln z_{it}^{\mathrm{TM}}(Q) - \ln z_{it}^{\mathrm{MA}}(Q)$ for each $z \in \{c, r, n\}$, where $z = n$ denotes the risk-adjusted cost $n_{it}^{j}(Q) \equiv c_{it}^{j}(Q) \,/\, r_{it}^{j}(Q)$ for $j \in \{\mathrm{TM,MA}\}$. We examine the derivatives $\Delta_{it}^{z}{}'(Q_{it})$, which provide the marginal effect of an increase in MA penetration. We estimate these derivatives for each county i and for $t = 2022$

using the estimated parameters.[10] We then average the estimated derivatives across counties, weighting each county by the number of beneficiaries with Part A and Part B in 2022.

To calculate standard errors for these estimated marginal effects, we draw 1,000 replicate parameter vectors from a normal distribution with mean equal to our point estimates and covariance equal to the corresponding estimated covariance matrix of our estimator. We then recompute the average marginal effect for each replicate parameter vector and compute the standard deviation of the replicate average marginal effects.[11]

Panel A of Figure 7 reports the resulting estimates. Across all assumptions about the nature of TM-to-MA switchers (that is, across all values of θ), the estimated effects on selection are small. Applying the marginal effect for the $\theta = 0$ scenario implies that a 10 percentage point increase in MA penetration would, on average, reduce the TM-MA difference in risk-adjusted cost by 0.3 log points, while the $\theta = 1$ scenario implies an increase of 0.1 log points.

Our results also show that, consistent with the motivation for our structural modeling exercise, the effect of MA penetration on average TM-MA differences can differ markedly from the effect on observed stayer-switcher differences. In particular, Panel B of Figure 7 repeats the preceding exercise, except that the object of interest is now the observed stayer-switcher log difference $\widetilde{\Delta}_{it}^{z}(Q) \equiv \ln z_{it}^{\mathrm{TM}}(Q) - \theta \ln z_{it}(Q) - (1-\theta) \ln z_{it}^{MA}(Q)$, not the average TM-MA log difference $\Delta_{it}^{z}(Q)$. For $\theta = 1$, where TM-to-MA switchers are assumed to reflect the enrollee on the margin between MA and TM, we find that a 10 percentage point increase in MA penetration results in a 2.1 log point reduction in stayer-switcher differences in risk-adjusted spending (broadly similar to the difference-in-differences estimates presented in the last section), even though the same parameters imply little effect on the difference between the average TM and MA enrollees.

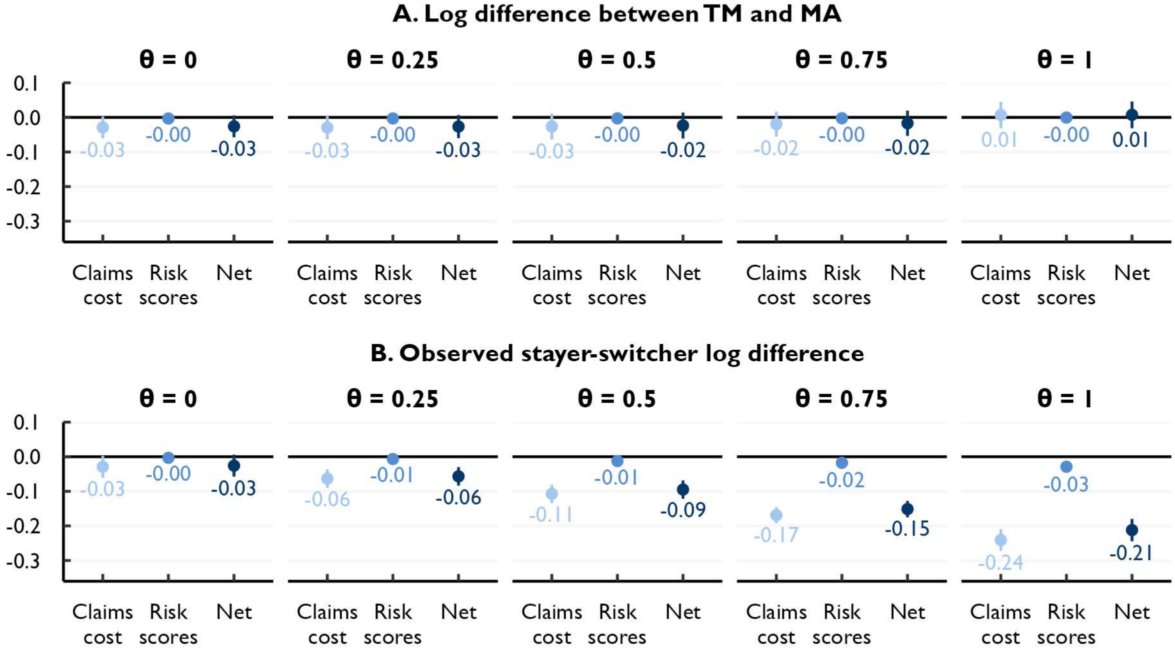
We now examine how larger changes in MA penetration would affect selection, focusing on effects on differences in risk-adjusted costs. To accommodate cross-county variation in baseline MA penetration, we consider scenarios where TM's market share falls by a uniform percentage in all counties. Formally, we estimate $\Delta_{it}^{n}(Q_{it} + \rho[1 - Q_{it}]) - \Delta_{it}^{n}(Q_{it})$ for each county i, for $t = 2022$, and for various $\rho \in [0,1]$. As above, we then average these estimates across all counties, weighting each county's estimate by the number of beneficiaries with Part A and Part B in 2022. We obtain standard errors using the same simulation procedure described above.

[10] The functions $z_{it}^{\mathrm{TM}}(Q)$ and $\ln z_{it}^{\mathrm{MA}}(Q)$ each depend on the realization of the random effect ν_i^z. Because we do not observe the random effects, we draw a synthetic random effect for each county based on the estimated random effect distribution. Because the number of counties is large, this should give virtually the same results as using the actual random effects when averaging across counties as we do here (at least if the model is correctly specified). Consistent with this, the estimated average marginal effects are insensitive to the specific random effect draws (or to setting all of the random effects to zero).

[11] Our method for obtaining standard errors has two limitations. First, the nlme package does not estimate the covariance between the estimators of the random effect standard deviation (τ_z) and the other main parameters ($\{\mu_t^z\}$, λ^z, and γ^z). Thus, when drawing replicate parameter vectors, we assume that these covariances are zero. Since the distribution of the random effects has very little effect on the average estimated derivatives, this assumption is likely innocuous. Second, because we estimate the models for claims spending and risk scores separately, we lack a joint covariance matrix that captures the correlations between the estimators for the two models; we thus assume that they are zero. The results reported in Figures 2 and 4 suggest that accounting for these correlations would likely reduce our standard errors.

Figure 7. Effect of a Marginal Increase in MA Penetration on Selection

Average effect of a marginal increase in penetration (log points per p.p. change in penetration)



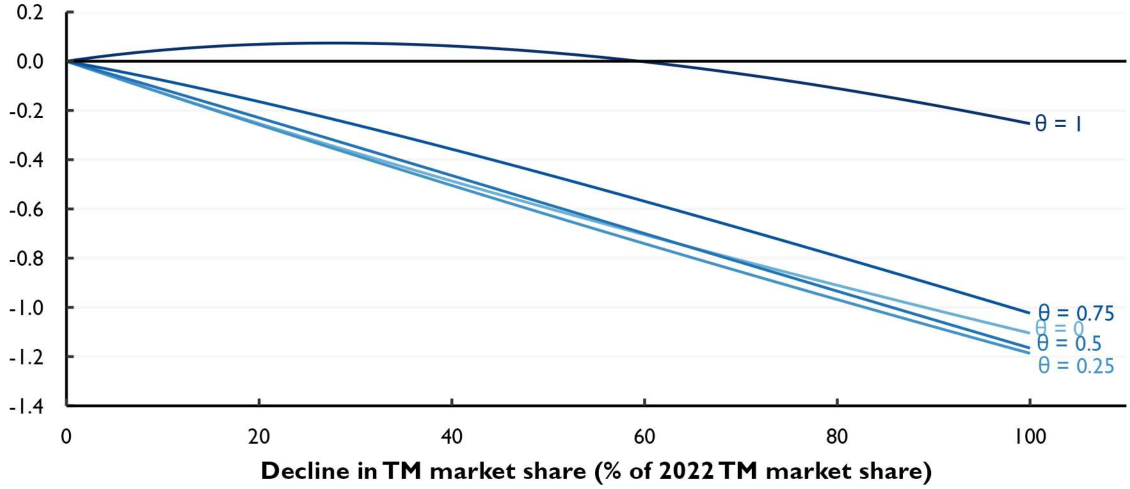
Note: Points and labels depict the average effect of a marginal increase in MA penetration in 2022 on the specified outcome, weighting each county by the number of Part A and B enrollees in the county in 2022. Error bars depict 95% confidence intervals. See text for details.

Figure 8 reports the results for the full range of changes in TM market share we consider, while Figure 9 reports selected point estimates and confidence intervals.[12] Across all scenarios, the predicted effects on selection are modest. In the scenario with $\theta = 1$, selection changes little as TM's market share shrinks. In the other scenarios, favorable selection declines as TM market share shrinks, but only modestly so. For example, in the scenario with the largest effect ($\theta = 0.25$), a 50% decline in TM market share produces a 0.6 log point decline in the TM-MA difference in risk-adjusted cost. These estimates are relatively precise; for all values of θ, our 95% confidence intervals for the effect of a 50% decline in TM market share exclude increases in the TM-MA difference in risk-adjusted costs larger than 0.9 log points and declines larger than 1.3 log points.

[12] The estimates shown in Figure ES-2 are identical to those shown in Figure 8 except that they have been transformed to percentage form; that is, if x denotes the estimate in Figure 8, then Figure ES-2 shows $\exp(x) - 1$. Strictly speaking, transforming the average change in the TM-MA log difference (what is shown in Figure 8) in this way does not produce the average change in the TM-MA ratio (what is shown in Figure ES-2), but they will be virtually identical for the small differences observed here. The upper and lower bound scenarios in Figure ES-2 correspond to $\theta = 1$ and $\theta = 0.25$, respectively. The $\theta = 0.25$ scenario results in the most negative estimates, except when considering very small changes in market share.

Figure 8. Change in Selection versus Change in TM Market Share

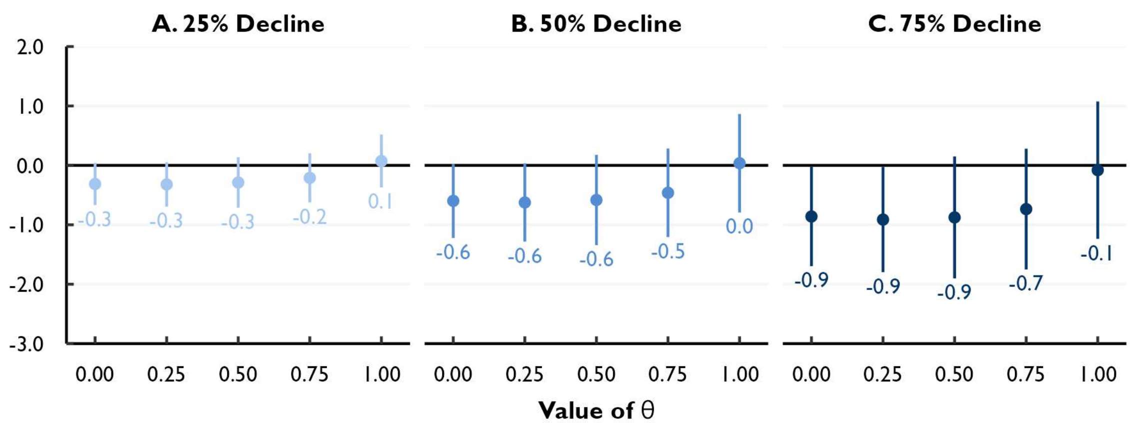
Average change in the TM-MA log difference in risk-adjusted cost (log points)



Note: Lines depict the average change in the TM-MA log difference in risk-adjusted cost for the specified assumption and decline in TM market share from its 2022 level, weighting each county by the number of Part A and B enrollees in the county in 2022. See text for details.

Figure 9. Effect of Discrete Declines in TM Market Share on Selection

Average change in the TM-MA log difference in risk-adjusted cost (log points)



Note: Points and labels depict the the average change in the TM-MA log difference in risk-adjusted cost for specified assumption and proportional decline in TM market share in 2022, weighting each county by the number of Part A and B enrollees in the county in 2022. Error bars depict 95% confidence intervals. See text for details.

Discussion

It is theoretically ambiguous how changes in MA penetration affect the degree of favorable selection into MA because rising MA penetration is likely to increase the average cost of both MA and TM enrollees, leaving the net effect uncertain. In this paper, we aim to resolve this uncertainty by estimating a structural model of the relationship between MA penetration and selection using data on stayer-switcher differences and MA penetration by county and year and considering a range of assumptions about the characteristics of TM-to-MA switchers. We use the model to simulate how increases in MA penetration would affect the degree of favorable selection into MA, finding that even large changes in MA penetration are likely to have small net effects on selection.

Our approach avoids some of the limitations of prior work that has examined the cross-sectional relationship between MA penetration and stayer-switcher differences (Lieberman et al. 2023; MedPAC 2025). Notably, we are able to explicitly account for the fact that TM-to-MA switchers may not be perfectly representative of MA enrollees overall. Additionally, because we use data for multiple years, we can control for persistent differences across counties that may confound the cross-sectional relationship between MA penetration and stayer-switcher differences.

Our approach does, however, have some limitations of its own. First, our estimates could still be confounded if changes in MA penetration are correlated with changes in county characteristics that affect favorable selection. Second, our structural model introduces strong functional form assumptions. If those assumptions are incorrect, it could distort our estimates and findings.

Nevertheless, our view is that the best interpretation of the available evidence is that further increases in MA penetration would have small effects on the degree of favorable selection into MA. If this view is correct, then it has a couple of notable implications. First, it suggests that changes in selection (and their corresponding effects on the generosity of MA plan payments) are unlikely to meaningfully amplify or dampen underlying trends in MA penetration.[13] In particular, it suggests that TM is currently at little risk of entering a selection-fueled "death spiral" in which increases in MA penetration exacerbate favorable selection, boost payments to MA plans, and thereby allow plans to lure still more beneficiaries away from TM.

Second—and related—it appears unlikely that rising MA penetration will change selection patterns in ways that substantially reduce the accuracy of MA payments. This echoes earlier findings that rising MA penetration is unlikely, at least in the medium-run, to reduce TM enrollment to a level where the estimates of local TM costs used to set MA payment benchmarks become statistically unreliable (Crow et al. 2025). Thus, while the MA payment system's *current* accuracy problems (e.g., MedPAC 2025) may justify substantial reforms—such as improvements to the program's risk adjustment system (e.g., McWilliams 2025a; 2025b; MedPAC 2025) or more fundamental reforms like the adoption of a "competitive bidding" regime that fully breaks the link between MA payment benchmarks and TM costs (e.g., MedPAC 2023; Ginsburg and Lieberman 2024)—concerns that rising MA penetration will exacerbate these accuracy problems likely do not.

[13] The evidence noted earlier that marginal increases in MA payment rates currently appear to have little effect on MA enrollment provides an additional reason to believe that these types of feedback effects are likely to be small, as they imply that even if rising MA penetration did change selection patterns and, in turn, plan payments, that would be unlikely to spur large follow-on changes in MA enrollment.

References

Baicker, Katherine, Michael E. Chernew, and Jacob A. Robbins. 2013. “The Spillover Effects of Medicare Managed Care: Medicare Advantage and Hospital Utilization.” *Journal of Health Economics* 32 (6): 1289–300. https://doi.org/10.1016/j.jhealeco.2013.09.005.

Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. 2025. *2025 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds*. https://www.cms.gov/oact/tr/2025.

Brown, Jason, Mark Duggan, Ilyana Kuziemko, and William Woolston. 2014. “How Does Risk Selection Respond to Risk Adjustment? New Evidence from the Medicare Advantage Program.” *American Economic Review* 104 (10): 3335–64. https://doi.org/10.1257/aer.104.10.3335.

Cabral, Marika, Michael Geruso, and Neale Mahoney. 2018. “Do Larger Health Insurance Subsidies Benefit Patients or Producers? Evidence from Medicare Advantage.” *American Economic Review* 108 (8): 2048–87. https://doi.org/10.1257/aer.20151362.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna. 2024. “Difference-in-Differences with a Continuous Treatment.” Working Paper No. 32117. Working Paper Series. National Bureau of Economic Research, February. https://doi.org/10.3386/w32117.

Chaisemartin, Clément de, Xavier D’Haultfœuille, Félix Pasquier, and Gonzalo Vazquez-Bare. 2022. “Difference-in-Differences for Continuous Treatments and Instruments with Stayers.” SSRN Scholarly Paper No. 4011782. Social Science Research Network, January 18. https://doi.org/10.2139/ssrn.4011782.

Chaisemartin, Clément de, Xavier D’Haultfœuille, and Gonzalo Vazquez-Bare. 2024. “Difference-in-Difference Estimators with Continuous Treatments and No Stayers.” *AEA Papers and Proceedings* 114 (May): 610–13. https://doi.org/10.1257/pandp.20241049.

Congressional Budget Office (CBO). 2024. “Medicare Baseline, June 2024.” June. https://www.cbo.gov/system/files/2024-06/51302-2024-06-medicare.pdf.

Crow, Samantha, Matthew Fiedler, and Julia Paris. 2025. *How Precise Are the Estimates of Traditional Medicare Costs Used to Set Medicare Advantage Benchmarks?* The Brookings Institution. https://www.brookings.edu/articles/how-precise-are-the-estimates-of-traditional-medicare-costs-used-to-set-medicare-advantage-benchmarks/.

Curto, Vilsa, Liran Einav, Amy Finkelstein, Jonathan Levin, and Jay Bhattacharya. 2019. “Health Care Spending and Utilization in Public and Private Medicare.” *American Economic Journal: Applied Economics* 11 (2): 302–32. https://doi.org/10.1257/app.20170295.

Einav, Liran, and Amy Finkelstein. 2011. “Selection in Insurance Markets: Theory and Empirics in Pictures.” *Journal of Economic Perspectives* 25 (1): 115–38. https://doi.org/10.1257/jep.25.1.115.

Einav, Liran, Amy Finkelstein, and Mark R. Cullen. 2010. “Estimating Welfare in Insurance Markets Using Variation in Prices.” *The Quarterly Journal of Economics* 125 (3): 877–921. https://doi.org/10.1162/qjec.2010.125.3.877.

Geruso, Michael, and Timothy Layton. 2020. “Upcoding: Evidence from Medicare on Squishy Risk Adjustment.” *Journal of Political Economy* 128 (3): 984–1026. https://doi.org/10.1086/704756.

Ginsburg, Paul, and Steven M. Lieberman. 2024. *Fixing Medicare Advantage With Competitive Bidding*. USC Schaeffer Center. https://schaeffer.usc.edu/research/fixing-medicare-advantage-competitive-bidding/.

Glazer, Jacob, and Thomas G. McGuire. 2017. "Paying Medicare Advantage Plans: To Level or Tilt the Playing Field." *Journal of Health Economics* 56 (December): 281–91. https://doi.org/10.1016/j.jhealeco.2016.12.004.

Jacobson, Gretchen, and David Blumenthal. 2022. "Medicare Advantage Enrollment Growth: Implications for the US Health Care System." *JAMA* 327 (24): 2393–94. https://doi.org/10.1001/jama.2022.8288.

Jacobson, Gretchen, Tricia Neuman, and Anthony Damico. 2019. *Do People Who Sign Up for Medicare Advantage Plans Have Lower Medicare Spending?* Kaiser Family Foundation. https://www.kff.org/report-section/do-people-who-sign-up-for-medicare-advantage-plans-have-lower-medicare-spending-issue-brief/.

Kronick, Richard, and F. Michael Chua. 2021. *Estimating the Magnitude of Medicare Advantage Coding Intensity and of the Budgetary Effects of Fully Adjusting for Differential MA Coding*. SSRN Scholarly Paper ID 3792038. Social Science Research Network. https://papers.ssrn.com/abstract=3792038.

Lancaster, Tony. 2000. "The Incidental Parameter Problem since 1948." *Journal of Econometrics* 95 (2): 391–413. https://doi.org/10.1016/S0304-4076(99)00044-5.

Lieberman, Steven M., Samuel Valdez, and Paul B. Ginsburg. 2023. *Medicare Advantage Enrolls Lower-Spending People, Leading to Large Overpayments*. USC Schaeffer Center. https://schaeffer.usc.edu/research/ma-enrolls-lower-spending-people-leading-to-large-overpayments/.

Lindstrom, Mary J., and Douglas M. Bates. 1990. "Nonlinear Mixed Effects Models for Repeated Measures Data." *Biometrics* 46 (3): 673–87. https://doi.org/10.2307/2532087.

McWilliams, J. Michael. 2022. "Don't Look Up? Medicare Advantage's Trajectory And The Future Of Medicare." *Health Affairs Forefront*, March 24. https://www.healthaffairs.org/do/10.1377/forefront.20220323.773602/.

McWilliams, J. Michael. 2025a. "Risk Adjustment Reform: Navigating Ideas And Tradeoffs (Part 1)." *Health Affairs Forefront*, March 26. https://www.healthaffairs.org/do/10.1377/forefront.20250317.758292/full/.

McWilliams, J. Michael. 2025b. "Risk Adjustment Reform: Navigating Ideas And Tradeoffs (Part 2)." *Health Affairs Forefront*, March 27. https://www.healthaffairs.org/do/10.1377/forefront.20250317.506040/full/.

Medicare Payment Advisory Commission (MedPAC). 2023. *Medicare and the Health Care Delivery System*. https://www.medpac.gov/wp-content/uploads/2023/06/Jun23_MedPAC_Report_To_Congress_SEC.pdf.

Medicare Payment Advisory Commission (MedPAC). 2024. *Medicare Payment Policy*. https://www.medpac.gov/document/march-2024-report-to-the-congress-medicare-payment-policy/.

Medicare Payment Advisory Commission (MedPAC). 2025. *Medicare Payment Policy*. https://www.medpac.gov/document/march-2025-report-to-the-congress-medicare-payment-policy/.

Mundlak, Yair. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica* 46 (1): 69–85. https://doi.org/10.2307/1913646.

Murray, Roslyn C., David J. Meyers, Erin C Fuse Brown, Travis C. Williams, and Andrew M. Ryan. 2024. "Association Between the Medicare Advantage Quartile Adjustment System and Plan Behavior and Enrollment." *JAMA Health Forum* 5 (1): e234822. https://doi.org/10.1001/jamahealthforum.2023.4822.

Newhouse, Joseph P., Mary Price, J. Michael McWilliams, John Hsu, and Thomas G. McGuire. 2015. "How Much Favorable Selection Is Left in Medicare Advantage?" *American Journal of Health Economics* 1 (1): 1–26. https://doi.org/10.1162/ajhe_a_00001.

Ochieng, Nancy, Meredith Freed, Jeannie Fuglesten Biniek, Anthony Damico, and Tricia Neuman. 2025. *Medicare Advantage in 2025: Enrollment Update and Key Trends*. KFF. https://www.kff.org/medicare/issue-brief/medicare-advantage-enrollment-update-and-key-trends/.

Pinheiro, José C., and Douglas M. Bates. 1996. "Unconstrained Parametrizations for Variance-Covariance Matrices." *Statistics and Computing* 6 (3): 289–96. https://doi.org/10.1007/BF00140873.

Schwartz, Aaron L., Seyoun Kim, Amol S. Navathe, and Atul Gupta. 2023. "Growth of Medicare Advantage After Plan Payment Reductions." *JAMA Health Forum* 4 (6): e231744. https://doi.org/10.1001/jamahealthforum.2023.1744.

Teigland, Christie, Zulkarnain Pulungan, Yalun Su, et al. 2023. *Harvard-Inovalon Medicare Study: Utilization and Efficiency Under Medicare Advantage vs. Medicare Fee-for-Service*. Inovalon. https://www.inovalon.com/wp-content/uploads/2025/05/INOV_Utilization-and-Efficiency-Under-Medicare-Advantage-vs.-Medicare-Fee-for-Service-5.21.25-v1.0.0.pdf.

Wooldridge, Jeffrey M. 2019. "Correlated Random Effects Models with Unbalanced Panels." *Journal of Econometrics*, Annals Issue in Honor of Jerry A. Hausman, vol. 211 (1): 137–50. https://doi.org/10.1016/j.jeconom.2018.12.010.

Xu, Lanlan, W. Pete Welch, Steven Sheingold, Nancy De Lew, and Benjamin D. Sommers. 2023. "Medicare Switching: Patterns Of Enrollment Growth In Medicare Advantage, 2006–22." *Health Affairs* 42 (9): 1203–11. https://doi.org/10.1377/hlthaff.2023.00224.

Appendix A: Additional model details

This appendix establishes the relationship between the concavity of $c(q)$ and the effect of MA penetration on favorable selection. To that end, let $\Delta(Q) = c^{\mathrm{TM}}(Q) - c^{\mathrm{MA}}(Q)$ denote the amount of favorable selection. At any point Q where c is continuous, Δ is differentiable and

$$\Delta'(Q) = \frac{1}{1-Q}\left[c^{\mathrm{TM}}(Q) - c(Q)\right] - \frac{1}{Q}\left[c(Q) - c^{\mathrm{MA}}(Q)\right]. \qquad (B1)$$

Suppose that there exists a linear function $g(q)$ with $g(Q) = c(Q)$ and $g(q) \leq c(q)$ for all $q \in [0,1]$. Letting m denote the slope of that function, it must be the case that

$$c^{\mathrm{TM}}(Q) \geq c(Q) + m\frac{1-Q}{2} \quad \text{and} \quad c^{\mathrm{MA}}(Q) \geq c(Q) - m\frac{Q}{2}. \qquad (B2)$$

Combining equations (B1) and (B2) yields $\Delta'(Q) \geq 0$. If $g(q) < c(q)$ on a set of positive measure, then the inequalities in equation (B2) are strict and, correspondingly $\Delta'(Q) > 0$.

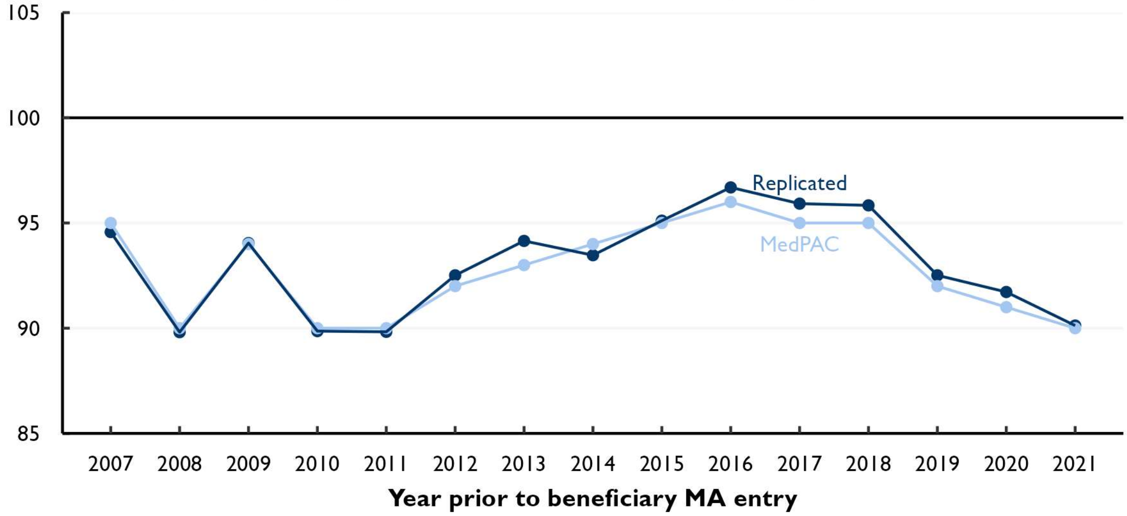
Similarly, if there exists a linear function $g(q)$ with $g(Q) = c(Q)$ and $g(q) \geq c(q)$ for all $q \in [0,1]$, then $\Delta'(Q) \leq 0$. If $c(q) < g(q)$ on a set of positive measure, then this inequality is strict.

An immediate corollary is that Δ is (strictly) increasing if the function c is (strictly) convex, (strictly) decreasing if the function c is (strictly) concave, and constant if c is linear.

Appendix B: Supplemental figure

Appendix Figure B-1. MedPAC vs. Replicated Switcher-Stayer Ratios

Ratio of risk-adjusted spending for TM-MA switchers and TM stayers (%)



Note: Figure reports the switcher-stayer switcher ratios reported in Figure 13-6 of MedPAC (2024), as well as our replicated versions of those estimates.